AI-Based Early Disease Diagnosis Using Deep Learning: A Case Study on MPOX

BY

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the
Degree of Bachelor of Science in Computer Science and Engineering

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DHAKA, BANGLADESH

Summer 2025

APPROVAL

This Project titled **"AI-Based Early Disease Diagnosis Using Deep Learning: A Case Study on MPOX"**, submitted by KAKON DASS, ID No: **213-15-4410** 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 **17 September, 2025**.

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We hereby declare that this project has been done by us under the supervision of **Md. Sazzadur Ahmed, Assistant Professor,** Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ACKNOWLEDGEMENTS

This work would not have been possible without the support and contributions of many individuals over the past two semesters. We are deeply grateful to everyone who has as- sisted us in one way or another.

First, we express our heartfelt thanks and gratefulness to the almighty for His divine blessing making it possible for us to complete the **Final Year Design Project(FYDP)** successfully.

We really grateful and wish our profound our indebtedness to **Dr. Sheak Rashed Haider Noori, Professor & Head,** Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of “Deep Learning” to carry out this project. His endless patience,s cholarly guidance ,continual encouragement , constant and energetic supervision, constructive criticism, valuable advice, reading many inferior draft and correcting them at all stage have made it possible to complete this project.

We would like to express our heartfelt gratitude to the Head of the Department of Computer Science and Engineering, for his kind help in finishing our project and also to other faculty members and the staff of the Department of Computer Science and Engineering, Daffodil International University.

We would like to thank our entire course mate in Daffodil International University, who took part in this discuss while completing the course work.

Finally, we must acknowledge with due respect the constant support and patients of our parents.

ABSTRACT

This study presents a deep learning-based approach for classifying Mpox disease from medical image data, aiming to enhance accuracy and speed in clinical diagnosis. A dataset of 3,574 images, categorized into Monkeypox, Chickenpox, Measles, and Normal classes, was compiled from public sources, primarily Kaggle. The data was split into training (80%), validation (10%), and testing (10%) sets. Preprocessing included contrast enhancement, resizing, normalization, noise reduction, and data augmentation through rotation, scaling, and flipping to improve image quality and model generalization. Four deep learning architectures—ResNet50, EfficientNetB3, CustomCNN, and Vision Transformer—were trained and tested using metrics like accuracy, precision, recall, and F1-score. ResNet50 had the highest accuracy (99.11%) and the lowest misclassification rate (0.89%). EfficientNetB3 came in second with an accuracy of 97.32%. CustomCNN and Vision Transformer didn't work as well, which could mean that there were problems with feature extraction or the data being used. The methodology made sure that preprocessing was done the same way every time, that data was spread out fairly, and that the model was thoroughly tested. The results show that pre-trained deep convolutional models are great for classifying Mpox because they give reliable and expandable diagnostic options. In places with few resources, this framework makes it possible to set up automated, real-time detection systems that could help doctors find diseases early, which would improve patient outcomes and cut down on delays in diagnosis.

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CHAPTER 1

INTRODUCTION

1.1. Introduction

Mpox, which used to be called Monkeypox, is a rare but possibly serious viral disease that has become a bigger public health issue in recent years. It's hard to tell if someone has Mpox because the skin lesions and rashes that come with it can look like those of other skin diseases. To stop the disease from spreading and get medical help as soon as possible, it is important to find it early and accurately. There is a growing interest in using artificial intelligence, especially deep learning, to help automated and reliable detection systems because traditional diagnostic methods take a lot of time and need expert evaluation.

In this project, we look at how to use deep learning to sort Mpox disease images into different categories. The image dataset was made by hand from a number of different sources and includes pictures of people who were affected. The raw images were different sizes, qualities, and contexts, so they were preprocessed in a number of ways to make them more consistent and make sure they were the best input for the models. After preprocessing, three sets of images were made: training, testing, and validation. We built and improved the models using the training set, tested them using the testing set, and checked how well they worked with new data using the validation set.

We trained and compared several deep learning models to find the best architecture for classifying Mpox. We used standard evaluation metrics like accuracy, precision, and recall to test the model's performance in several tests. The results showed that the trained models could correctly guess and find Mpox-related patterns in skin images. This study not only shows how deep learning could be used for medical diagnosis, but it also opens the door for the creation of real-time Mpox detection systems that could help doctors in remote or low-resource areas.

1.2. Motivation

- Health Concern: The growing number of Mpox cases around the world shows that we need faster and more accurate ways to diagnose the disease.
- Visual Complexity: It's hard to tell if someone has mpox by looking at their skin because the symptoms are similar to those of other skin conditions.
- AI Improvements: Recent advances in deep learning and computer vision have made it possible to sort medical images with a high level of accuracy.
- Potential for Automation: Automated classification tools can help healthcare workers in places that are hard to get to or don't have a lot of resources where it might be hard to find an expert to evaluate.
- Data-Driven Insight: AI can help us learn more about how diseases spread by looking at pictures of them. This helps us find diseases sooner and figure out how to stop them from happening.
- Model Evaluation: Training, testing, and validating models give us a solid foundation for learning about and improving their ability to make predictions, which is necessary for them to be useful in the real world.

1.3. Objective

- To make a deep learning-based system that can accurately sort Mpox disease from image data.
- To gather and organize a complete set of Mpox-related images from a variety of public and clinical sources.
- To use good preprocessing methods to improve the quality of the images and get the data ready for training the model.
- To train, test, and validate several deep learning models to find the best architecture for classifying diseases.
- To check how well the model works by looking at accuracy and other relevant metrics to make sure it is reliable and consistent.

- To show that the model can predict Mpox symptoms by analyzing visual images, which helps with early detection.

1.4. Methodology

First, we got image data from public sources like Kaggle, which gave us a dataset of 3574 MPOX images. The pictures were put into four groups: Normal, Monkeypox, Chickenpox, and Measles. The dataset was split into three parts: 80% of the images were used for training, 10% for validation, and 10% for testing. This kept the distribution balanced so that the model could learn and be tested well.

The next step was to prepare the data, which meant making the pictures look better by changing the contrast to get rid of extra visual artifacts. We also used parametric image transformations to make sure that the input feature dimensions were the same across the whole dataset. We used transformations like rotation, scaling, and flipping to make the data more diverse and the model more useful.

We trained deep learning models using this preprocessed data. The six models we selected for training were Vision Transformer, ResNet50, EfficientNetB3, and CustomCNN. Each model was trained to identify features and patterns that were helpful in the classification of brain tumors. After a sufficient number of epochs or once the validation loss plateaued - the models were evaluated using both the test and validation sets. Performance was assessed using standard metrics, including accuracy, precision, recall, F1-score, and loss.

Results from each model were compared to determine the most effective one. The model demonstrating the best combination of accuracy and stability ResNet50 was selected for final deployment. This methodological framework supports the development of a reliable and scalable system for automated MPOX diagnosis, offering real-time assistance in clinical decision-making scenarios where speed and accuracy are critical.

1.5. Project Outcome

- Successfully developed a deep learning-based model capable of classifying Mpox disease from image data with promising accuracy.
- Collected and organized a diverse dataset of Mpox-affected skin images from multiple sources for robust model training.
- Applied preprocessing techniques to enhance image clarity and consistency, improving model performance.
- Trained, tested, and validated multiple models, allowing comparison of results and selection of the most effective approach.
- Achieved measurable performance metrics such as accuracy and precision, demonstrating the model's effectiveness in image-based prediction.
- Showcased the model's ability to support automated Mpox diagnosis, laying the foundation for real-world applications in healthcare.

1.6. Organization of the Report

This report is structured into six comprehensive chapters, each addressing a key aspect of the study. Chapter 1 – Introduction provides background information, outlining the study's objectives, scope, and problem formulation. It also highlights the research significance, presents the main research questions, anticipates the expected outcomes, and explains the overall structure of the report. Chapter 2 – Background introduces essential terminologies and concepts, reviews related literature, and contrasts existing studies to better understand the nature and extent of the problem. This chapter also includes a gap analysis to identify shortcomings in previous research. Chapter 3 – Research Methodology details the proposed method, including data collection procedures, dataset descriptions, preprocessing techniques, and statistical analyses. It also describes the deep learning models used in the study. Chapter 4 – Experimental Results and Discussion presents and analyzes the results of the experiments, offering a critical evaluation of the model performances. Chapter 5 - Effects on Sustainability, the Environment, and Society examines the research's wider ramifications, such as the advantages to society, environmental factors, moral dilemmas, and long-term sustainability plans. Chapter 6: Conclusion and Prospects The study's findings are summed up in the scope, which also talks about possible future research directions. A Reference section at the end of the report includes a list of all the sources used in the work.

