DETECTION OF MONKEY-POX DISEASE USING STATE OF ART DEEP LEARNING TECHNIQUES

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the
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APPROVAL

This Project titled **"Detection of Monkey-Pox Disease Using State of art Deep Learning Techniques "**, submitted by Md.Hamim Hossen , ID No: **192-15-2887** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 13 January, 2025.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Md. Sazzadur Ahamed , Assistant Professor**, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this projectnor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

The viral infection known as Monkey-pox has recently shown a significant increase in its spread. Diagnosing the disease poses a challenge for experts due to its resemblance to other illnesses, particularly those related to smallpox. This study contributes to the advancement of Monkey-pox disease detection through the introduction of a highly effective deep-learning methodology. We present an innovative method employing deep learning algorithms to accurately and efficiently identify pox diseases using image processing techniques. We evaluate several deep learning CNN architectures (ResNet50, InceptionV3, DenseNet121, and EfficientNetB2) based on their accuracy and computational efficiency. Employing data augmentation techniques enhances model generalization and diminishes overfitting, enabling robust feature learning. Our findings emphasize DenseNet121's superiority, achieving an outstanding 93.18% accuracy. DenseNet121 consistently demonstrates superior confidence rates and accuracy across disease categories, showcasing its reliability in pox disease identification. Moreover, DenseNet121 exhibits faster prediction times compared to other models, enhancing its suitability for practical implementation.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

Monkeypox, one of the world's most perilous and life-threatening illnesses, is caused by the monkeypox virus primarily originating from monkeys. Although commonly found in Asia, the Middle East, and western Africa, it has recently surfaced in various global regions. The virus can infect any species but primarily transfers to humans through bat or monkey bites. Early symptoms encompass a broad spectrum of discomforts, including muscle aches, headaches, fatigue, and fever, lasting two to four weeks. The incubation period typically ranges from 6 to 13 days, occasionally extending up to three weeks. The disease manifests in two phases: an initial invasion phase characterized by backaches, fever, lymph node swelling, intense headaches, muscle pain, and decreased energy; followed by the development of skin lesions after 1-3 days of fever.

The virus commonly spreads through close contact or contact with contaminated objects like mattresses or clothing[1]. Monkeypox, a zoonotic illness stemming from the Orthopoxvirus genus, exhibits clinical features closely resembling those of chickenpox, measles, and smallpox[2]. The subtle distinctions in the skin rash among these illnesses, along with the infrequency of monkeypox, have posed considerable challenges for healthcare practitioners in promptly diagnosing this condition. Additionally, the availability of confirmatory PCR tests remains limited. Despite a reported case fatality ratio of 3-6% in recent outbreaks, early identification of monkeypox, contact tracing, and isolation are crucial to curbing the virus's community transmission.

In such circumstances, AI-based automated computer-aided systems could significantly mitigate its worldwide dissemination[2]. This study holds significant importance in two key areas: first, creating and validating a DL-based model capable of precisely identifying and classifying monkeypox and chickenpox using digital skin lesion images. Second, it evaluates this model against state-of-the-art pre-trained models. These endeavors are vital for early virus identification, particularly in endemic regions, benefiting healthcare professionals and aid workers and preventing potential disease outbreaks. The proposed CNN model, trained with augmented images, shows potential in effectively detecting lesions, aiding in follow-up and treatment assessments.

1.2 Motivation

The detection of Monkey-pox poses a significant challenge within the spectrum of infectious diseases. Its elusive nature often leads to misdiagnosis, emphasizing the urgent need for a reliable and rapid detection method. Deep Learning (DL) emerges as a promising solution, offering a transformative approach to interpret intricate skin lesion patterns beyond human perception.

Our drive stems from the pressing need to equip healthcare systems with cutting-edge tools. We are committed to leveraging DL's capabilities to build a robust Monkey-pox detection model. This initiative aligns with our dedication to proactive healthcare interventions, aiming to revolutionize the speed and precision of diagnosis. Through the deployment of advanced technology, our goal is to empower healthcare professionals and vulnerable communities, enabling early identification and containment of outbreaks.

Our motivation is fueled by the potential profound impact of an efficient DL-based detection system: saving lives, averting epidemics, and bolstering global health resilience against emerging infectious threats.

1.3 Research Questions

- Q1: Is it possible to accurately detect the specific disease name using the proposed methodology?
- Q2: Can our methodology be effectively implemented on web-site for convenient and accessible disease detection?
- Q3: Which individuals or groups will be benefited greatly from this application ?

1.4 Project Outcome

Anticipated outcomes from Monkey-pox detection using deep learning:

- **Heightened Precision:** Deep learning models excel in accurately distinguishing Monkey-pox lesions amidst similar skin conditions, curbing diagnostic errors.
- **Rapid Identification:** A swift detection system's creation allows prompt Monkeypox identification, expediting crucial medical intervention.

- **Error Reduction:** Deep learning minimizes false results, ensuring precise identification, thereby averting unnecessary treatments or delays in appropriate care.
- **Enhanced Healthcare Reach:** Implementing a DL-based detection system improves healthcare access, particularly in remote or underserved areas, enabling timely diagnosis.
- **Early Outbreak Control:** Timely detection aids swift containment, aiding health authorities in curbing the spread of Monkeypox outbreaks.
- **Support for Medical Professionals:** Providing a dependable tool aids healthcare providers in informed decision-making, streamlining patient care.
- **Optimized Resource Utilization:** Efficient detection minimizes needless tests and consultations, optimizing resource allocation in healthcare settings.
- **Advancing Research:** Deep learning data contributes to better understanding Monkeypox epidemiology, supporting ongoing research endeavors.
- **Strengthened Global Health Readiness:** Successful Monkeypox detection models bolster strategies against emerging infectious diseases, fortifying global health preparedness.
- **Public Health Influence:** Implementation of a DL-based Monkeypox detection system ultimately saves lives, controls outbreaks, and elevates overall public health standards.

1.5 Report Layout

Chapter 1 provides a detailed overview of our thesis project, discussing the reasons for its selection, the planned methodology, the research motivation, and the expected outcomes. Essentially, it expands upon the introduction of the project.

Chapter 2 offers a comprehensive analysis of previous works in this field. It summarizes their findings and limitations while highlighting the research's scope and inherent challenges.

Chapter 3 thoroughly explores the research methodology, covering essential elements such as the chosen research subject and tools for data collection, the meticulous data collection process, the statistical analysis techniques used, and specific implementation requirements.

Chapter 4 is dedicated to presenting and analyzing the experimental results obtained during our study. It also includes a descriptive analysis of these findings.

Chapter 5 explores impact on society, environment and sustainability obtain during our study. It also includes a descriptive .

Chapter 6 serves as a concise conclusion, summarizing the key insights from our research and discussing potential future research directions. It encapsulates the culmination of our findings and highlights the significance of the conducted research. Additionally, this chapter includes a comprehensive list of references that contributed to our thesis research project's development.

CHAPTER 2
BACKGROUND

2.1 Introduction

Monkeypox detection through deep learning harnesses sophisticated neural network designs to discern and categorize monkeypox virus infections from medical datasets or images. Convolutional neural networks (CNNs) form the crux of these deep learning models, undergoing training on a wide array of images featuring monkeypox-related markers, lesions, or identifiable symptoms.

This pioneering method seeks to automate and heighten diagnostic precision by identifying specific visual indicators associated with the disease. By employing extensive datasets annotated with instances of monkeypox, these models acquire the ability to differentiate between infected and uninfected samples, aiding healthcare practitioners in early detection and timely intervention. The integration of deep learning in monkeypox detection presents the potential for faster, more effective, and life-saving diagnoses, thereby contributing significantly to the management and containment of this infectious ailment.

2.2 Related works

The following recent inquiries provide significant understanding regarding the historical background and progressions within this field:- Chiranjibi Sitaula et al.[3] investigates AI-based detection of Monkeypox amid declining COVID-19 cases. It explores 13 deep learning models, customized for virus detection, exhibiting promising precision, recall, F1-score, and accuracy around 85%. Ensemble methods enhance performance, particularly in distinguishing chickenpox and normal images compared to measles and monkeypox.

Ali et al.'s[4] study addresses the crucial need for monkeypox detection outside Africa. It introduces the "Monkeypox Skin Lesion Dataset (MSLD)" and employs VGG-16, ResNet50, and InceptionV3 models, achieving 79.26% to 82.96% accuracies. The study underscores the necessity for a more extensive and diverse dataset to enhance model generalization.

Ahsan et al.'s[5] paper addresses the monkeypox virus's pandemic threat, introducing the "Monkeypox2022" dataset for machine learning disease diagnosis. The study showcases a modified VGG16 model with high accuracy and utilizes LIME for virus-related feature insights. Dilber et al.[6] the study introduces a CNN model for accurate monkeypox detection from digital skin images, outperforming other deep learning models, showcasing promise in disease identification and classification.

Alrusaini et al.[7] assess deep learning models' accuracy in detecting Monkeypox through web-scraped images. VGG-16 emerges most effective (accuracy = 0.96, F1-score = 0.92), advocating AI's potential pending healthcare approval. Khan et al.[8] stress the need for reliable Monkeypox diagnosis, proposing an AI-based detection system. Inception-Resnet achieves 97% accuracy, offering potential benefits for improved screening in healthcare.

Saha et al.'s[9] study tackles early Monkeypox diagnosis challenges, emphasizing its similarity to chickenpox and measles. Employing pre-trained CNN models and majority voting, it highlights MobileNetV2, Xception, and Lenet's efficacy in distinguishing Monkeypox.

Chandrahaas et al.[10] address the pressing need for swift Monkeypox detection post-COVID-19. Their study, comparing AlexNet and GoogLeNet, highlights AlexNet's superior 83.61% accuracy, emphasizing AI solutions for early diagnosis and virus containment. Haque et al.'s[11] study focuses on human monkeypox outbreaks post-COVID-19. Utilizing deep transfer learning and attention mechanisms, Xception-CBAM-Dense stands out with 83.89% accuracy, highlighting attention mechanisms' role in disease classification.

Rezuana Haque et al.[12],the study introduces a novel method for early monkeypox detection using modified transfer learning and ensemble algorithms. It attains high accuracy, outperforming individual models, showcasing promise in disease identification.

Ali et al.[13] present MSLD v2.0, a diverse dataset with mpox and non-mpox lesions, employing advanced deep learning models and color space augmentation to combat bias. Achieving 83.59% accuracy, it supports a web app for mpox patient identification with six classification classes.

Talha et al.[14] the research introduces a deep learning model distinguishing monkeypox from other diseases, achieving 91.09% accuracy. This indicates potential for utilizing deep learning in disease identification. Akula et al.[15] explore Mpox skin lesion classification using CNN models, with Xception topping accuracy at 89.24%. The study advocates for broader datasets to bolster model generalizability across four classes. Arpita Mitra's et al.[16] study addresses the urgent need for Monkeypox detection post-COVID-19. Utilizing CNN technology, specifically VGG-19 models, the proposed approach achieves an impressive accuracy of 91.87%, showcasing its potential for early and accurate identification.