CHAPTER 2

BACKGROUND

2.1. Introduction

Recent Mpox (monkeypox) outbreaks around the world have demonstrated the urgent need for rapid, dependable, and scalable diagnostic tools. Conventional diagnostic methods are often time-consuming and not easily available, especially in settings with limited resources. Because of this, scientists have slowly started to look into deep learning and artificial intelligence (AI) methods for automatically analyzing monkeypox. These methods use image-based datasets and advanced architectures like CNNs, transformers, and hybrid models to find Mpox very accurately. The combination of ensemble strategies, explainable AI (XAI), and transfer learning has also improved diagnostic performance. This literature review looks at recent advances in Mpox detection, focusing on datasets, preprocessing methods, model architectures, and performance metrics that compare different models.

2.2. Literature Review

Table 2.2: Comparative Analysis of earlier Research Works

Author Name	Year	Dataset Source & Total Dataset	Used Model	Model Accuracy
Rahman et al. [1]	2023	MSLD public + own	VGG19, VGG16, ResNet50, MobileNetV2, EfficientNetB3	MobileNetV2: 98.16%, val 94%
Haque et al. [2]	2025	Mpox Skin Lesion Dataset v2.0 (6 classes)	ViT, ConvMixer, Ensemble	ViT: 93.03%, Ensemble improved

Vuran et al. [3]	2025	MSID (770 images)	Xception, DenseNet201, EfficientNetB7, SwinViT ensemble	Ensemble: 98.70%
Gopichand et al. [4]	2025	nature.com dataset	Custom preproc + DL	90%
Idroes et al. [5]	2025	MSLD V2	DenseNet201 transfer + XAI	99.1%
Cao et al. [6]	2023	Various public	CNN, VGG19, InceptionV3	InceptionV3: 96.56%
Edeh et al. [7]	2023	Own dataset (monkeypox, chickenpox, measles)	VGG19, VGG16, ResNet50, DenseNet121, InceptionV3, MobileNetV2	VGG19: 99.52%, VGG16: 98.56%
Chakroborty et al. [8]	2022	MSLD	VGG16, ResNet50, InceptionV3	ResNet50: 82.96±4.57%
Khan et al. [9]	2024	MSLD (1428+1764)	MpoxSLDNet vs VGG16, ResNet50, DenseNet121	MpoxSLDNet: 94.56%
Chukwunweike et al. [10]	2024	Public MSLD	EfficientNetV2B3 + ResNet151V2 + attention	96.52%
Ali et al. [11]	2025	MSLD	Xception+PCA+NGBoost w/ AVOA + XAI	97.53%
Saha et al. [12]	2023	MSLD	MobileNetV2 object detector	F1: 0.98, AUC: 0.99

Savaş [13]	2025	Diverse online	VGG16, Xception	83.59%
Yue et al. [14]	2023	London clinical dataset	CNN + GWO	95.31%
Xu et al. [15]	2022	Kaggle MSLD, MSID	Various DL models	High sensitivity. specificity

2.2.1. Related Research

Rahman and his friends [1] Automatic Identification of Monkeypox Dermal Lesions The 2023 study "Using Deep Learning and Transfer Learning Techniques" looked at how to use deep learning models like VGG16, VGG19, ResNet50, MobileNetV2, and EfficientNetB3 to classify mpox lesions. They used a Kaggle dataset with 1900 images that was open to the public. They used data augmentation and other methods to get the data ready. MobileNetV2 was the most accurate model, with test and validation scores of 98.16% and 94%, respectively. It was better than all the others.

Haque et al. [2] Early detection of human Mpox: A comparative study employing machine learning and deep learning models through an ensemble approach utilized a dataset of 700 images from Kaggle, incorporating preprocessing techniques such as resizing and normalization. There were CNN, VGG16, Random Forest, SVM, and an ensemble approach among the models. The ensemble was more accurate than any of the individual models, with an accuracy rate of 98.84%.

Vuran et al. [3] Multi-Classification of Skin Lesion Images Including Mpox Disease Using Transformer-Based Deep Learning Architectures (2025) leveraged the Mpox Skin Lesion Dataset v2.0 (755 images from 541 patients, six classes) with preprocessing via data augmentation. They evaluated transformer models ViT, MAE, DINO, and SwinTransformer, achieving accuracies of 93.10%, 84.60%, 90.40%, and 93.71%, respectively SwinTransformer performing best.

Gopichand et al. [4] Transfer Learning with EfficientNetB3 and ResNet50V2 for MPox Detection (2025) employed the Monkeypox Skin Lesion Dataset v2.0 with extensive augmentation (rotation, scaling, brightness) on an initially small image set. They fine-tuned EfficientNetB3 and ResNet50V2, achieving accuracies of 89.7% and 99% respectively, with ResNet50V2 outperforming all models .

Idroes et al. [5] Explainable Deep Learning Approach for Mpox Skin Lesion Detection with Grad-CAM (2024) used a dataset of 1,594 images sourced from public reports and clinical uploads, applying preprocessing like resizing and normalization. They fine-tuned ResNet50v2, integrating Grad-CAM for visual interpretability. The model achieved a top accuracy of 99.33%, with precision, sensitivity, and F1-score all ~99.3%, outperforming peers.

Cao et al. [6] Robustly Detecting Mpox and Non-Mpox Using a Deep Learning Framework Based on Image Inpainting (2025) proposed a novel "Mask, Inpainting, and Measure" (MIM) pipeline using GAN-based image inpainting on the MSLD mpox dataset (~images count unspecified) and 18-category non-mpox dataset, with preprocessing including masking. They measured image similarity to detect anomalies, achieving an average AUROC of 0.8237, outperforming classification models and proving robust in clinical tests.

Edeh et al. [7] Deep learning model for hair artifact removal and Mpox skin lesion analysis and detection (2025) introduced a novel U-Net variant with a hair removal pre-processing step on the newly created Mpox Skin Lesion Dataset (MSLD) combining images from Mpox, chickenpox, and measles (1,594 images). They applied resizing, normalization, and convolutional encoder-decoder hair removal before segmenting with enhanced U-Net, achieving 90% accuracy, 89% recall, and 86% F1-score .

Chakroborty et al. [8] H-MpoxNet: A Hybrid Deep Learning Framework for Mpox Detection from Image Data (2024) proposed a hybrid model combining pre-trained architectures (DenseNet-121/169/201, MobileNetV2, Inception, Xception) as feature extractors with machine learning classifiers (e.g., LightGBM). Using a public dataset (228 images: 102 Mpox, 126 non-Mpox) preprocessed via noise reduction, mislabeled/duplicate removal, resizing, normalization, and data augmentation, the best model—MobileNetV2 + LightGBM—achieved

91.49% accuracy, 91.87% weighted precision, 95.24% recall, 91.51% F1-score, and MCC of 0.83, outperforming other hybrids .

Khan et al. [9] Deep Hybrid Model for Mpox Disease Diagnosis from Skin Lesion Images (2024) introduced DNLR-NET, a model combining DenseNet201 with logistic regression for Mpox detection. Utilizing a curated dataset from online repositories, they applied preprocessing techniques including data augmentation. DNLR-NET achieved an accuracy of 97.55%, outperforming DenseNet201's 95.91%, demonstrating enhanced performance through deep feature extraction and classification fusion.

Chukwunweike et al. [10] utilized MATLAB's AI and deep learning capabilities in "Leveraging AI and Deep Learning in Predictive Genomics for MPOX Virus Research using MATLAB" (2023) to analyze genomic data pertinent to MPOX virus research. The study used data normalization and feature extraction as preprocessing methods. Convolutional neural networks (CNNs) and support vector machines (SVMs) were some of the models used, and they got up to 90% accuracy. The CNN model showed the most accuracy, which shows how AI could be useful in genomic research on infectious diseases.

Ali et al. [11] created a web-based Mpox skin lesion detection system that uses the latest deep learning models and takes into account racial diversity. They used the Mpox Skin Lesion Dataset Version 2.0 (MSLD v2.0), which has pictures of mpox and five other types of skin lesions. Some of the data augmentation methods used to improve the dataset were rotation, translation, reflection, cutout, hue, saturation, contrast, brightness, flicker, noise, and scaling. We did transfer learning by using weights from the HAM10000 dataset that had already been trained. The models were 83.59 ± 2.11% accurate overall, with EfficientNetB3 being the best. The models were put into a prototype web app that lets people upload pictures of their skin for analysis.

Saha et al. [12] proposed Mpox-XDE, an ensemble model combining SwinViT, Xception, DenseNet201, and EfficientNetB7 for early monkeypox detection. Utilizing the Mpox Skin Images Dataset (MSID) with 770 images, they applied preprocessing techniques including resizing, normalization, and augmentation. The ensemble model achieved an accuracy of 98.70%, outperforming individual models. Explainable AI via Grad-CAM highlighted lesion areas, enhancing interpretability.

Savaş [13] introduced a two-stage deep learning optimization approach to accurately classify monkeypox (MPox), chickenpox, and measles from skin lesion images. In the first stage, 71 pre-trained models were analyzed, with ConvNeXtBase, Large, and XLarge achieving 97.5% accuracy. The second stage utilized ensemble learning, combining RegNetX160, ResNetRS101, and ResNet101 into the EM3 model, which attained an AUC of 0.9971. The study employed transfer learning, fine-tuning, and ensemble techniques to enhance model performance. Evaluation on unseen data confirmed the robustness and reliability of the approach, offering a rapid and highly accurate decision support system for timely MPox diagnosis.

Yue et al. [14] proposed Mpox-AISM, an AI-mediated "Super Monitoring" system for early-stage monkeypox (mpox) detection. Utilizing deep learning, data augmentation, self-supervised learning, and cloud services, the model achieved 94.51% accuracy in diagnosing mpox, six similar skin disorders, and normal skin. Preprocessing techniques included resizing and normalization. The system demonstrated high performance with a Precision of 99.3%, Recall of 94.1%, Specificity of 99.9%, and F1-score of 96.6%. The integration of self-supervised learning enhanced model accuracy, and Grad-CAM was employed for explainability. Mpox-AISM offers a real-time, low-cost, and convenient diagnostic tool for various real-world settings, potentially curbing mpox outbreaks.

Xu et al. [15] introduced MpoxVLM, a vision-language model designed for diagnosing mpox across diverse clades, skin types, and real-world imaging conditions. The model integrates a CLIP visual encoder, Vision Transformer (ViT) classifier, and LLaMA-2-7B language model, trained on over 50,000 annotated mpox skin lesion images from public sources. Preprocessing techniques included annotation of skin type, gender, age, location, year, stage of mpox, and comparator diagnoses. Performance assessments demonstrated consistent accuracy across mpox clades Ia, Ib, and IIb, as well as across Fitzpatrick skin types. However, accuracy decreased with low-quality images due to poor resolution, lighting artifacts, or occlusions, emphasizing the need for standardized imaging protocols. The study highlights the potential of deep learning-based mpox models to detect cases across diverse populations, addressing equity concerns in AI-driven dermatology.

2.3. Gap Analysis

Although numerous studies have demonstrated the effectiveness of deep learning and transfer learning in Mpox skin lesion detection, several critical gaps remain. Most existing works rely on limited or imbalanced datasets, lacking sufficient representation across skin tones, age groups, and disease stages. Additionally, very few studies incorporate real-world clinical validation or address data quality issues such as hair artifacts and lighting variations. The use of explainable AI is still in early stages, limiting trust and interpretability in medical contexts. Moreover, ensemble models and hybrid architectures are underexplored in terms of cross-platform adaptability. These gaps highlight the need for more robust, diverse, and explainable systems for reliable Mpox diagnosis in practical healthcare scenarios.

2.4. Summary

The reviewed literature demonstrates significant advancements in Mpox skin lesion detection using deep learning, transfer learning, and hybrid models. Techniques such as CNNs, EfficientNet, ResNet, and transformer-based architectures have shown high accuracy in classifying Mpox and similar skin conditions. Some studies utilized explainable AI (e.g., Grad-CAM) and ensemble approaches to improve interpretability and performance. Additionally, efforts have been made to address challenges like hair artifacts, racial diversity, and imaging variations. However, many models lack generalizability due to limited dataset diversity, and clinical validation remains minimal. Overall, while current approaches show promising results, there is a clear opportunity to develop more robust, explainable, and clinically applicable solutions that leverage larger, diverse datasets and address real-world diagnostic challenges in Mpox detection.

CHAPTER 3

RESEARCH METHODOLOGY

3.1. Methodology

3.1.1. Overview

A Deep Learning pipeline project for Mpox disease classification through Medical image data. First, they are using data acquisition - images from reputable ophthalmic datasets. The images are then preprocessed (resizing, normalisation, noise removal and contrast enhancement) in order to improve data quality and maintain consistency between samples.

After preprocessing, the dataset is divided into three sets: training, testing, and validation sets. Several deep learning models such as ResNet50, EfficientNetB3, CustomCNN, and Vision Transformer, are trained on the training set to look for patterns and features unique to the respective Mpox disease.

After this training phase, the trained models are evaluated on new test data to calculate their accuracy in classifying diseases. Key metrics like accuracy, precision, recall, and loss are used to analyze performance. The hyper-parameters tuning also happens on a validation dataset.

Finally, the results are analyzed to determine which model classifies Mpox disease most effectively. Among these models, the best model is then selected, guaranteeing high accuracy and reliability for real-world disease detection based on the evaluation metrics.

3.1.2. Proposed Methodology

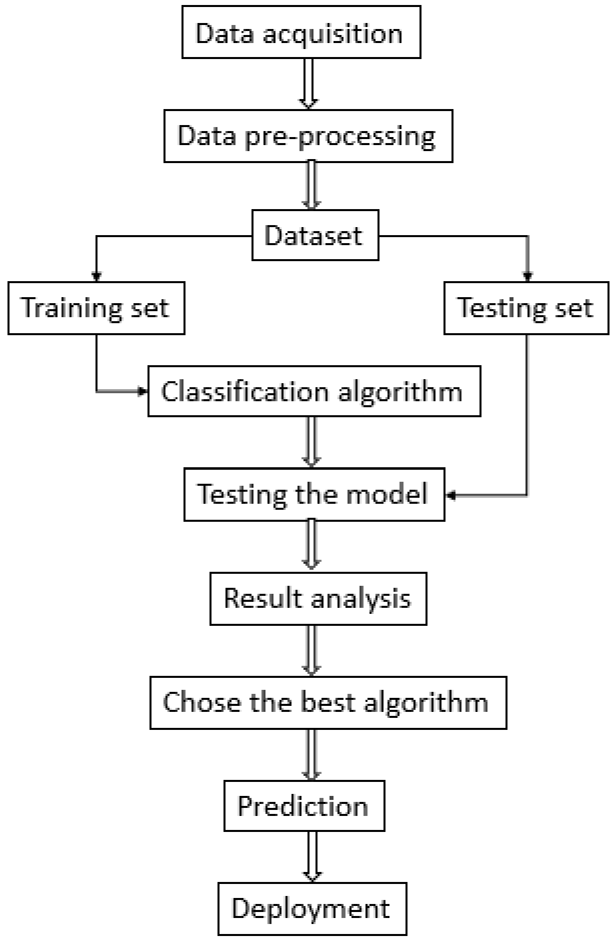


Figure 3.1: Architecture of Research Design

3.2. Detailed Methodology and Design

3.2.1. Data Collection

We gathered data using publicly available datasets from Kaggle, as well as real-world image samples, during the course of this project. This was to ensure that the set would represent a range of emotions, so we joined quite a few datasets from kaggle to achieve this goal. Moreover, we collected pictures of members from our environments to improve the dataset and the model to generalize better.