The current progress in detecting monkeypox remains unsatisfactory. While certain methods show promising results, they demand high computational time and are effective only with small datasets. Other approaches are faster but lack efficient performance. Addressing these limitations requires extensive research in healthcare.

2.3 Research Summary

Following Table 2.1 is showing a summary of related works.

TABLE 2.1: PREVIOUS RESEARCH REVIEW TABLE

Ref. N0.	Contribution	Methodology (Model/Algorithms)	Data set Name	Accuracy	Limitations
1.	Comparative analysis of 13 DL models improves detection.	13 pre-trained models used for Monkeypox virus detection.	Monkeypox image dataset collected from publicly	87.13%	Small dataset size restricts performance; deploying memory-constrained DL models needs consideration for improvement.
2.	Creation of Monkeypox Skin Lesion Dataset and application in deep learning classification.	The study employed VGG-16, ResNet50, and InceptionV3 for disease classification.	The dataset is collected from publicly available case reports and websites through manual searching, without using automatic web scrapers.	82.96%	The dataset size may limit model generalizability due to its small scale.
3.	Developed Monkeypox2022 dataset and ML model for accurate diagnosis.	The modified VGG16 model was used in this study.	the Monkeypox image data is collected from various sources such as websites, newspapers, and online portals and publicly shared samples.	97%	Continuous data updates, imbalanced data evaluation, comparison with other studies, mobile tool deployment.
4.	Explored diverse deep learning models for	The models used in this study were VGG-19, VGG-16,	The "monkeypox 2022 remastered" dataset was obtained from Kaggle.	99.25%	Dependency on image quality and similarity between

	diagnosing monkeypox from datasets.	MobileNet V2, GoogLeNet, and EfficientNet-B0.			pox diseases affects accuracy.
6.	Evaluated deep learning models for Monkeypox detection using web-scraped data.	The models used in this study were GoogLeNet, ResNet50, VGG-16, SqueezeNet, and InceptionV3.	used a web-scraping tool to search Google for Monkeypox, Measles, Smallpox, and healthy skin images.	96%	Further analysis needed for distinguishing Monkeypox from similar skin lesions diseases.
7.	Developed AI-based system for efficient monkeypox virus detection using transfer learning models.	The models used in this study for monkeypox virus detection are Inception-Resnet, VGG16, Inception, VGG19, and Resnet50.	The dataset used in this proposed work is obtained from Kaggle online repository and some new patients' data are added from various sources	97%	Small dataset used, limited application of pre-trained models.
8.	Utilized various CNN models for diverse monkeypox classification scenarios effectively.	The models used in this study included VGG-16, VGG-19, Restnet50, Inception-V3, Densnet, Xception, MobileNetV2, Alexnet, Lenet, and Majority Voting.	The images were collected by surfing the inter-net with relevant search results. They augmented the images using Keras ImageDataGenerator	97%	Reduced accuracy with limited data, imbalanced datasets affect model performance.
10.	Explored CNN models for rapid monkeypox detection, favoring AlexNet's accuracy.	The models used in this study were AlexNet and GoogLeNet for monkeypox detection.	internal secondary data from google and datasets from Kaggle.	83.61%	Reliance on smaller dataset affects overall model accuracy.
11.	Integrated CBAM into deep transfer learning models for effective monkeypox image-based classification.	The study used VGG19, Xception, DenseNet121, EfficientNetB3, and MobileNetV2 for monkeypox classification.	To classify Monkeypox among chickenpox, measles, and monkeypox we used Monkeypox Skin Lesion Dataset (MSLD) #This image dataset includes a total of 228 original images of measles and chickenpox	83.89%	Inadequate original images of monkeypox hindered comprehensive model training.
13.	Created MSLD v2.0 dataset, improved model accuracy for infectious skin disease classification.	VGG16, ResNet50, DenseNet121, MobileNetV2, EfficientNetB3, InceptionV3, Xception.	Mpox Skin Lesion Dataset Version 2.0 (MSLD v2.0)	83.59 ± 2.11%.	Dataset size and diversity, ethnic under-representation, lightweight model efficiency, and generalizability.

15.	Evaluating CNN models on a limited dataset for accurate Mpox lesion classification.	CNN models: VGG-16, VGG-19, ResNet50V2, ResNet101V2, Xception, DenseNet121, MobileNetV2.	Kaggle dataset consists of four classes which are similar to Mpox. the Mpox skin lension dataset intimately available from Kaggle(770 images).	89.24%	Dataset covers limited demographics, hindering broader model generalization and applicability.
16.	The study's contribution lies in introducing AI-driven VGG-19 for Monkeypox detection, enhancing early identification.	VGG-19	Kaggle dataset	91.87%	Improved performance requires a comprehensive, accurate dataset from medical sources.

2.4 Disease Context

Our research aims to manage distinct diseases linked to specific pox types—chickenpox, monkeypox, and healthy skin. Effective management and early detection of these diseases are pivotal in ensuring optimal pox-related outcomes.

Monkey-pox Chickenpox Healthy skin

Fig. 2.1 Affected pox and following diseases

2.4.1 Monkey Pox

Monkeypox, an infrequent zoonotic ailment, originates from the monkeypox virus in the Orthopoxvirus genus. Its transmission commonly arises from contact with infected animals such as rodents or primates, and sporadically through human-to-human contact. Manifestations encompass fever, headaches, muscle aches, and a unique rash that progresses into pustules and crusts. Despite being less severe than smallpox, its potential for outbreaks elevates its significance as a health hazard. Therefore, the necessity for vigilant containment and preventive strategies is crucial to restrain its dissemination among human populations. Stringent measures and robust public health interventions are imperative to mitigate the disease's impact and minimize its transmission rate, emphasizing the urgency to address and thwart the risks associated with monkeypox.

2.4.2 Chicken Pox

Chickenpox, caused by the varicella-zoster virus (VZV) within the herpesvirus family, transmits through respiratory droplets, direct contact with lesions, or airborne means. It presents as a rash with itchy, fluid-filled blisters, accompanied by fever and fatigue. While generally mild in healthy children, its severity can heighten in adults and immunocompromised individuals. Although usually manageable, the disease holds potential risks in specific populations, demanding attentiveness—particularly in vulnerable groups—to prevent complications and ensure timely medical attention if necessary. Monitoring these groups becomes crucial for early intervention and preventive measures to curtail potential adverse outcomes associated with the infection.

2.4.3 Healthy skin

Healthy skin signifies the absence of visible skin lesions, rashes, or irregularities. It presents as smooth, uniform skin, free from redness, swelling, or anomalies. Recognizing these traits is pivotal in diagnosing skin conditions, enabling the differentiation between normal and pathological states. This understanding aids clinicians in accurate assessments and effective treatment plans. Proficiency in healthy skin characteristics allows medical experts to identify abnormalities promptly, aiding in the management of skin disorders. This knowledge is critical in clinical evaluations, underscoring the significance of identifying healthy skin attributes for precise dermatological assessments and enhancing diagnostic accuracy for various skin-related issues.

2.5 Challenge

Detecting monkeypox through deep learning encounters various challenges. Limited datasets hinder model training and validation, impacting classification accuracy. The disease's rarity and similarity to other skin conditions pose challenges in early diagnosis, potentially leading to misclassification. Imbalanced datasets—varying proportions of monkeypox samples versus other skin diseases—can skew model performance. Furthermore, addressing the scarcity of diverse datasets representing different demographics and geographical regions poses a challenge. Ensuring model robustness against racial biases in image datasets is critical. Additionally, deploying deep learning models in resource-constrained environments requires optimizing computational resources for real-time diagnosis. Interpretability of model decisions and generalizing model performance to new, unseen data remain ongoing challenges. Addressing these hurdles necessitates comprehensive dataset curation, model robustness testing, and ethical considerations to enhance the reliability and effectiveness of monkeypox detection using deep learning techniques.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

In this segment, we comprehensively explore various facets of our research, encompassing key domains: the research focus, tools, data collection, processing, methodology, statistical analyses, and implementation requisites. Starting with the research focus and tools used, we delve into the specific subject area and employed instrumentation. Moving to data collection, we elucidate the meticulous approach undertaken to acquire requisite data. Subsequently, in data processing, we outline techniques applied to refine and preprocess collected data, optimizing it for model application. The proposed methodology section offers a succinct overview of algorithms and approaches within our classification framework. Transitioning to statistical analysis, we present analytical methods and flowcharts used in our project. Finally, this chapter culminates in a comprehensive summary detailing the resources and components leveraged throughout our research efforts.

3.2 Research Subject and Equipment

The research subject focuses on employing deep learning techniques to detect monkeypox. The investigation primarily involves the utilization of Convolutional Neural Network (CNN) architectures for the classification of monkeypox from skin lesion images. The necessary equipment comprises high-performance computing resources, GPUs (Graphics Processing Units), and software frameworks like TensorFlow or PyTorch for model development and training.

3.3 Data Collection and Acquisition

To perform this experiment, we have collected internal secondary data from google and datasets from Kaggle. Additional images of healthy skin were added to the dataset to increase the size. The dataset contains data filed in two different formats: preprocessed_original_images and augmented_images. preprocessed_original_images file contains the original unprocessed images, whereas augmented_images file contains the augmented data. augmented_images file contains 1028 chickenpox, 1222 healthy and 1219 monkeypox images. preprocessed_original_images file contains 75 chickenpox, 123 healthy and 284 monkeypox images. Both augmented data and raw original data were used in this study.

3.4 Statistical Analysis

In our research report, a total of 3469 image data points were collected, representing 3 different classes. Among the classes, the class "Healthy Skin" had the highest number of images, with a count of 1222. The 2nd class "Monkeypox" had the 2nd highest number of images, with a count of 1219. and On the other hand, the class "Chickenpox" had the fewest images, with a count of 1028.To provide insights into the image characteristics, an analysis of the average height and width was conducted on a sample of the dataset. The average height was found to be approximately 224 pixels, while the average width was approximately 224 pixels. This yielded an aspect ratio of approximately 0.9307.These statistical findings shed light on the distribution of image data and the image characteristics within the dataset, providing valuable information for further analysis and interpretation in the research report.