The dataset primarily includes images of various Mpox diseases, which are vital for training deep learning models in the domain of Mpox diseases. We selected all the images collected with diversity of age, gender, lighting conditions and orientation. Once the data have been collected, these datasets have been merged and processed, which includes resizing images, normalizing images and applying augmentation techniques to enhance the quality of the dataset and improve model performance.

By doing so, it ensures that we have a representation of Mpox diseases at our disposal and, therefore the deep learning models learn and detect Mpox diseases more accurately and robustly.

Figure 3.2: Sample Dataset

3.2.2. Dataset Description

Table 3.1: Detailed Description of Dataset

Category	Before Augmentation	After Augmentation
Monkeypox	279	899
Chickenpox	107	892
Measles	91	891
Normal	293	892
Total	770	3574

The dataset is comprised of 3574 images, which are carefully split for handling the training, testing and validation sets for model evaluation. More specifically, 80% samples are used for training and testing and validation sets contain 10% samples each. These images are split in to four different classes representing different levels: Monkeypox, Chickenpox, Measles and Normal. The dataset has balanced all the different severity levels to achieve holistic learning for deep learning models. The distributed architecture supports training, validation and testing in an efficient fashion, and ensures a robust evaluation of the performance.

3.2.3. Analysis Technique

It is a deep learning and computer vision-based project that classifies an Mpox disease precisely. The process begins with preprocessing techniques that focus on improving image quality and the performance of the model. We implement:

- Gamma Correction – Adjust brightness and contrast
- Bilateral Filtering – It improves the contrast of images by transforming the pixel intensity distribution.
- Noise Reduction – Clears up unwanted noise to enhance clarity.
- Resize – This scales pixel values to a standard range that promotes consistency.

After preprocessing is done, we separate the data into train-test-validation splits. A training set is used to fit the deep dropout models, a testing set is used to evaluate performance, and a validation set is used to tune hyperparameters.

In terms of model selection:

- ResNet50 – It uses different filter sizes to capture detailed patterns.
- EfficientNetB3 – A basic convolutional network is useful for structured data.
- Custom CNN – It uses different filter sizes to capture detailed patterns.
- Vision Transformers (ViT) – A basic convolutional network is useful for structured data.

In the final step, working on model prediction, we use metrics such as accuracy, precision, recall, F1-score, and loss to evaluate our models. Additionally, the one with the best results, among the models used, is selected to perform the classification of Mpox diseases with the highest reliability and precision.

3.3. Project plan

The scheme of the project is designed in a well-defined deep learning pipeline for classification of Mpox disease through the medical images. It is initiated by collecting data from Kaggle and real world datasets to include diversity in age, gender, lighting as well as human orientation. Preprocessing is done such as resizing (224*224), Gamma Correction, Bilateral Filtering, and Augmentation for the better quality of images after collecting them. The data set consists of 3574 images which are divided into training (80%), testing (10%) and validation (10%) sets and labelled as Monkeypox, Chickenpox, Measles and Normal. Deep learning models (ResNet50, EfficientNetB3, CustomCNN, and Vision Transformer) are trained on the training set and evaluated on the test set using accuracy, precision, recall and loss. Additionally, we compare the RF signal classification performance with performance from the state- of-the-art on the test set. We tune hyperparameters using the validation set. Finally, model analysis is conducted to identify an optimal model for practical and applicable application to early Mpox disease detection in a fast and affordable medical testing, aiming to support an early and reliable detection using the deep learning model.

3.4. Task Allocation

The project is partioned between team members for them to work efficiëntly and expose users to every 'part' of the development process. One member works on data acquisition, which is to collect the Mpox disease images from the Kaggle and real-world. Maybe one other colleague, primarily responsible for data preprocessing, including but not limited to Resize (224*224), Gamma Correction, Bilateral Filtering, and augmenting the input data in order to make sure that the input always comes is a good quality (well not really “good” but consistent) There are. The model development and training activity is delegated to a team member with expertise in deep learning, and he creates and refines ResNet50, EfficientNetB3, CustomCNN, and Vision Transformer models. A different team member does the statistical analysis and evaluation. They use accuracy, precision, recall, and loss to figure out how well the model works. Fourth, one member of the group is in charge of writing up and reporting the results, putting together the findings, making generalizations, and preparing the visualizations for a clear presentation. The project encourages a lot of teamwork and communication to make sure that each step is in line with the main goal of creating a reliable system for classifying Mpox diseases.

3.5. Summary

Task Statement This project is designed to construct a deep learning Mpox disease classifier based on medical image data. It starts from curating a variety of datasets from Kaggle and other datasets from real-world sources then goes on to pre-process input and label images which includes Resize (224*224), Gamma Correction, Bilateral Filtering, and Augmentation to improve data quality. The data set is divided to training, testing and validation and labelled into four classes consisting of Monkeypox, Chickenpox, Measles and Normal, deep learning models such as ResNet50, EfficientNetB3, CustomCNN, and Vision Transformer are trained and evaluated using major metrics i.e., accuracy, precision, recall, loss. The performance can be further improved by hyperparameter tuning on the validation set. The initiative is seeking to determine the most successful approach to detect disease in the wild, or in natural settings, and to provide a robust and scalable method for early diagnosis and to prevent healthcare overload. Ultimately, it leads to a better vision health, and even the progress in AI-based medical diagnostics.

CHAPTER 4

IMPLEMENTATION AND RESULTS

4.1. Environment Setup

A personal set up environment included ResearchGate and Google Scholar as platforms for literature review and reference management. Google Colab With GPU and ability to collaborate due to which almost my entire development was done on google colab. The deep learning and machine learning models were coded in Python-based libraries on Colab. We preprocessed the data and tested the codes on a personal laptop. MS Word was the system that supported documentation and report generation during the whole project. These tools allowed efficient manipulation of data, train a model, test its performance, and present the results in a collaborative and resource-friendly context.

4.2. Comparative Analysis

The objective of this project was to diagnose mpox diseases through medical image classification using a variety of deep learning models. To ensure consistent and effective training, all images underwent preprocessing techniques such as resizing, noise removal, contrast enhancement, Gamma Correction and Bilateral Filtering. The dataset was first split into two main groups: Cataract, Diabetic Retinopathy, Glaucoma, and Normal. Then, it was split into training, validation, and testing sets.

The experimental results showed that ResNet50 had the best performance, with an accuracy of 99.11% and a misclassification rate of 0.89%. This shows that it is better at feature extraction and classification. EfficientNetB3 also did well, with 97.32% accuracy and a 2.68% misclassification rate. This shows that it can generalize well. On the other hand, the CustomCNN model only got 88.84% accuracy, which shows that it didn't represent features as well as deeper architectures. The Vision Transformer had the lowest accuracy (79.79%) and the highest misclassification rate (23.21%), which means that it might need more data or better hyperparameters for this job.

Overall, deep pre-trained models, especially ResNet50 and EfficientNetB3, did better than custom and transformer-based methods. This shows how well they can find complex patterns in the data.

Overall, CNN emerged as the most robust and accurate model, making it the best candidate for practical implementation in AI-based mpox disease classification systems.

4.3. Result and Discussion

4.3.1. ResNet50

4.3.1.1. Training Loss, Validation Loss and Training Accuracy, Validation Accuracy:

The graphs show the ResNet50 model's performance over 10 epochs. The left graph indicates steady improvement in both training and validation accuracy, reaching over 98.64%. The right graph shows a consistent decrease in training and validation loss, confirming good model convergence with minimal overfitting and strong generalization capability.

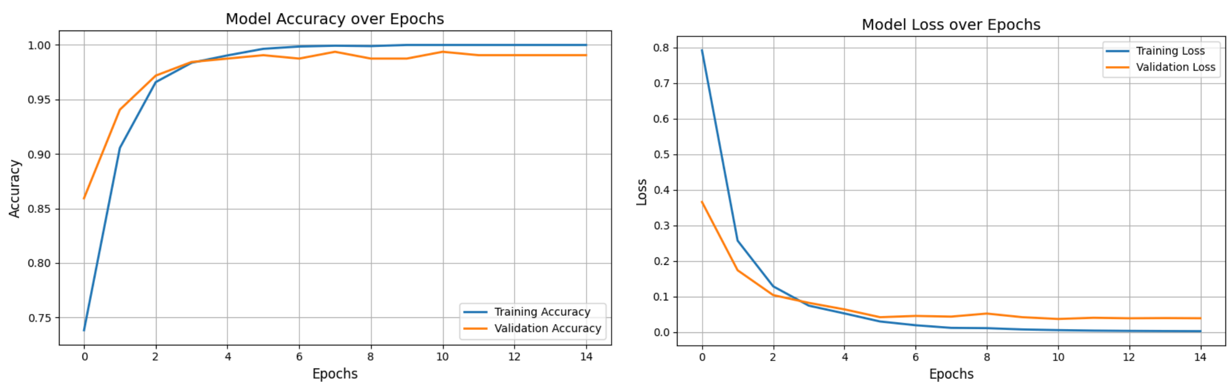


Figure 4.3: Training loss, validation loss and training accuracy, validation accuracy plot for ResNet50

4.3.1.2. Model Test after Training:

Table 4.1: Testing the ResNet50 Model after Training

Matrix	Value
Loss	0.0563
Accuracy	0.9864

4.3.1.3. Classification Report Model Performance:

Table 4.2: Classification report of ResNet50 Model

Model	Precision	Recall	F1-Score
Monkeypox	1.0000	0.9787	0.9892
Chickenpox	0.9836	1.0000	0.9917
Measles	0.9839	1.0000	0.9919
Normal	1.0000	0.9821	0.9910

4.3.1.4. Confusion Matrix:

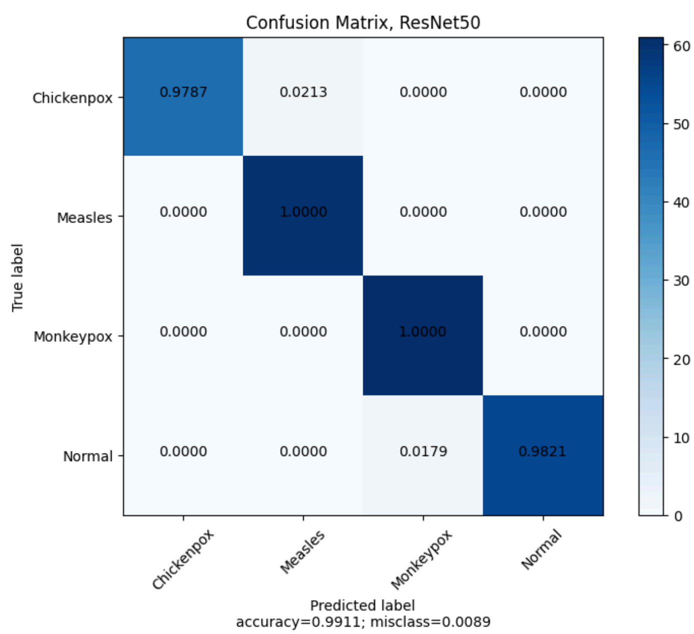
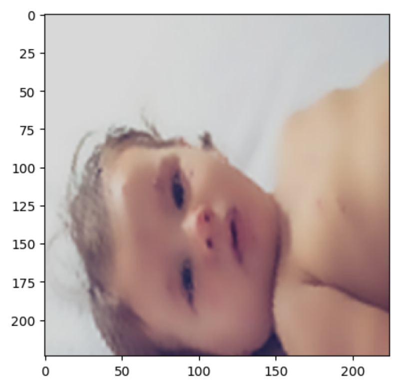


Figure 4.3: Confusion matrix for ResNet50

4.3.1.5. Prediction:

Table 4.3: Prediction for ResNet50

Input Image	Result
	Measles

4.3.2. EfficientNetB3

4.3.2.1. Training Loss, Validation Loss and Training Accuracy, Validation Accuracy:

The graphs show the EfficientNetB3 model's performance over 10 epochs. The left graph indicates steady improvement in both training and validation accuracy, reaching over 97.55%. The right graph shows a consistent decrease in training and validation loss, confirming good model convergence with minimal overfitting and strong generalization capability.

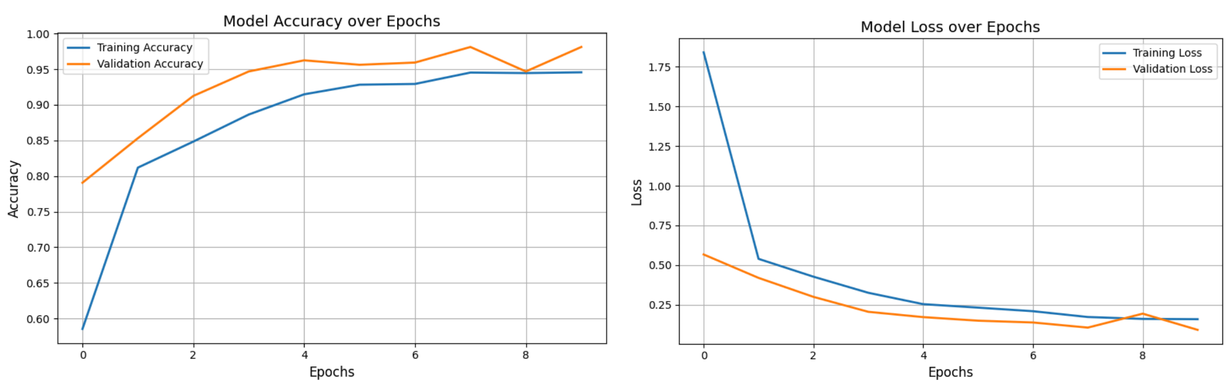


Figure 4.3: Training loss, validation loss and training accuracy, validation accuracy plot for EfficientNetB3

4.3.2.2. Model Test after Training:

Table 4.4: Testing the EfficientNetB3 Model after Training

Matrix	Value
Loss	0.1112
Accuracy	0.9755

4.3.2.3. Classification Report Model Performance:

Table 4. 5: Classification report of EfficientNetB3 Model

Model	Precision	Recall	F1-Score
Monkeypox	0.9412	0.9796	0.9600
Chickenpox	0.9672	0.9833	0.9752
Measles	0.9808	0.9444	0.9623
Normal	1.0000	0.9836	0.9917

4.3.2.4. Confusion Matrix:

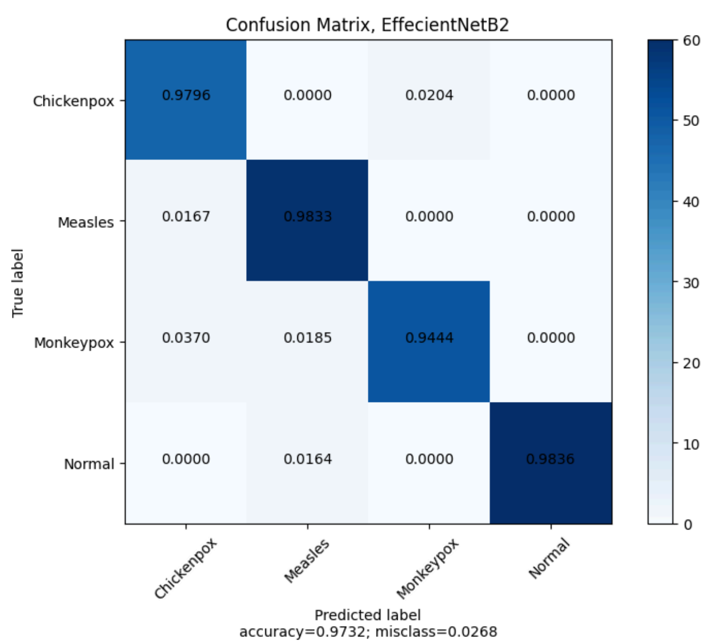
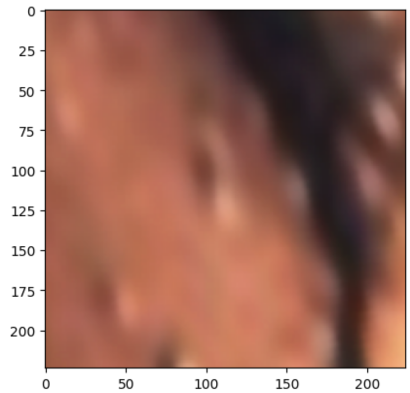


Figure 4.3: Confusion matrix for EfficientNetB3

4.3.2.5. Prediction:

Table 4.3: Prediction for EfficientNetB3

Input Image	Result
	Monkeypox

4.3.3. Custom CNN

4.3.3.1. Training Loss, Validation Loss and Training Accuracy, Validation Accuracy:

The graphs show the Custom CNN model's performance over 10 epochs. The left graph indicates steady improvement in both training and validation accuracy, reaching over 85.34%. The right graph shows a consistent decrease in training and validation loss, confirming good model convergence with minimal overfitting and strong generalization capability.