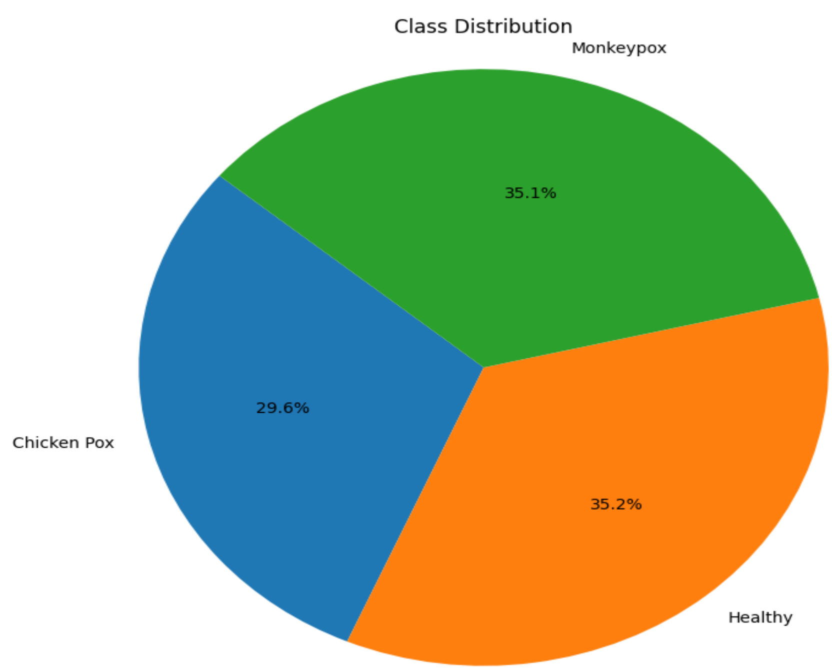

Fig. 3.1: A pie chart of the class distribution in the data set

3.4.1 Classes

This research project amassed and analyzed a dataset containing 3469 images distributed across three distinct classes, representing two diseases and healthy conditions. The table below offers a comprehensive view of these classes, displaying the respective image counts. This tabulated representation demonstrates the dataset's diversity and distribution, emphasizing the differing sample sizes within each class.

TABLE 3.1: CLASS DISTRIBUTION OF THE DATASET

CLASS	IMAGE COUNT
MonkeyPox	1219
ChickenPox	1028
Healthy Skin	1222

3.5 Data enhancement and Image Pre-processing

Throughout this study, we utilized two distinct data augmentation methods to augment the training process. The initial technique encompassed conventional augmentation methods like image flipping, scaling, cropping, length and width distortion, and color gamut transformation. These methods substantially bolstered the variety within the training samples, thereby enhancing the network's proficiency in extracting significant features.

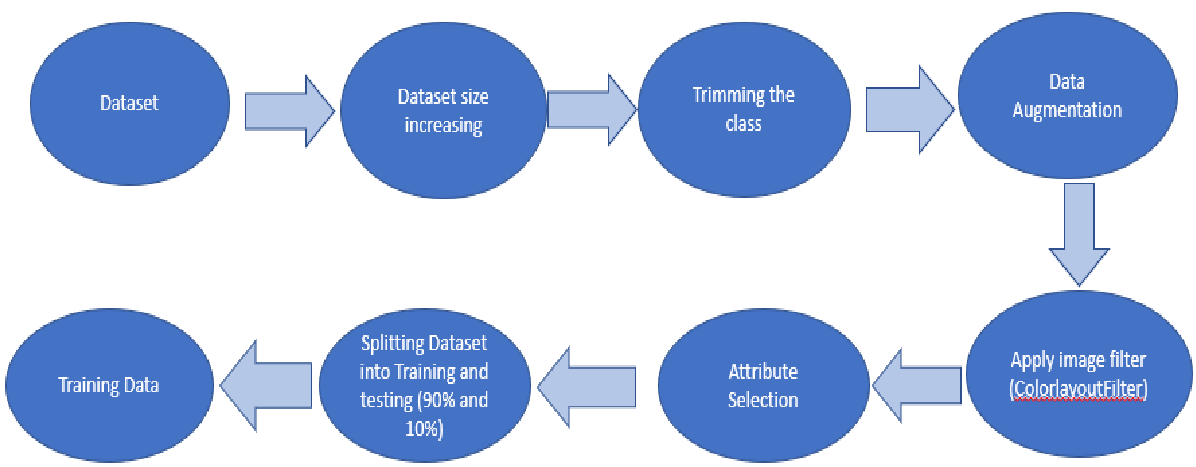

Fig. 3.2: Flow diagram of the data per-processing

Additionally, we integrated the mosaic data augmentation method following the framework outlined in the YOLOv5 paper. This technique involved the random cropping and merging of four images into a singular image for training purposes. While the mosaic method significantly diversified the samples, it slightly deviated from the typical image distribution. To counterbalance this, we employed a hybrid approach: utilizing the mosaic augmentation for the initial 30% of training iterations and transitioning to standard augmentation for the subsequent 70%. This strategy aimed to harmonize diversity and maintain alignment with natural image characteristics, enhancing the overall efficacy of network training. All images were resize uniformly to 224 × 224pixels in our experiments to ensure consistent input dimensions for the model. During the training phase, we opted for a batch size of 30, effectively optimizing training efficiency and resource utilization.

3.5.1 Image Augmentation

Utilizing image augmentation techniques significantly enhances training dataset quality and diversity for deep learning models. Through applying various modifications and transformations to existing images, augmentation diversifies datasets by introducing variations in lighting, viewpoints, scales, and other essential factors. This process not only fortifies the model's robustness but also combats overfitting, enhancing its capacity to generalize to new data. In the ensuing section, we'll explore how image augmentation significantly boosts the efficacy and precision of our deep learning-powered multi-pox disease detection system.

3.5.1.1 Trimming Dataset

In order to decrease the standard error within a dataset containing outliers and slight deviations from normality, we utilized a trimming method. This method encompassed capping the maximum number of samples in each class at 1000 and guaranteeing that the minimum number of samples in any class was 450. Our objective was to enhance the overall quality and inclusiveness of the labeled dataset by equalizing the sample distribution across various classes. The detailed breakdown of specific categories and their respective quantities of diseases within the labeled dataset can be found in Table 3.2.

TABLE 3.2: CLASS DISTRIBUTION AFTER TRIMMING

Class	Number
Monkey Pox	1219
ChickenPox	1028
Healthy Skin	1222
Total images for the training set	3469

3.6 Proposed Methodology

In this section, we provide a thorough overview of the algorithms, methodologies, and models employed in our approach. By harnessing the power of deep learning and advanced image processing techniques, our methodology strives for precise identification and classification of diseases impacting various poxes. We'll delve into the intricate specifics of our methodology, emphasizing essential stages such as data preprocessing, model training, and performance evaluation. This proposed methodology acts as a guiding framework for our research, paving the path toward creating an effective and dependable system for detecting multi-pox diseases.

3.6.1 Deep Learning Algorithm

For monkeypox detection, Convolutional Neural Networks (CNNs) serve as a potent deep learning algorithm. CNNs specialize in image-based tasks by leveraging hierarchical layers to automatically learn and extract intricate features from images. The network's convolutional layers identify patterns such as textures, edges, and shapes, while pooling layers condense learned features, enhancing computational efficiency. Specifically, for monkeypox detection, a tailored CNN architecture undergoes training on a diverse dataset, fine-tuning parameters through backpropagation, and optimizing weights to accurately identify disease-specific features. Transfer learning, utilizing pre-trained models on larger datasets, aids in limited data scenarios. With its ability to discern subtle image nuances, CNNs excel in pinpointing distinctive disease markers, enabling precise detection and classification of monkeypox-related patterns within medical imagery.

3.6.2 CNN Model Architecture

The Convolutional Neural Network (CNN), a prominent deep learning algorithm, has gained widespread recognition for its autonomous discernment of pertinent features, obviating the need for human intervention [16]. This has led to extensive applications across diverse domains, especially in computer vision. Neural network pooling operations typically employ the maximum value within a pooling window for down-sampling [17]. Activation function layers, like ReLU, introduce crucial non-linearity to the network architecture. Dropout layers mitigate overfitting by randomly deactivating neurons. Fully connected layers compute class probabilities or scores, often serving as inputs to classifiers, where the softmax classifier is commonly used.

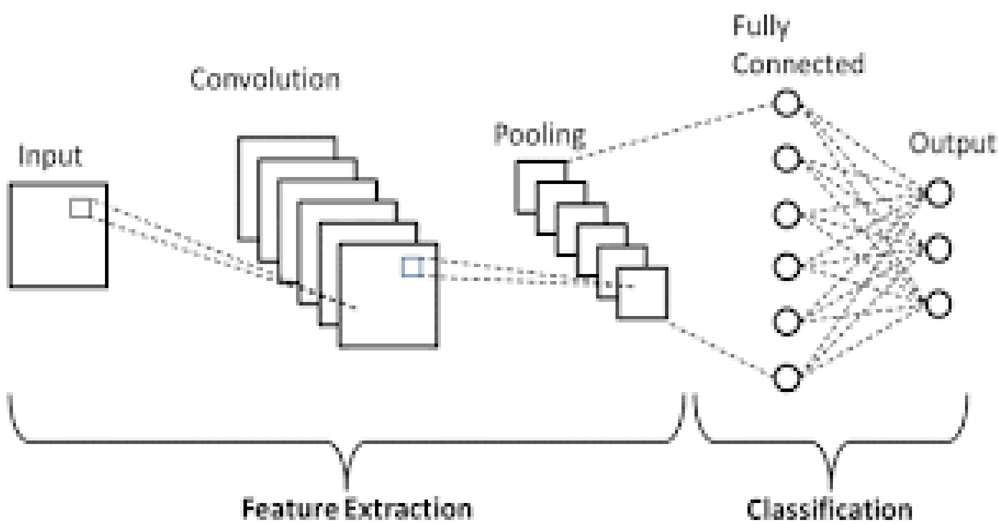

Fig 3.4: CNN architecture for the detection and classification of pox disease[25]

The CNN architecture consists of five primary components as illustrated in Figure 3.4: the input layer, convolution layer, down-sampling layer, fully connected layer, and output layer. Within the CNN framework, input data is treated as a two-dimensional image, seamlessly integrating the feature extraction module into its structure. The hidden layers encompass multiple two-dimensional planes housing numerous neurons.