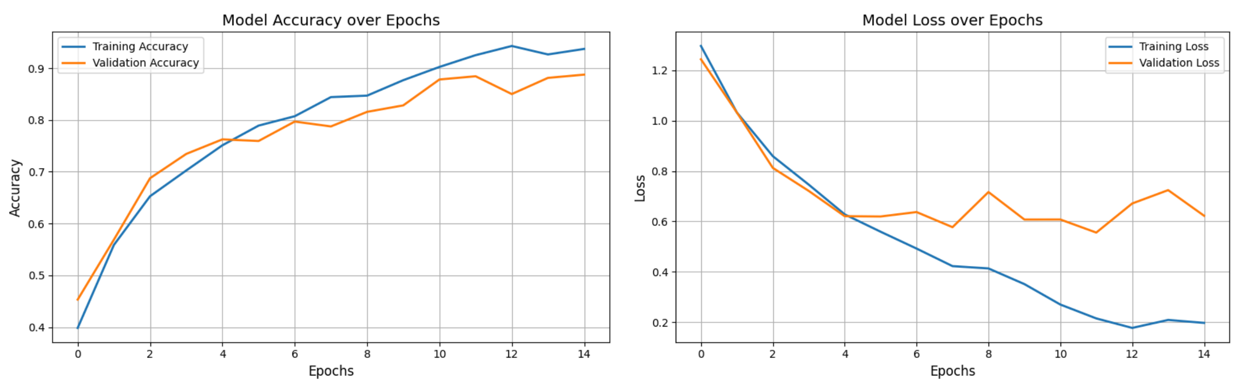


Figure 4.3: Training loss, validation loss and training accuracy, validation accuracy plot for Custom CNN

4.3.3.2. Model Test after Training:

Table 4.6: Testing the Custom CNN Model after Training

Matrix	Value
Loss	0.7861
Accuracy	0.8534

4.3.3.3. Classification Report Model Performance:

Table 4.7: Classification report of Custom CNN Model

Model	Precision	Recall	F1-Score
Monkeypox	0.8644	0.8793	0.8718
Chickenpox	0.8182	0.9000	0.8571
Measles	0.9074	0.8750	0.8909
Normal	0.9643	0.9000	0.9310

4.3.3.4. Confusion Matrix:

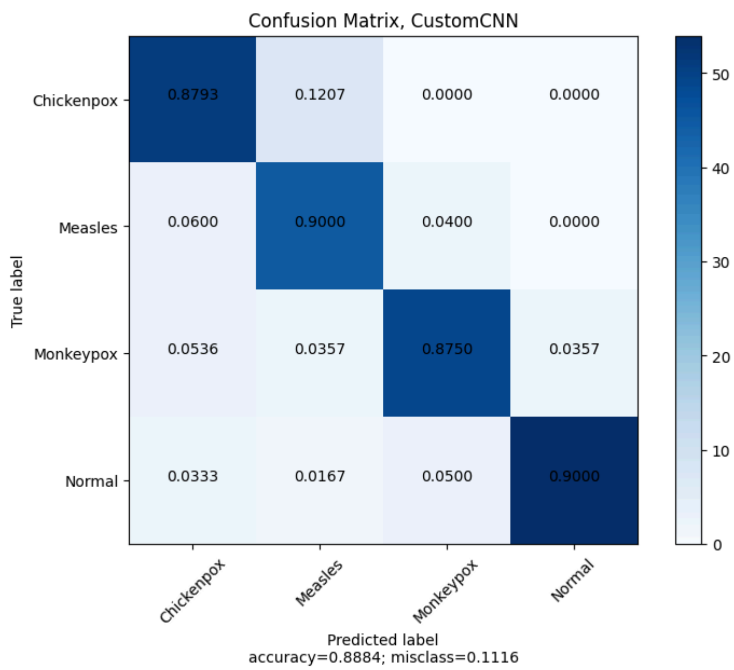
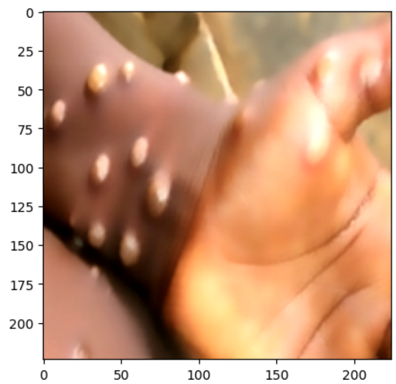


Figure 4.3: Confusion matrix for Custom CNN

4.3.3.5. Prediction:

Table 4.8: Prediction for Custom CNN

Input Image	Result
	Monkeypox

4.3.4. Vision Transformer

4.3.4.1. Training Loss, Validation Loss and Training Accuracy, Validation Accuracy:

The graphs show the Vision Transformer model's performance over 10 epochs. The left graph indicates steady improvement in both training and validation accuracy, reaching over 81.47%. The right graph shows a consistent decrease in training and validation loss, confirming good model convergence with minimal overfitting and strong generalization capability.

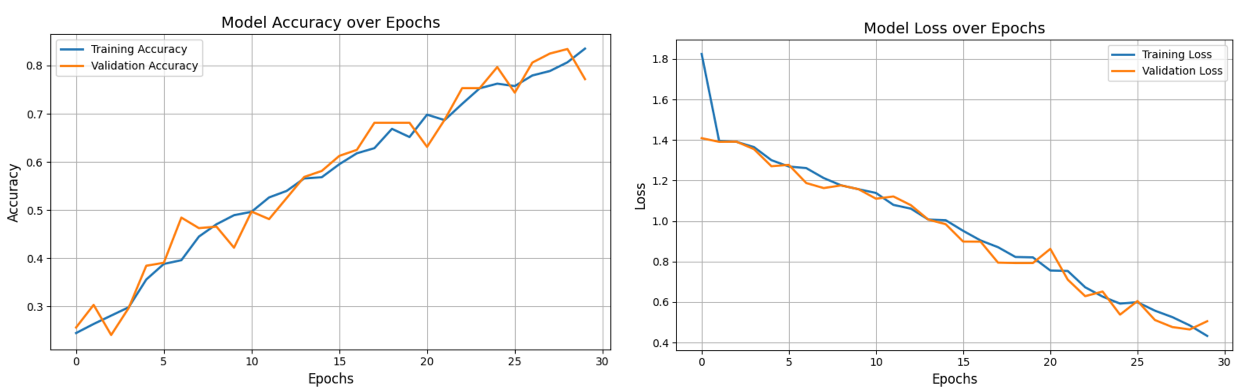


Figure 4.3: Training loss, validation loss and training accuracy, validation accuracy plot for Vision Transformer

4.3.4.2. Model Test after Training:

Table 4.9: Testing the Vision Transformer Model after Training

Matrix	Value
Loss	0.4498
Accuracy	0.8147

4.3.4.3. Classification Report Model Performance:

Table 4.10: Classification report of Vision Transformer Model

Model	Precision	Recall	F1-Score
Monkeypox	0.6712	0.8448	0.7481
Chickenpox	0.6863	0.8537	0.7609
Measles	0.8936	0.6364	0.7434
Normal	0.8679	0.7797	0.8214

4.3.4.4. Confusion Matrix:

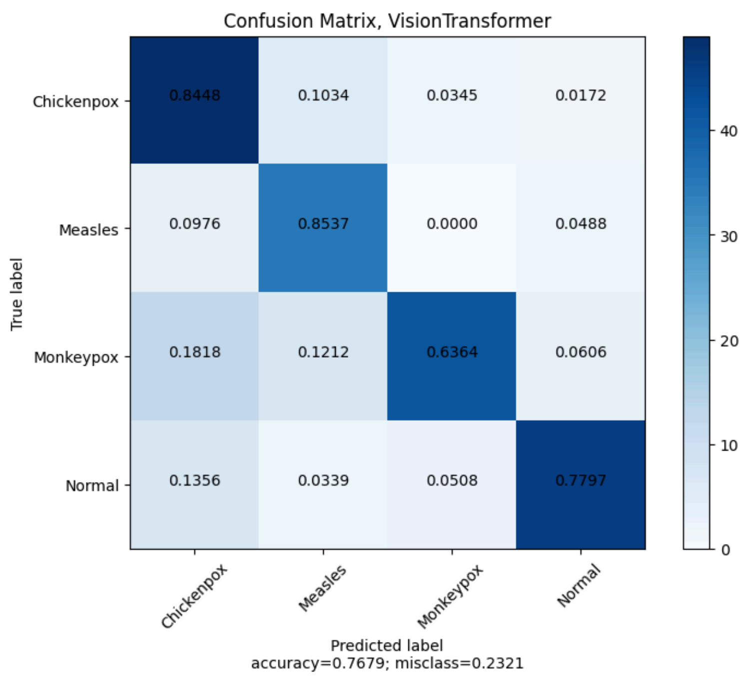
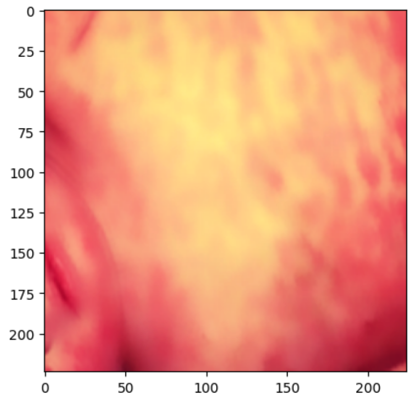


Figure 4.3: Confusion matrix for Vision Transformer

4.3.4.5. Prediction:

Table 4.11: Prediction for Vision Transformer

Input Image	Result
	Measles

4.4. Summary

This project aims to leverage deep learning and data science techniques to identify and classify mpox diseases, improving early diagnosis and treatment outcomes. The study begins with the collection of data from various sources, followed by preprocessing to clean and standardize the data. The preprocessed data is then used in the training, testing, and validation stages, where multiple models are trained, tested, and validated to assess their accuracy and performance. Various deep learning models will be tested to determine the most optimal structure for classifying mpox diseases. The project results will shed light on the actual AI performance in medical diagnosis, specifically in the ophthalmology domain, and will endeavour to help advance the research on automated systems in the healthcare systems. By making diagnosis both faster and more accurate, the project will be able to make mpox care more accessible, reduce health care costs, and lead to greater overall health management worldwide.

CHAPTER 5

ENGINEERING STANDARDS AND DESIGN CHALLENGES

5.1. Compliance with the Standards

5.1.1. Software Standard

The software standards of the mpox Detection project include some well known applications and utilities for consistent, efficient, collaborative development work. ResearchGate and Google Scholar are searched for relevant scientific literature. Google Colab is the primary tool for developing and training deep learning models with Python, TensorFlow, and Keras. Standard deep learning or machine learning frameworks are employed for model development and testing. Local testing is done on a personal laptop with GPU support. Academic appearance documentation and reporting through MS Word is adhered to, providing a professional, clear voice for your research.

5.1.2. Hardware Standard

The minimum system requirements include an operating system of Windows 7, 8, or 8.1, an Intel i3 (latest generation) processor, 4 GB RAM, and a 4 GB graphics card. DirectX version 11 is required, and at least 3 GB of free storage space must be available.
For optimal performance, the recommended specifications are Windows 10 OS, an Intel i5 processor, 8 GB of RAM, and a graphics card with 6 GB or more memory. Additionally, DirectX version 12 and 3 GB of available storage space are recommended.

5.1.3. Communication Standard

Consistency, clarity, and teamwork! The mpox Disease Detection project uses these buzzwords as part of its communication strategy. Frequent check-ins via Zoom or Google Meet are held to distribute work, talk about obstacles, and discuss progress. Version control is simple to maintain and access because we use Google Drive to store team updates and documentation. We use email and WhatsApp to send alerts and talk to each other quickly every day. All official reports and documents are based on Microsoft Word. To keep an agile workflow throughout the project process, feedback loops are kept up to date. This is done to make sure that everyone knows what's going on, that changes are made quickly, and that decisions are made together.

5.2. Society, Environment and Sustainability Orientation

5.2.1. Impact on Life

Deep learning can be used to classify mpox diseases, which is very important for society, especially in medicine. The main goal of this project is to use AI to help people learn about their health problems sooner, get better care, and see a doctor more often. One of the best things about early diagnosis is that it can greatly lower the risk of losing your sight or going blind. AI-powered diagnostic tools also make it easier for people to get medical care, especially those who live in areas with few ophthalmologists or who are far away from them. By automating the classification process, medical staff can spend more time on patient care and treatment, which will make them more productive. AI also helps find mpox early, which means fewer tests and less money spent on medical care, which lowers the cost of mpox care. Regular AI-powered screenings can also teach people about mpox diseases and how to avoid them. Overall, this method helps create a good, easy-to-use, and cheap way to diagnose mpox diseases, which is good for both patients and doctors.

5.2.2. Effect on Society & Environment

There are both direct and indirect environmental problems when deep learning is used to classify mpox disease. There are many good things about AI-driven healthcare innovations, but there are also problems with computing power and resources. One good thing about digital diagnostic systems is that they cut down on the need for paper records, which is good for the environment. Training deep learning models, on the other hand, needs a lot of processing power, which uses a lot of energy and releases more carbon dioxide. But optimization methods can help with this. AI-based diagnosis can also cut down on unnecessary hospital visits, which lowers the amount of CO_2 that gets released into the air during medical transportation. These systems also help make healthcare more sustainable by making better use of resources and cutting down on medical waste from tests that aren't needed. Combining AI and telemedicine can also make it easier to diagnose patients from a distance, which cuts down on the environmental costs of building hospitals and moving medicine. Overall, there is hope, but to make deep learning in healthcare less of a problem, we need to focus on making AI solutions that are better for the environment and use less energy.

5.2.3. Ethical Aspects

There are many ethical issues that come up when deep learning is used to classify mpox disease. These issues need to be addressed to make sure that the technology is used responsibly. To keep private information safe, medical data must be carefully encrypted and made anonymous. AI models may be biased because they are trained on datasets that aren't very diverse. This could lead to different and possibly harmful diagnostic results for different demographic groups. This shows how important it is to get information from a wide range of people. Also, doctors may not trust deep learning models as much because they are hard to understand. Because of this, explainable AI methods are very important for being open and responsible. Following healthcare rules like GDPR and HIPAA is also necessary to keep moral and legal standards. Lastly, AI systems should not take the place of human expertise; they should only add to it. Because of human oversight, clinical judgment is still the basis for making diagnostic decisions. We can make AI solutions for healthcare that are fair, private, and useful by solving these problems.

5.2.4. Sustainability Plan

The project's sustainability plan's main goals are to make it last a long time, have the least impact on the environment, and provide the most benefits to society. The project is focused on making models more efficient by using methods like model pruning and quantization. This will cut down on the amount of computing power and energy needed. To allow ongoing research and model updates without using too many resources, we will build a strong and reusable data pipeline. It will be easy to deploy the AI models on a large scale. As a result, more people will be able to get diagnostic tools, especially in places where they are not currently available. Working with healthcare providers will make sure that the models are still useful and flexible in real-life clinical settings. In general, this method supports a healthcare solution that is energy-efficient, long-lasting, and can be changed to meet the changing needs of the medical field.