3.6.3 ResNet50 model

ResNet, also recognized as the Residual Network, stands out as a distinctive variant of convolutional neural networks (CNNs) due to its inclusion of a residual structure. This architectural innovation empowers ResNet to effectively retain original information while minimizing network parameters. Introduced by He et al. [18], ResNet showcases exceptional depth, spanning multiple layers, thereby augmenting its capability for feature representation and extraction. CNNs hold widespread utility in computer vision applications, and the 50-layer ResNet employs a bottleneck design within its building blocks. This design incorporates 1×1 convolutions to diminish parameters and matrix multiplications, expediting the training process for each layer. The below architecture shows a defined view of ResNet50 model

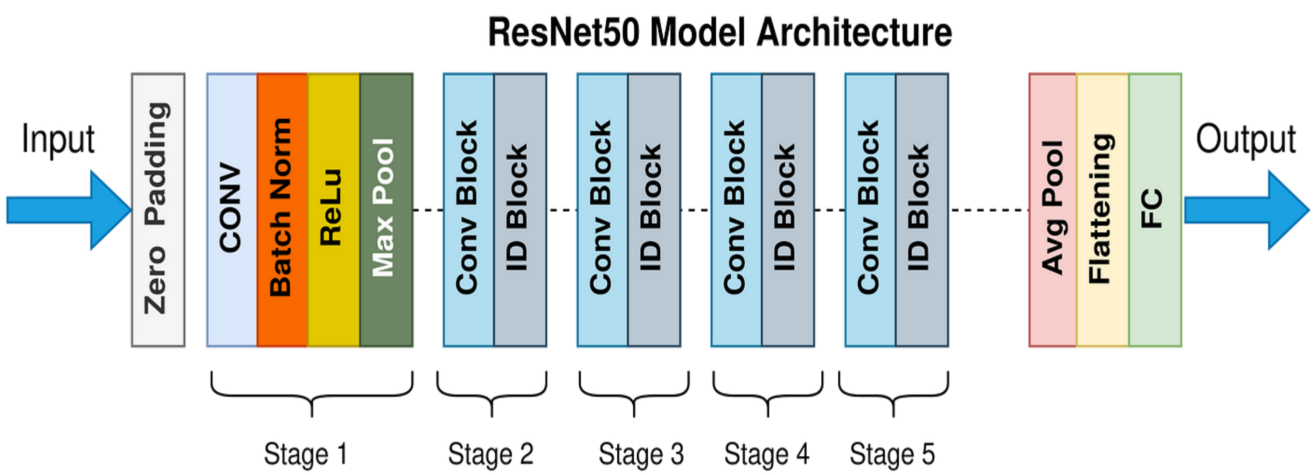

Fig. 3.5: Architecture of ResNet50[26]

Utilizing a stack of three layers instead of two, ResNet proficiently learns and models residuals, enabling the network to grasp intricate relationships and finer details, thus elevating its overall performance. The input image size for ResNet50 stands at 224x224 pixels. Illustrated in Figure 3.5 and introduced by et al. [19], the ResNet50 architecture comprises a framework organized into identity and convolution blocks, structured within modules. This stacked convolutional structure spans 49 layers, accompanied by a fully connected layer, culminating in a 50-layer residual neural network. Previous studies have highlighted the convolutional layer's efficacy as a high-level feature extractor . In alignment with these methodologies, our research utilizes a CNN model that extracts image features from the final convolutional layer of the network.

3.6.4 InceptionV3 model

Inceptionv3 is a convolutional neural network employing diverse branches of convolutional layers with varying kernel sizes to capture features across multiple scales. This strategy enhances accuracy and efficiency in contrast to conventional convolutional neural networks.The inception micro-architecture embodies a network structure comprising stacked modules and periodic max-pooling layers that reduce the grid resolution by a factor of two. To optimize memory efficiency during training, inception modules were primarily integrated into higher layers while preserving lower layers in a traditional convolutional approach, addressing inherent infrastructural inefficiencies . These inception modules aim to serve as "multi-level feature extractors" by incorporating ‘1×1’, ‘3×3’, and ‘5×5’ convolutions within the same network module. Outputs from these convolutional filters are stacked along the channel dimension and fed into subsequent layers . With over 20 million parameters, industry-leading hardware professionals have trained this model. Its architecture comprises symmetrical and asymmetrical building blocks, integrating convolutional, average pooling, max pooling, concatenation, dropout, and fully connected layers. Batch normalization is extensively employed, applied to the input of the activation layer. For classification, the softmax function is utilized . The below architecture shows a defined view of Inception V3 model

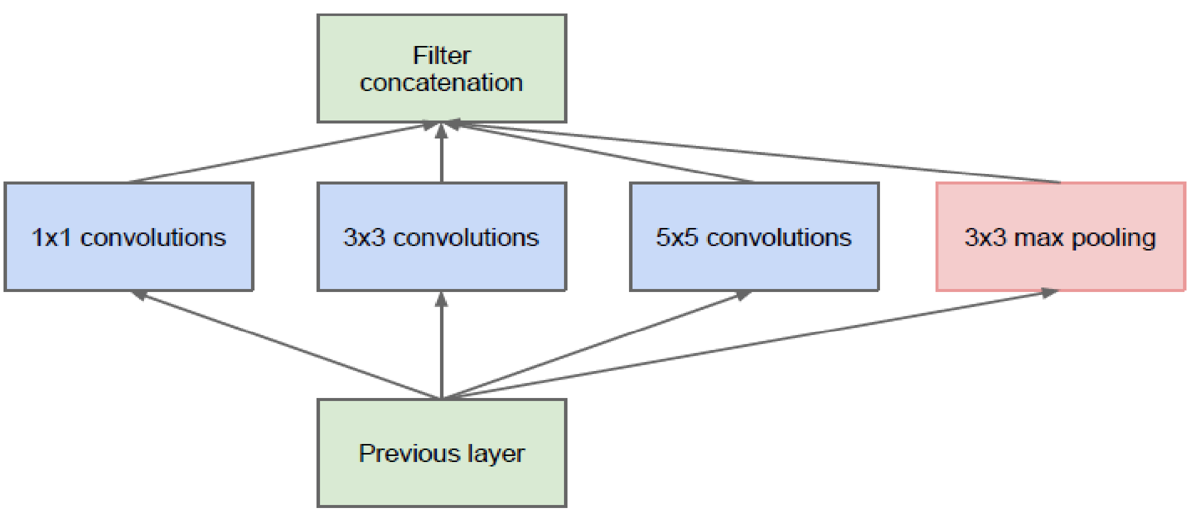

Fig. 3.6: Architecture of Inception V3 model[27]

3.6.5 DenseNet121 model

DenseNet121 is a convolutional neural network architecture known for its efficient parameter utilization and feature reuse. Comprising 121 layers, it employs dense connectivity patterns between layers, allowing each layer to receive feature maps from all preceding layers, fostering strong feature propagation. This connectivity pattern reduces the vanishing-gradient problem and encourages feature reuse, enhancing model accuracy while maintaining computational efficiency. DenseNet121's architecture facilitates deeper networks without encountering degradation issues, enabling robust feature extraction and classification in computer vision tasks like image recognition, object detection, and segmentation. Its design has made it a popular choice in various deep learning applications due to its balance between accuracy, efficiency, and architectural simplicity.

DenseNet121, represents a deep CNN architecture founded on densely connected layers, establishing direct connections between each layer in a feed-forward manner. This design promotes extensive feature reuse across layers, fostering the network's ability to acquire more condensed representations. Notably, it stands among the deep CNN networks designed specifically for the analysis of intricate images[20]. The below architecture shows a defined view of DanseNet121

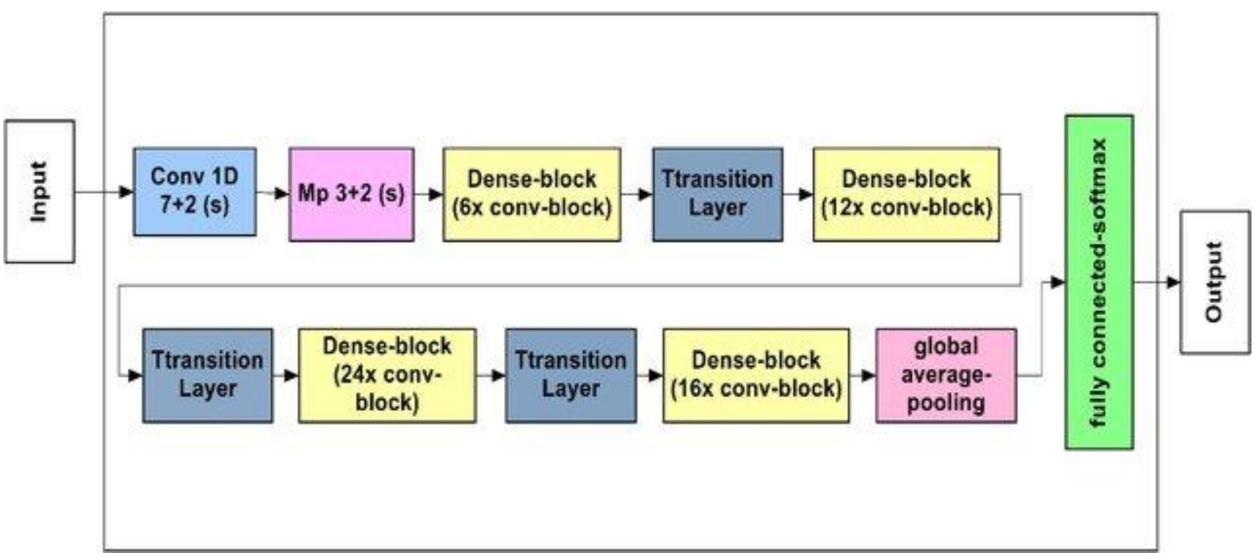

Fig. 3.6: Architecture of DenseNet121 model [28]

3.6.6 EfficientNetB2 Model

EfficientNetB2, an iteration within the EfficientNet series, stands out as a formidable Convolutional Neural Network (CNN) with amplified depth and width compared to its predecessors. Boasting 339 layers (excluding the top layer), it employs an intricate scaling technique to harmonize model efficiency and accuracy. The architecture incorporates a stem block managing input processing, normalization, convolution, and activation, alongside a body comprising five modules that integrate depth-wise convolution, batch normalization, and activation layers. Acknowledged for its versatility in tackling diverse computer vision tasks, EfficientNetB2 adeptly balances between model intricacy and performance, making it a compelling choice for applications like image recognition, object detection, and segmentation within the realm of deep learning. The below architecture shows a defined view of EfficientNetB2

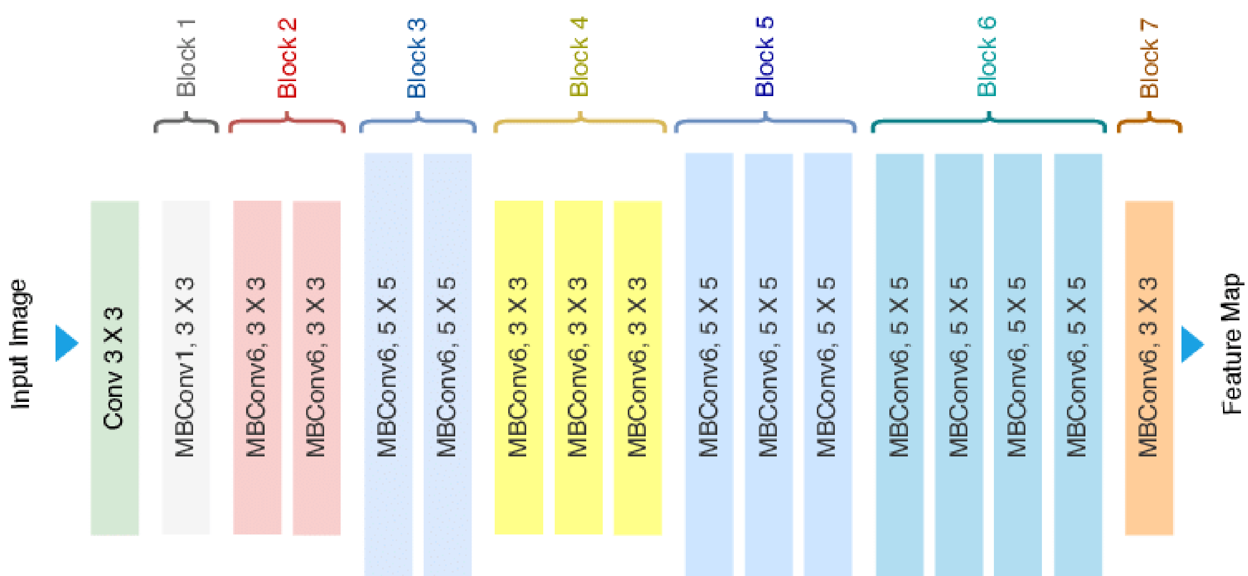

Fig. 3.7: Architecture of EfficientNetB2 Model[29]

3.7 Working Procedure

In our investigation into multi-pox disease detection, we employed data augmentation as a crucial method to enhance the effectiveness and overall ability of our deep learning models. The process of pox detection via deep learning involves several key stages. Initially, a comprehensive dataset of pox-related images is amassed and prepared, ensuring diverse representations. Image preprocessing methods, like resizing, normalization, and augmentation, are applied to standardize the data and augment the dataset's variability. Subsequently, a suitable deep learning model, often Convolutional Neural Networks (CNNs), is selected and trained using the curated dataset to learn distinctive features associated with pox infections. The model undergoes rigorous evaluation and validation using separate test sets to assess its accuracy and generalization capabilities. Fine-tuning and optimization techniques are then employed to enhance the model's precision and sensitivity in identifying pox-related patterns in images. Continuous monitoring, model refinement, and potential retraining further bolster the system's efficacy in robust pox detection. The below architecture shows a defined view of proposed method

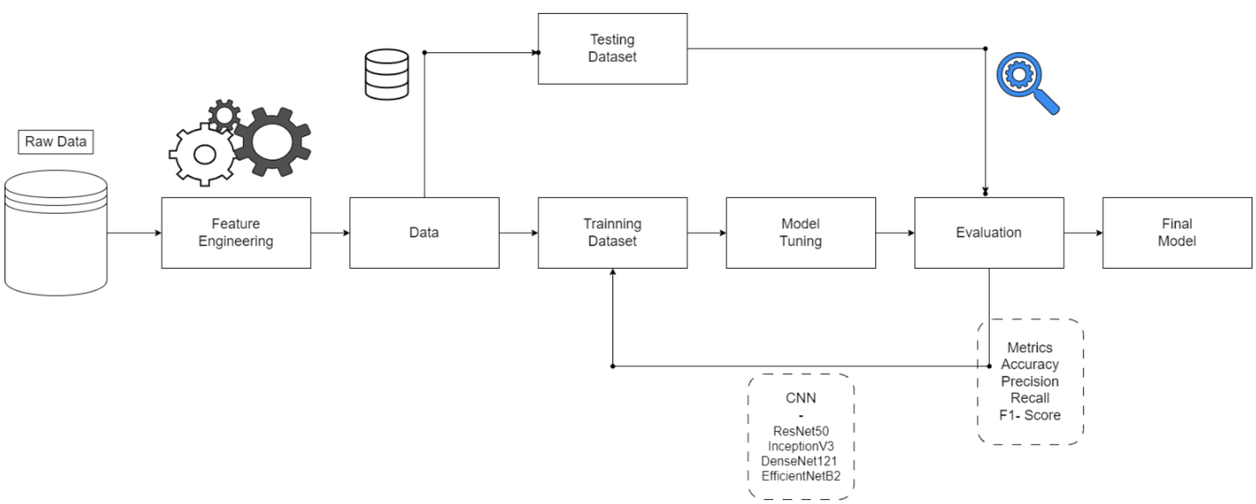

Fig. 3.8: Overall Architecture of proposed method

When evaluating models, the focus lies on accuracy, precision, recall, and F1-scores. Accuracy denotes correct predictions against all possible ones. Precision measures truly positive predictions against actual positives. Recall mirrors precision, gauging predicted positives that are actual positives. F1-score is the harmonic mean of recall and precision, crucial metrics for Monkeypox detection reliability from skin images. An F1-score of at least 0.90, as per [21], signifies an effective predictive analysis. This study prioritizes accuracy and F1-score, crucial for model reliability, considering their combined utility. While other metrics are reported, equations from were used to compute these metrics.

$$Accuracy = \frac{TP + TN}{Total\ Number\ of\ Tuples} \qquad (1)$$

$$Precision = \frac{TP}{TP+FP} \qquad (2)$$

$$Recall = \frac{TP}{TP+FN} \qquad (3)$$

$$F1\ Score = 2 \times \frac{Precision\ \times Recall}{Precision + Recall} \qquad (2)$$

During evaluation, TP (True Positive) signifies correctly predicted positive samples, FP (False Positive) denotes incorrectly predicted negative samples, and FN (False Negative) represents incorrectly predicted positive samples.

3.8 Implementation Requirements

The vital implementation requisites for our multi-pox disease detection system encompass hardware, software, and computational infrastructure essential for model training and deployment. We detail the data acquisition phase, involving dataset collection, labeling, and organization. Additionally, specific tools, libraries, or frameworks utilized in implementation are addressed. By elucidating these requirements, we establish the groundwork for achieving our research objectives, ensuring a smooth and effective development process for our multi-pox disease detection system.

Hardware/Software Requirements

- 64-bit OS Windows 11 (Windows 7 or above)
- RAM 16GB (more than 8 GB)
- WEB Browser (preferably Google Chrome)
- Ryzen 5 3600X Processor; Similar to Intel Core i5 12Gen (Ryzen 5/Intel Core i5 or above)
- Graphics GeForce GTX 1660 6GB (not necessary)

Developing Tools

- python 3.10.9
- Google CoLab
- CNN Models
- Pandas
- Numpy
- Keras
- Tansorflow (executing the computational operations at the backend)
- Matplotlib

CHAPTER 4

IMPLEMENTATION RESULTS AND DISCUSSION

4.1 Experimental Setup

In our experimental setup, a meticulous procedure was executed for data collection and preparation in our model implementation and code development. The key steps included:

- Data Collection: A comprehensive collection of healthy and diseased plant leaf images was curated from diverse sources, including reputable repositories like Kaggle and Mendeley, to address disease detection comprehensively.
- Data Normalization: We systematically finalized and normalized the collected data, ensuring a consistent and standardized dataset for subsequent analysis and model development.
- Labeling and Class Formation: Through careful labeling and organization, the dataset was meticulously categorized into distinct classes, enabling effective classification and analysis.
- Image Preprocessing:

a)Resizing and Reshaping: Advanced image manipulation techniques were employed to uniformly resize and reshape all images, ensuring consistent dimensions for seamless integration into subsequent research stages.

b)Pooling Layer: Skillful utilization of sophisticated pooling layers aided in eliminating negative pixels and extracting valuable image features strategically. This process significantly enhanced image quality and usability for subsequent analysis and processing.

4.2 Experimental Results

We evaluated the models using key metrics: precision, accuracy, and F1-score. Additionally, training and validation losses, along with confidence rates, gauged prediction certainty matching actual and predicted classes. The experimental results are detailed in Tables 4.1 and 4.2, showcasing the study's outcomes.

TABLE 4.1: EXPERIMENTAL RESULT OF DEEP LEARNING MODELS FOR ResNet50 AND InceptionV3

Class Name	ResNet50				InceptionV3			
	Precision	Recall	F1 score	Avg. Acc.	Precision	Recall	F1 score	Avg. Acc.
Chicken Pox	0.7778	1.0000	0.8750	89%	0.7000	1.0000	0.8235	90.91%
Healthy	0.9048	10000	0.9500		0.9500	1.0000	0.9744	
Monkey pox	1.0000	0.7778	0.8750		1.0000	0.7778	0.8750	

TABLE 4.2: EXPERIMENTAL RESULT OF DEEP LEARNING MODELS FOR DenseNet121 AND Efficient Net B2

Class Name	DenseNet1 21				EfficientNetB2			
	Precision	Recall	F1 score	Avg. Acc.	Precision	Recall	F1 score	Avg. Acc.
Chicken Pox	0.7778	1.0000	0.8750	93.18%	0.7770	1.0000	0.8730	91%
Healthy	0.9500	10000	0.9744		0.9500	1.0000	0.9744	
Monkey pox	1.0000	0.8333	0.9091		1.0000	0.7778	0.8750	