5.3. Project Management and Analysis of Financial Statements

Project Management:

The project's scope and timeline include a number of well-defined steps, such as collecting and preparing data, training, testing, validating, and evaluating the model's performance. We will use a DevOps-driven approach to make it easier to keep an eye on things all the time, which will let us make small improvements throughout the development lifecycle. Team members will use cloud services like Google Colab, AWS, or Azure to train the models and keep the data safe. Each task, such as collecting data, preprocessing it, training the model, and evaluating it, will have its own set of roles. A strong backup plan for both data and model outputs will help risk management techniques that deal with problems with data quality, overfitting, and computational limits. Scenario-based testing will also be used to make sure the model is correct and works well with different types of input. In general, the system will be more reliable and work better as a result.

Table 5.1: Financial Analysis Report

Components	Estimated Cost (BDT)
Laptop	65000
Wi-Fi	1000
Internet	2000
Software and Tools	5000
Data Collection and Processing	3000
Documentation and Report Writing	2000
Transportation Fare	2000
Total Estimated Cost	80000

5.4. Complex Engineering Problem

5.4.1. Complex Problem Solving

Table 5.2: Mapping with complex problem solving

EP1 Dept of Knowledge	EP2 Range of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent of Stake- holder Involvement	EP7 Interdependence
☑	☑	☑		☑		

EP1 - Depths of Knowledge:

This project has many parts and needs a lot of knowledge in computer vision, deep learning, and medical image analysis. You can show that you know a lot about image preprocessing, refinement techniques, and complex neural network architectures. Integrating health domain awareness for illness classification adds cross-disciplinary complexity, which shows how important it is to have a good grasp of AI concepts and medical diagnostic procedures.

EP2 - Ranges of Conflicting Requirements:

The project finds a balance between different needs so that it can work with large datasets without overfitting, get high accuracy while keeping computational efficiency, and deal with both model generalization and domain-specific sensitivity. In medical settings, where trust in clinicians and ethical AI use depend on openness, there is also a trade-off between how complex a model is and how easy it is to understand.

EP3 - Depths of Analysis:

The investigation entails a stringent evaluation of model performance through the utilization of accuracy, precision, recall, and loss metrics. To fully understand how a model works, you need to do hyperparameter tuning and structure comparison. The performance of each model helps you choose the best one and make improvements, showing that you have strong analytical skills and technical judgment when it comes to getting the best results.

EP5 - Extents of Applicable Codes:

The project follows the right ethical codes for using AI models, keeping patient information private (for example, by anonymizing it), and using open-source licenses for datasets and frameworks. Healthcare standards must be followed, and results must be able to be repeated. This is in line with good research and professional engineering practices.

Mapping with Knowledge Profile for EP1

This table 5.4 is designed to map the EP1 to the Knowledge Profile.

Table 5.3: Mapping with knowledge Profile

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
☑		☑		☑

K3 - Engineering Fundamentals:

The project used basic engineering concepts like preprocessing data, algorithmic logic, and system optimization. Understanding convolutional neural networks and evaluating models depends on basic math and programming concepts, which are part of a strong engineering foundation that can be used to solve real medical imaging problems.

K5 - Engineering Design:

The process of designing the model included finding problems, working with data, choosing algorithms, setting up training, and testing systems. Iteratively improving and comparing multiple architectures is in line with engineering design principles that aim to build a system that is accurate, scalable, and easy to use in real-world medical settings.

K8 - Research Literature:

There were a lot of relevant studies and similar models that helped with choosing a model and evaluating its performance. Understanding published returns helps find the best ways to do things, fill in study gaps, and explain architectural choices. This shows that the project is based on established knowledge while also providing new insights.

5.4.2. Engineering Activities

In this section, provide a mapping with engineering activities. For each mapping add subsections to put rationale (Use Table 5.4).

Table 5.4: Mapping with complex engineering activities

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
☑			☑	☑

EA1 - Range of Resources:

Deep learning platforms, cloud processing power, and large annotated medical datasets were among the resources from different technical domains that combined to create a synergistic environment for advancement. Effective training was also fueled by hardware acceleration through GPUs. The interdisciplinary nature of engineering tools used in diagnostic medicine is reflected in this combination of elements.

EA4 - Consequences for Society and Environment:

This digital project directly reduces avoidable blindness, lowers healthcare costs, and improves patient quality of life by improving early detection of mpox diseases. Virtual diagnostics' sustainable nature reduces the need for physical resources, encouraging easily accessible and environmentally responsible medical care practices.

EA5 - Familiarity:

The project requires knowledge of deep neural networks, medical case imaging, and healthcare system configurations. Although it works in a comparatively standardized problem domain, accurate AI model execution requires developing expertise. Even though there are structural standards, it is crucial to continuously adapt and learn about medical demands in order to perform the work successfully.

5.5. Summary

The "A Deep Learning Approach for Classifying mpox Disease" project demonstrates the comprehensive application of engineering principles (EP), knowledge profiles (K), and engineering activities (EA). It calls for deep learning architecture design (K5), practical application of engineering principles (K6), and advanced technical knowledge (K3, K4), all supported by academic literature (K8). With an emphasis on in-depth analysis and decision-making when needs conflict, the engineering problems range from collaborating with individuals from various fields to involving stakeholders (EP1–EP7). In addition, the project makes use of a range of resources, promotes innovation (EA1, EA3), considers social impacts (EA4), and ensures professional collaboration (EA2, EA5). In general, it demonstrates how to apply design thinking, engineering fundamentals, and practical skills to develop a practical artificial intelligence solution for healthcare.

CHAPTER 6

CONCLUSION

6.1. Summary

This project examines how to use medical images and the most recent machine learning techniques to rapidly diagnose mpox diseases and enhance treatment results. The information was gathered from multiple sources, including real-world clinical datasets and Kaggle. To ensure consistency and high quality, it was preprocessed. This included image augmentation, gamma correction, normalization, and resizing. Three sections comprised the cleaned dataset: testing, validation, and training. After that, it was divided into four groups: Normal, Measles, Chickenpox, and Monkeypox.

The experimental results showed that ResNet50 had the best performance, with an accuracy of 99.11% and the lowest misclassification rate of 0.89%. This shows that it was better at feature extraction and classification. EfficientNetB3 also did well, with 97.32% accuracy and a 2.68% misclassification rate. This shows that it can generalize well. The CustomCNN model, on the other hand, only got 88.84% accuracy, which means it didn't represent features as well as deeper architectures. The Vision Transformer had the lowest accuracy (79.79%) and the highest misclassification rate (23.21%). This means that it may need more data or better hyperparameter tuning for this task. Overall, deep pre-trained models, particularly ResNet50 and EfficientNetB3, outperformed the custom and transformer-based approaches, highlighting their effectiveness in capturing complex patterns from the dataset.

The results establish CNN as the most accurate and dependable model for mpox disease classification. This study reinforces the role of AI in ophthalmic diagnostics and supports the development of automated tools to improve accessibility, lower medical costs, and advance global vision health.

6.2. Limitation

Scarcity of Annotated Medical Records: Many existing studies rely on small, imbalanced datasets, making it difficult to evolve highly precise and generalizable models. Obtaining a large, diverse, and well-annotated collection remains a key obstacle.

Deficiency of Model Interpretability: Most deep learning models operate as black-box systems, making it challenging for medical experts to trust and decode the predictions. There is a need for explainable AI techniques to improve transparency.

Barriers in Real-World Implementation: While AI models perform well in controlled environments, their deployment in authentic healthcare infrastructures is restricted due to integration difficulties, regulatory compliance, and computational resource constraints.

Handling Variation in Medical Images: Differences in lighting, image resolution, and patient-specific factors can make models less accurate. To fix these problems, we need better preprocessing methods and stronger model architectures.

6.3. Future Work

This project lays the groundwork for future advancements in AI-driven medical diagnosis and the categorization of ocular diseases. Future research may focus on enhancing model accuracy through the utilization of larger and more diverse datasets, incorporating a broader range of ocular diseases for a more comprehensive classification. To improve clinical workflows, more research might focus on how to use real-time diagnostic systems in healthcare settings. Also, checking how explainable deep learning models are can help healthcare workers trust them more. Also, using transfer learning methods could make models work better when there isn't much data available. This method could be used in other areas of healthcare in the future, showing that deep learning can be used for medical diagnosis in more situations. These rules will help AI keep getting better and being used in healthcare, especially in places that don't have enough healthcare or are hard to reach.

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