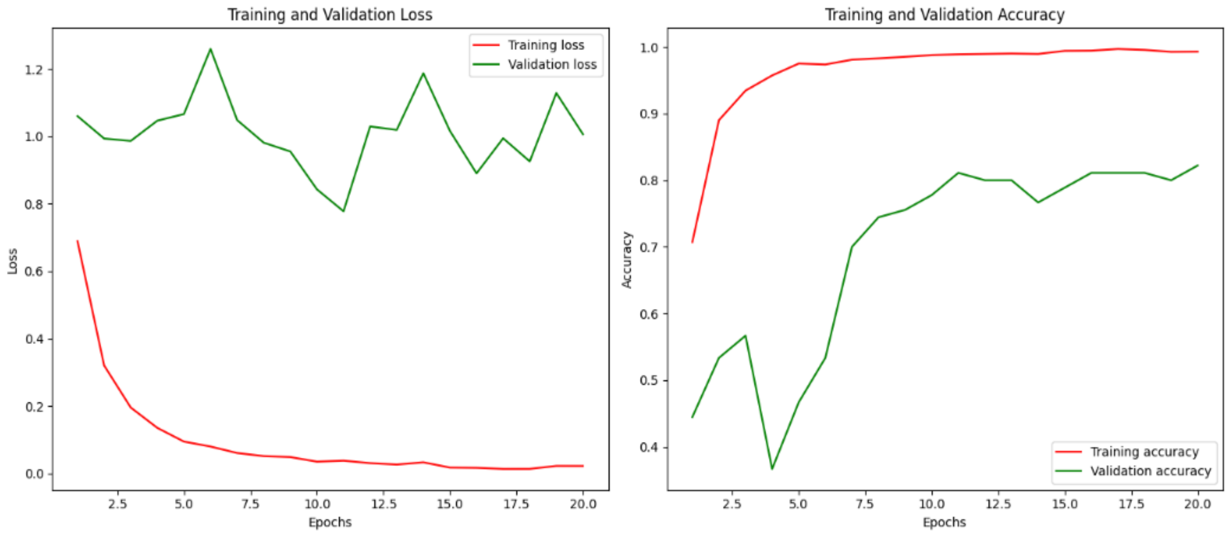

Fig. 4.1: ResNet50 accuracy checking graph

Fig. 4.2: InceptionV3 accuracy checking graph

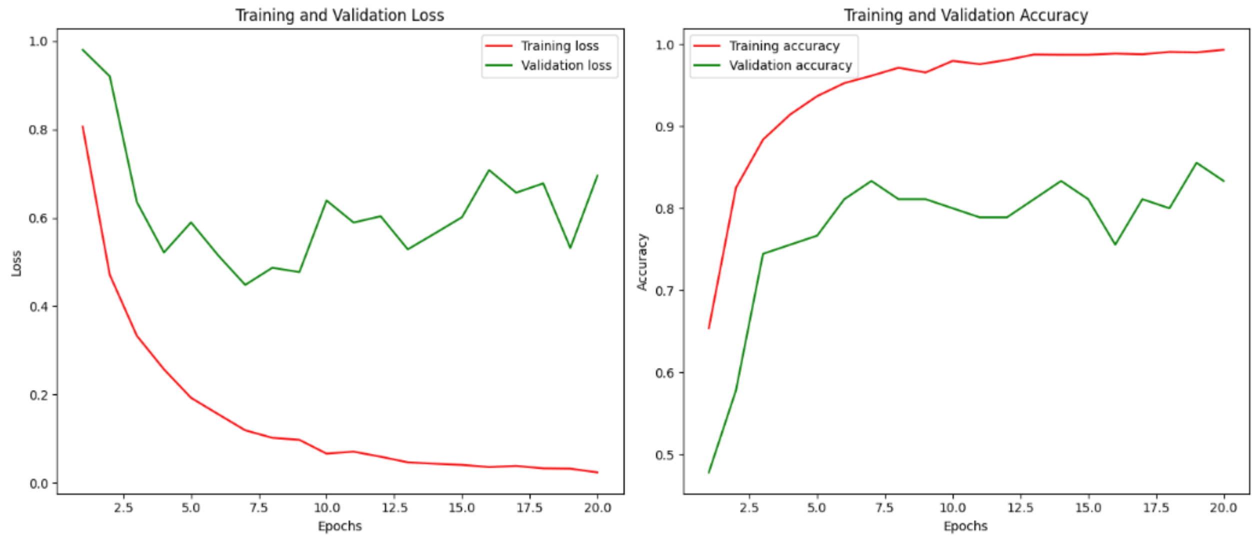

Fig. 4.3: DenseNet121 accuracy checking graph

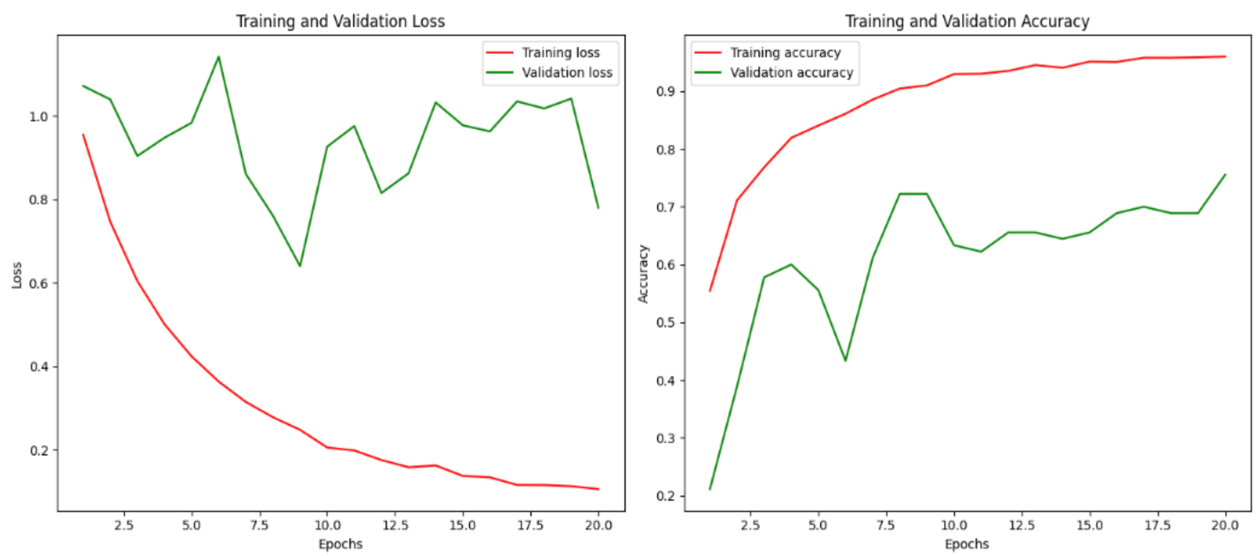

Fig. 4.4: InceptionV3 accuracy checking graph

The image processing-driven monkeypox disease prediction and detection system surpassed prior research endeavors. Using DenseNet121, we achieved a remarkable accuracy of 93.18%, outperforming other models—EfficientNetB2, InceptionV3, and ResNet50—with accuracies of 91%, 90.91%, and 89%, respectively. Among these algorithms, DenseNet121 displayed the highest accuracy and confidence rates. Additionally, specific classes showed high confidence rates in alternative algorithms, indicating specialization. The amalgamation of multiple algorithms holds potential for enhanced performance and accuracy. Instances with compromised image quality saw reduced confidence rates; however, consistently high-quality images attained a 100% confidence rate. Notably, DenseNet121 remained impactful in predictions despite limited computational resources, unlike InceptionV3 and ResNet50, which faced underfitting challenges. DenseNet121's confusion matrix demonstrated a remarkable 90.91% accuracy across each category. When examining confidence rates for Monkeypox or Healthy Skin images, DenseNet121 consistently maintained or increased rates while other models experienced drops. Moreover, DenseNet121 achieved its peak accuracy within 20 epochs, surpassing other models. Notably, it excelled in speed, requiring only 1.5 seconds per image compared to 3-6 seconds for other models, showcasing its efficiency in predicting various pox diseases. Hence, DenseNet121 stands out for its efficiency, speed, and superior predictions in diverse pox disease scenarios.

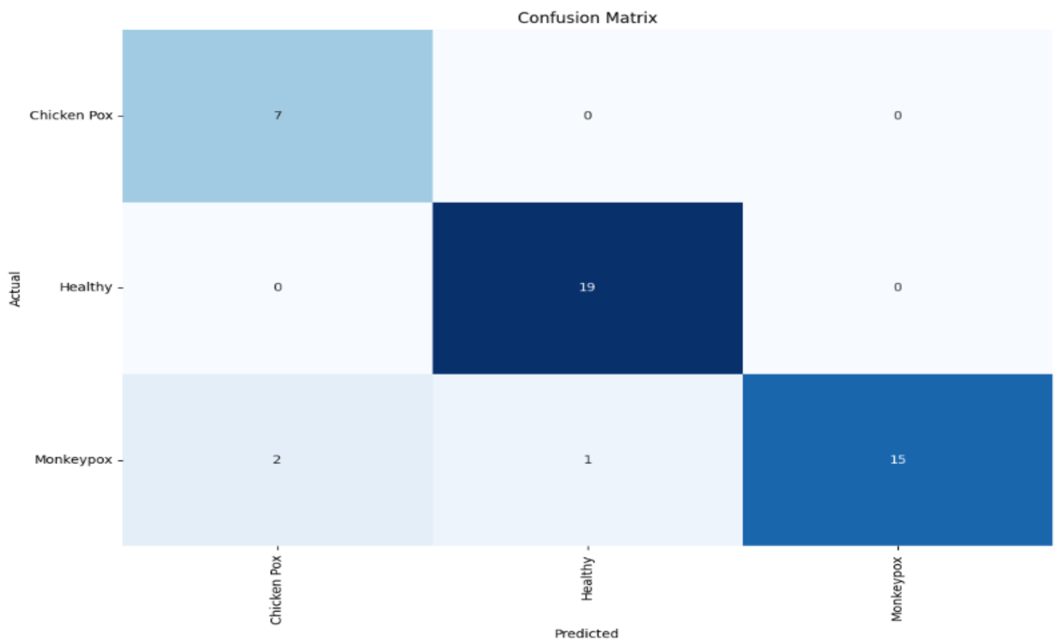

Fig.4.5: Confusion matrix for the DenseNet121 model

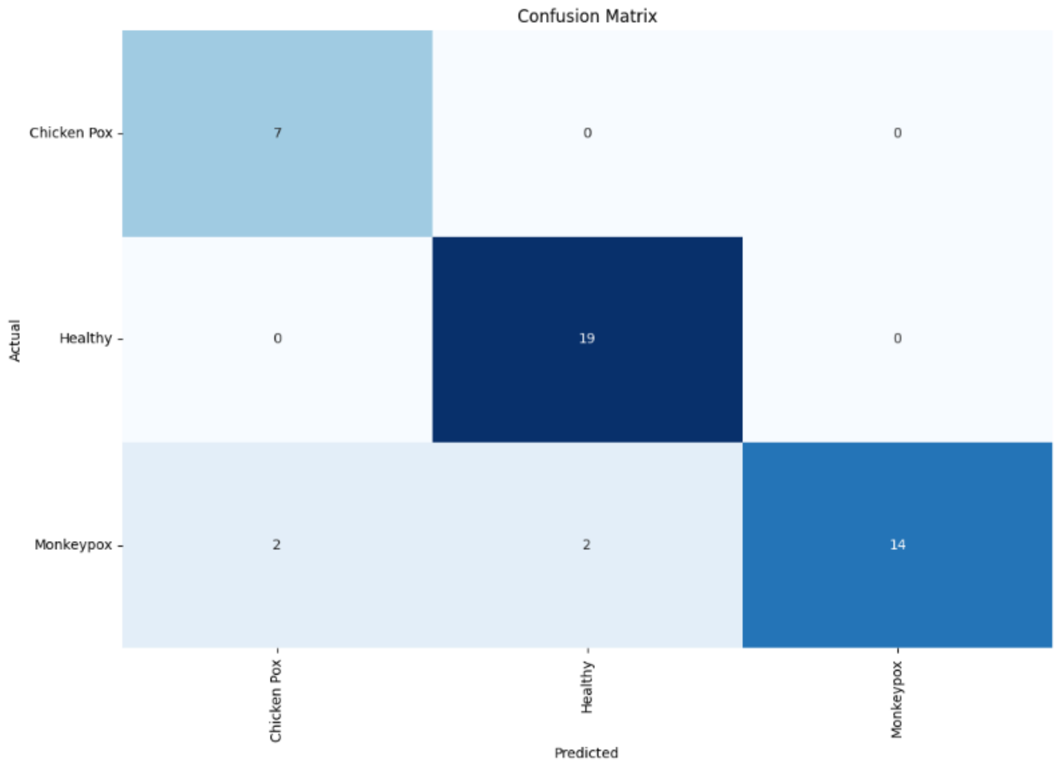

Fig.4.6: Confusion matrix for the ResNet50 model

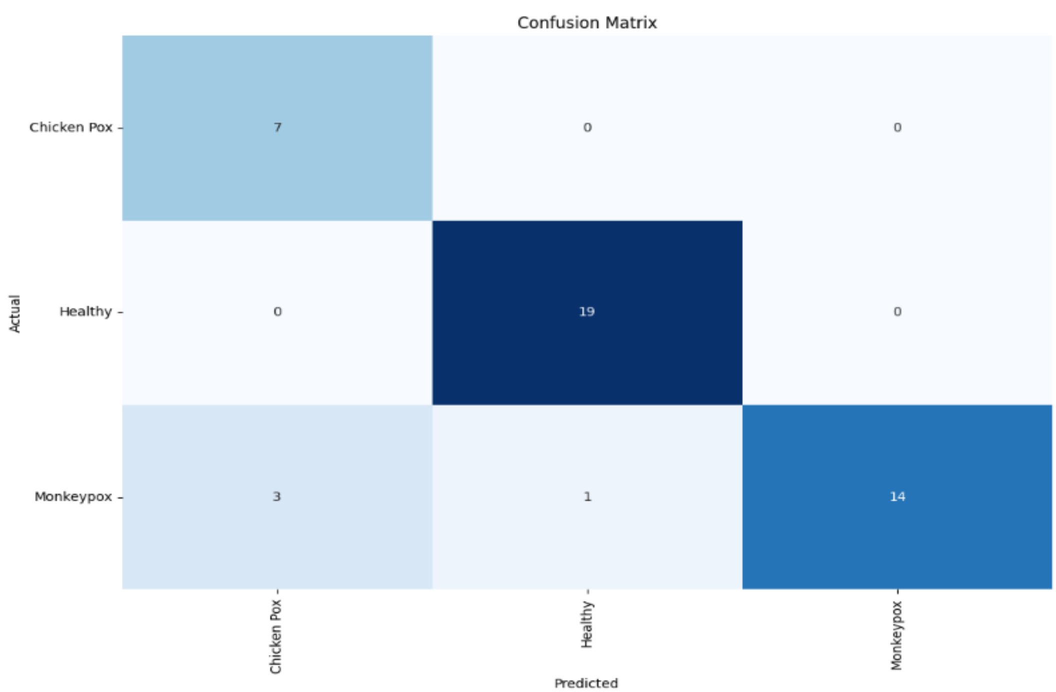

Fig.4.7: Confusion matrix for the InceptionV3 model

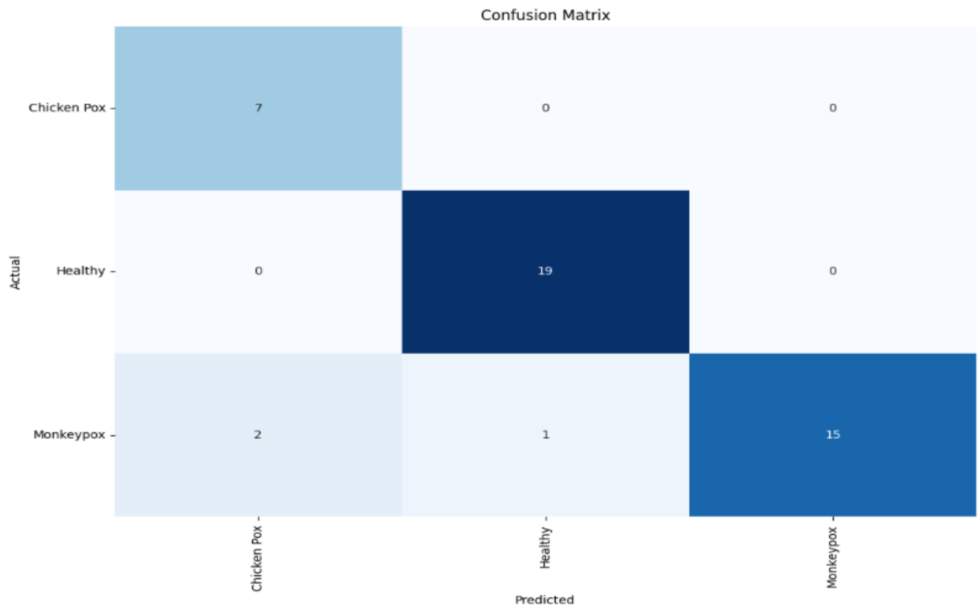

Fig.4.8: Confusion matrix for the EfficientNetB2 model

4.5 Descriptive Analysis

Our exploration into pox disease prediction and detection using image processing has marked substantial progress compared to prior studies. The DenseNet121 algorithm showcased an impressive accuracy of 93.18%, outperforming EfficientNetB2, InceptionV3, and ResNet50, which achieved 91%, 90.91%, and 89% accuracies, respectively. Among the four considered classification algorithms, DenseNet121 consistently demonstrated superior accuracy and confidence rates. Combining multiple algorithms holds promise for enhanced performance and precision. Specific algorithms displayed higher confidence rates for certain disease categories, indicating specialization. However, for overall performance and reliability, DenseNet121 emerged as the most consistent model. Image quality significantly influenced results, with compromised quality leading to reduced confidence rates. Clear, well-captured images were crucial for optimal outcomes,

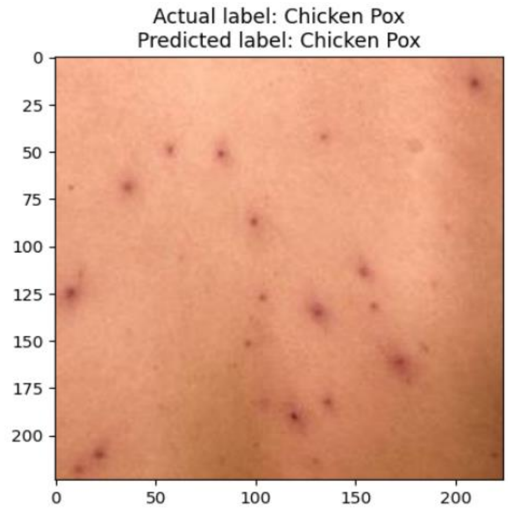

Fig. 4.9: Detection of pox disease

Fig. 4.10: Plot of 6 images detection of the pox diseases with model confidence

with DenseNet121 consistently achieving a 100% confidence rate with high-quality images. Comparatively, other models experienced declining confidence rates for specific diseases like

Monkeypox or Chickenpox with similar image quality. In contrast, DenseNet121 maintained stable or increasing confidence rates, highlighting its superiority.

4.6 Discussion

DenseNet121 showcased outstanding computational efficiency, requiring merely 1.5 seconds to predict a single pox disease. In contrast, alternative models demanded 3-5 seconds, occasionally stretching to 6 seconds due to image quality issues. The speed and efficiency of DenseNet121 position it as highly suitable for practical implementation. Its impact on pox disease prediction is substantial, offering superior efficiency, faster processing, and unparalleled accuracy compared to other models. The research results significantly contribute to advancing pox disease detection, offering an efficient and reliable solution that can aid in effective disease management.

Fig. 4.11 : User interface for detecting Monkey-pox disease

The Python Flux framework has been utilized to create a user-friendly interface for detecting Monkey-pox disease, enabling individuals affected by the illness to easily identify and manage their condition.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

There are significant societal benefits to using deep learning for monkeypox detection. This technique makes it possible to quickly and accurately identify the pox viruses, which helps with early intervention and can potentially stop the disease's spread and save lives. Deep learning-powered automated detection systems improve local response capacities in areas with limited access to healthcare, especially during outbreaks. This development enhances the fight against epidemics and adds to the security of world health. These technology advancements improve public health resilience by lessening the effects of pox outbreaks, highlighting the revolutionary potential of deep learning in disease surveillance and control. The wider availability of these breakthroughs represents a step toward more egalitarian healthcare and the promotion of a more robust and healthy global community.

5.2 Impact on Environment

The environment may benefit from the use of deep learning for the identification of monkeypox in both humans and animals. This technique aids in quick containment by providing early and accurate identification, which lessens the need for mass killing of infected animals. This procedure, which is frequently used when disease epidemics occur, has serious negative effects on the environment. Deep learning helps to preserve biodiversity and ecological balance by reducing such interventions. Furthermore, effective disease management minimizes the need for unnecessary medical resources, which lessens the environmental impact of healthcare operations. Essentially, using deep learning to detect the pox harmonizes environmental preservation efforts with public health programs, promoting a more long-term strategy for disease prevention and a more harmonious coexistence of environmental and human welfare.

5.3 Ethical Aspects

There are ethical issues that need to be carefully considered when using deep learning for monkeypox diagnosis. This raises important issues including algorithmic bias, informed consent, and data privacy. To preserve individual privacy, it is critical to ensure that patient data used for model training is anonymized and managed securely. It is morally required to communicate openly and to acquire people's informed permission before using their data. Furthermore, it is important to tackle plausible partialities present in the deep learning algorithms to prevent prejudice or imbalances in the results of detection. Rebuilding people's and communities' confidence through ethical deep learning in healthcare applications requires finding a compromise between the advantages of early pox detection and the moral obligations associated with data processing and algorithmic fairness.

5.4 Sustainability Plan

To implement monkeypox detection using deep learning effectively, a sustainable plan must be established, covering multiple facets. First and foremost, foster continuous collaboration among researchers, healthcare professionals, and technology experts to enhance and update deep learning models consistently. Create a resilient system for data collection, giving priority to privacy and security, while also addressing the environmental impact of data storage and processing. Invest in educational and training programs to empower healthcare professionals, enabling them to proficiently use and adapt to evolving technology. Form partnerships with both governmental and non-governmental organizations to secure funding for research, implementation, and accessibility initiatives. Lastly, promote public awareness and support for sustainable healthcare practices, highlighting the long-term advantages of early pox detection through deep learning. This holistic approach ensures the lasting effectiveness and ethical deployment of this technology for societal improvement.

CHAPTER 6
SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATIONS FOR FUTURE RESEARCH

6.1 Summary of the Study

Our study on Monkeypox disease prediction and detection using image processing has led to significant strides. The DenseNet121 algorithm achieved an impressive 93.18% accuracy, surpassing models like EfficientNetB2, InceptionV3, and ResNet50. It consistently demonstrated superior accuracy and confidence rates among the considered classification algorithms. Combining multiple algorithms shows potential for further performance enhancement. Image quality greatly influenced outcomes, with compromised quality leading to reduced confidence rates. DenseNet121 consistently achieved a 100% confidence rate with high-quality images. Its computational efficiency, predicting a single pox disease in just 1.5 seconds, makes it highly practical. DenseNet121's impact on pox disease prediction—offering efficiency, speed, and exceptional accuracy—is profound. These findings significantly contribute to pox disease detection advancement, providing an efficient and dependable solution for effective disease management.

6.2 Conclusion

This study introduces a new deep-learning-based strategy for effectively identifying various pox categories, offering a realistic and practical solution for multi-pox disease classification. Unlike previous methods that rely on sample collection and lab evaluations, our approach utilizes in-situ photos captured by diverse camera devices, which are then processed in real-time using a sophisticated GPU-powered software and hardware system. The objective of this study was to identify the most suitable deep-learning architecture for real-time pox detection. Extensive experimentation and comparisons of deep-meta-architectures (e.g., DenseNet121, EfficientNetB2, InceptionV3, and ResNet50) demonstrated the accuracy of the detector in recognizing two distinct classes of illnesses, handling complex intra- and inter-class variations. DenseNet121 consistently demonstrated superior performance compared to the other evaluated classification algorithms. However, there is potential for enhancing performance and accuracy by incorporating additional methods. It is important to acknowledge the limitations of this work, particularly regarding the quality of data collection. Future research will focus on expanding our findings, refining our methodologies, and applying our disease detection concept to different pox types for practical applications. This study presents a significant contribution to the field of medical research. The proposed approach offers a promising solution for real-time, non-invasive pox disease identification, paving the way for further advancements in diagnostic tools and disease management strategies.

6.3 Implication for Further Study

this study, the early detection of monkeypox and chickenpox is vital for the rapid and adequate treatment of the disease. This ultimately prevents outbreaks and mortality associated with the disease. The similarity in the lessons of monkeypox and chickenpox can create a problem of misdiagnosis, especially in endemic regions where communicable disease experts are insufficient. In future, we have a scope to present much accurate model using these models and develop a user-interface which is accessible to common people so that they can test themselves using mobile application or web application. We believe that adequate precautions and actions can be taken in early stages of the infection so that the infection rate can be reduced. This would be useful in the rapid detection of the disease. Hence, preventing preventable monkeypox and chickenpox outbreak in the future. Future work can be carried out on developing a CNN model capable of accurately classifying . There are two limitations in the proposed research work; first, the dataset used is comparatively small and second, only 4 pre-trained models are applied. In future, work will be carried out on large dataset and more machine learning and deep learning algorithms will be applied. Furthermore, in future, various skin diseases such as chickenpox, smallpox, measles, Cowpox, lumpy skin disease etc will be targeted.

REFERENCES

[1] Khan, G. Z. (2023). Efficient Technique for Monkeypox Skin Disease Classification with Clinical Data using Pre-Trained Models. Journal of Innovative Image Processing, a(b), Pages 192-213. doi:0.36548/jiip.2023.2.009

[2] Shams Nafisa Ali, M. T. (2022). Monkeypox Skin Lesion Detection Using Deep Learning Models: A Feasibility Study. IEEE, 01-04. Retrieved from https://arxiv.org/abs/2207.03342

[3] Shahi, C. S. (2022). Monkeypox Virus Detection Using Pre trained Deep Learning based Approaches. Journal of Medical Systems, pp.01-09. doi:https://doi.org/10.1007/s10916-022-01868-2

[4] Shams Nafisa Ali, M. T. (2022). Monkeypox Skin Lesion Detection Using Deep Learning Models: A Feasibility Study. IEEE, 01-04. Retrieved from https://arxiv.org/abs/2207.03342

[5] Md Manjurul Ahsan, M. R. (2022). IMAGE DATA COLLECTION AND IMPLEMENTATION OF DEEP LEARNING-BASED MODEL IN DETECTING MONKEYPOX DISEASE USING MODIFIED VGG16. 01-14. Retrieved from https://arxiv.org/abs/2206.01862

[6] Dilber Uzun Ozsahin, Mubarak Taiwo Mustapha, Berna Uzun, Basil Duwa and Ilker Ozsahin. (2023). Computer-Aided Detection and Classification of Monkeypox and Chickenpox Lesion in Human Subjects Using Deep Learning Framework. 01-14. doi:https://www.mdpi.com/2075-4418/13/2/292

[7] Alrusaini, O. (2023). Deep Learning Models for the Detection of Monkeypox Skin Lesion on Digital Skin Images. Journal of Advanced Computer Science and Applications, 636-644. doi:10.14569/IJACSA.2023.0140170

[8] Khan, G. Z. (2023). Efficient Technique for Monkeypox Skin Disease Classification with Clinical Data using Pre-Trained Models. Journal of Innovative Image Processing, a(b), Pages 192-213. doi:0.36548/jiip.2023.2.009

[9] Sourav Saha, Trina Chakraborty, Rejwan Bin Sulaiman, Tithi Paul. (2023, Jan 20). A Comparative Analysis of CNN-Based Pretrained Models for the Detection and Prediction of Monkeypox. 01-10. Retrieved from https://arxiv.org/abs/2302.10277

[10] B. V. Chandrahaas, Sachi Nandan Mohanty, Sujit Kumar Panda, G. Michael. (2023, May 25). An Empirical Study on Classification of Monkeypox Skin Lesion Detection. 01-05. doi:10.4108/eetpht.v8i5.3352

[11] Md. Enamul Haque, Md. Rayhan Ahmed, Razia Sultana Nila, Salekul Islam. (2022, Nev 21). Classification of Human Monkeypox Disease Using Deep Learning Models and Attention Mechanisms. 01-05. Retrieved from https://arxiv.org/abs/2211.15459

[12] Rezuana Haque , Arifa Sultana , Promila Haque. (2023). Ensemble of Fine-tuned Deep Learning Models for Monkeypox Detection: A Comparative Study. 01-09. Retrieved from https://ieeexplore.ieee.org/document/10170232

[13] Shams Nafisa Ali, Md. Tazuddin Ahmed, Tasnim Jahan, Joydip Paul,S. M. Sakeef Sani,Nawsabah Noor, Anzirun Nahar Asma, Taufiq Hasan. (2023). A Web-based Mpox Skin Lesion Detection System Using State-of-the-art Deep Learning Models Considering Racial Diversity. xx, 01-09. Retrieved from https://paperswithcode.com/paper/a-web-based-mpox-skin-lesion-detection-system

[14] Alakus, T. B. (2023, July). Prediction of Monkeypox on the Skin Lesion with the Siamese Deep Learning Model. BALKAN JOURNAL OF ELECTRICAL & COMPUTER ENGINEERING, 11(3), 225-231. Retrieved from https://dergipark.org.tr/en/pub/bajece/issue/79097/1255798

[15] APOORVA AKULA, SHASHANK PUSHKAR. (2023, April). Mpox Skin Lension Detection using Deep Learning Approaches. 01-20. doi:https://www.authorea.com/doi/full/10.22541/au.168055075.53254806

[16] Dilber Uzun Ozsahin, Mubarak Taiwo Mustapha, Berna Uzun, Basil Duwa and Ilker Ozsahin. (2023). Computer-Aided Detection and Classification of Monkeypox and Chickenpox Lesion in Human Subjects Using Deep Learning Framework. 01-14. doi:https://www.mdpi.com/2075-4418/13/2/292

[17] B. V. Chandrahaas, Sachi Nandan Mohanty, Sujit Kumar Panda, G. Michael. (2023, May 25). An Empirical Study on Classification of Monkeypox Skin Lesion Detection. 01-05. doi:10.4108/eetpht.v8i5.3352

[18] Sourav Saha, Trina Chakraborty, Rejwan Bin Sulaiman, Tithi Paul. (2023, Jan 20). A Comparative Analysis of CNN-Based Pretrained Models for the Detection and Prediction of Monkeypox. 01-10. Retrieved from https://arxiv.org/abs/2302.10277

[19] Dilber Uzun Ozsahin, Mubarak Taiwo Mustapha, Berna Uzun, Basil Duwa and Ilker Ozsahin. (2023). Computer-Aided Detection and Classification of Monkeypox and Chickenpox Lesion in Human Subjects Using Deep Learning Framework. 01-14. doi:https://www.mdpi.com/2075-4418/13/2/292

[20] APOORVA AKULA, SHASHANK PUSHKAR. (2023, April). Mpox Skin Lension Detection using Deep Learning Approaches. 01-20. doi:https://www.authorea.com/doi/full/10.22541/au.168055075.53254806

[21] Alrusaini, O. (2023). Deep Learning Models for the Detection of Monkeypox Skin Lesion on Digital Skin Images. Journal of Advanced Computer Science and Applications, 636-644. doi:10.14569/IJACSA.2023.0140170

[22] Muhammed ÇELİK, Özkan İNİK. (2023). Detection of Monkeypox Among Different Pox Diseases with Different Pre-Trained Deep Learning Models. Journal of the Institute of Science and Technology, 01-12. doi: 10.21597/jist.1206453

[23] GÜLMEZ, B. (2022). MONKEYPOXHYBRIDNET: A HYBRID DEEP CONVOLUTIONAL NEURAL NETWORK MODEL FOR MONKEYPOX DISEASE DETECTION. 49-64. Retrieved from https://www.researchgate.net/publication/366186859_MonkeypoxHybridNet_A_hybrid_deep_convolutional_neural_network_model_for_monkeypox_disease_detection

[24] Ren, G. (2022). Monkeypox Disease Detection with Pretrained Deep Learning Models. 52(2), pp. 288-296. doi:10.5755/j01.itc.52.2.32803

[25] https://www.upgrad.com/blog/basic-cnn-architecture/

[26] Zhang, A., Lipton, Z. C., Li, M., & Smola, A. J. (2021). Jointly optimizing network width and depth for accurate object detection. In Advances in Neural Information Processing Systems (Vol. 34, pp. 6234-6246)

[27] Szegedy, C., Vanhoucke, V., Ioffe, S., & Shlens, J. (2016). Rethinking the Inception Architecture for Computer Vision. arXiv preprint arXiv:1512.00567

[28] Tareq, Imad & Elbagoury, Bassant & El-Regaily, Salsabil & El-Horbaty, El-Sayed. (2022). Analysis of ToN-IoT, UNW-NB15, and Edge-IIoT Datasets Using DL in Cybersecurity for IoT. Applied Sciences. 12. 9572. 10.3390/app12199572.

[29] https://blog.roboflow.com/what-is-efficientnet/

[30] Mitra, A. (2023). Monkeypox Disease Detection using Deep Learning Techniques. Pp: 1- 22. Retrieved from https://norma.ncirl.ie/id/eprint/6620

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