Advanced Techniques for Skin Disease Classification Using Machine Learning

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***Abstract*— The global emergence of Mpox (formerly known as Monkeypox) has highlighted the critical need for rapid and accessible diagnostic tools, particularly in resource-limited settings. Early diagnosis is often challenging due to the clinical similarity of Mpox lesions to those caused by other skin diseases such as chickenpox, measles, and cowpox. This study explores the potential of machine learning, particularly deep learning models, to assist in the automated classification of Mpox lesions. Using the Mpox Skin Lesion Dataset, augmented with images from additional skin diseases and healthy skin, we benchmark the performance of state-of-the-art models including DenseNet-121, ResNet-50, Xception, and hybrid CNN+SVM approaches. To improve model performance and generalization, we employed various data augmentation techniques such as rotation, flipping, brightness adjustments, and noise injection. Our findings reveal that deep learning models, particularly ResNet-50, outperform hybrid methods, showcasing their ability to accurately classify lesions despite dataset imbalances and data scarcity. This research underscores the potential of deep learning to aid in the early detection of Mpox and other skin diseases, offering insights for future diagnostic frameworks.**

Keywords*— *Image classification, Machine Learning, transfer learning, Neural Networks, Data augmentation

1. Introduction

1.1 Problem Statement

The recent global outbreak of Mpox which was formerly known as Monkeypox has emerged as a significant public health challenge, affecting over 110 countries[1]. Early clinical diagnosis of Mpox is particularly difficult because its symptoms, such as skin rashes, can resemble those of other conditions. In situations where Polymerase Chain Reaction (PCR) tests are not readily available, computer-aided diagnostic tools can prove to be invaluable. Machine learning methods, known for their ability to analyze complex patterns, have shown great promise in this area**.** The primary objective of this study is to evaluate different image classification models on the Mpox dataset. The images need to be classified among six classes – Chickenpox, Monkeypox, Cowpox, Measles, HFMD and Healthy skin. The models considered include DenseNet, ResNet, Xception, and various hybrid approaches that combine CNN with traditional machine learning classifiers. Specifically, the hybrid methods analyzed are CNN+Naive Bayes, CNN+Random Forest, CNN+SVM, and CNN+kNN. Each of these models offers distinct architectural advantages that could potentially leverage the diversity provided by augmentation. This study aims to determine which architecture benefits most from augmented data in terms of classification accuracy, F1 score and generalizability. The findings of this research can provide valuable insights for practitioners, helping them select the most appropriate models and data preparation techniques for image classification tasks, particularly when dealing with limited datasets. The results are expected to inform best practices in the design of image classification pipelines in domains where data scarcity is a challenge.

1.2 Related Work

The classification of skin lesions has been a widely researched area, especially in the context of medical image analysis. A significant amount of work has focused on leveraging deep learning techniques to detect and classify dermatological conditions. For instance, [2][8] demonstrated the effectiveness of deep convolutional neural networks (CNNs) in classifying skin cancer with a high level of accuracy, which has inspired similar efforts for classifying other skin lesions, including those caused by infectious diseases like Mpox [3]. Additionally, the application of deep neural networks to medical image classification has been shown to outperform traditional machine learning models, especially when dealing with complex image features such as those found in skin lesions [4].

Data augmentation and transfer learning are also commonly used techniques in the classification of medical images, particularly when data is limited. In the context of skin lesion classification, [5] showed that applying data augmentation techniques such as rotation and flipping significantly improved model performance by providing more varied data for training. This is especially important for small datasets, where overfitting is a major concern. Moreover, [6] explored transfer learning from large datasets like ImageNet, showing that models like ResNet and DenseNet can be fine-tuned on medical datasets for better performance with limited labeled data.

Recent work has also focused on comparing various deep learning architectures for skin lesion classification. For example, [7] compared DenseNet, ResNet, and Xception in the context of skin cancer classification and found that DenseNet outperformed the other models in terms of both accuracy and model convergence. However, the study highlighted that no single model works best for all datasets, suggesting the need for experimentation across different tasks and datasets.

Given the nature of the Mpox dataset, which shares characteristics with other dermatological images, this project builds on existing research by applying and comparing four deep learning models—DenseNet-121, ResNet-50, Xception, and CNN. The CNN model is further combined with traditional machine learning approaches such as SVM, Naive Bayes, kNN, and Random Forest to classify Mpox lesions. This research aims to contribute to the growing body of work in medical image classification and provide valuable insights into the optimal approaches for classifying Mpox skin lesions.

2. METHOD

2.1 Novelty

The novelty of this project lies in the evaluation and comparison of four distinct machine learning architectures—DenseNet-121, ResNet-50, Xception, and CNN+SVM—on the Mpox skin lesion dataset. While deep learning models like ResNet and DenseNet have been applied to skin lesion classification before, few studies have specifically addressed Mpox lesions, which differ from traditional dermatological images in various ways. The limited availability of labeled Mpox lesion data further exacerbates the challenge of training high-performance models.

We also perform data augmentation on the Mpox dataset which is a process of artificially increasing the size and diversity of a dataset by applying various transformations to the existing data. For a limited dataset, especially in medical image analysis like Mpox, data augmentation is crucial for improving model robustness and reducing overfitting.

In addition to the choice of models, our work introduces a comparative analysis of not just the models themselves but also the impact of using different combinations of deep learning architectures and classical machine learning techniques (CNN+SVM). By hybridizing a convolutional neural network (CNN) with a support vector machine (SVM), we aim to combine the powerful feature extraction abilities of CNNs with the superior discriminative capabilities of SVMs. This is a less commonly explored approach in the domain of medical image classification for skin lesions and is expected to provide valuable insights into improving classification performance, particularly when the dataset is small and unbalanced.

2.2 Rationale

The reason we believe this approach will perform well lies in the combination of several factors as mentioned below.

2.2.1 Model Selection

In recent years, deep learning (DL), particularly the various forms of Convolutional Neural Networks (CNNs), has transformed numerous areas of medical science. These advancements are largely due to their exceptional ability to learn complex patterns, surpassing the performance of traditional machine learning techniques. The models chosen—DenseNet-121, ResNet-50, Xception, and CNN+SVM—have been shown to perform well on image classification tasks in general and specifically on medical images. DenseNet-121, for example, utilizes dense connections between layers, which helps in the efficient reuse of features, making it especially suitable for datasets with limited size[9]. ResNet-50 uses residual connections to help the model train deeper architectures without suffering from vanishing gradients, which is important for complex image data [10]. Xception, with its depth-wise separable convolutions, is known for reducing the number of parameters while maintaining accuracy, making it efficient for high-dimensional data [11]. The CNN+SVM hybrid, on the other hand, benefits from the strengths of both CNN's ability to extract hierarchical features and SVM's ability to create optimal decision boundaries for classification [12].

2.2.2 Data Augmentation

To address the dataset's imbalances and enhance generalizability, we applied a variety of data augmentation techniques during preprocessing. These augmentations were designed to introduce variability into the dataset, simulating different real-world conditions and improving the model's robustness. [13] **Rotation:** Images were randomly rotated within a range of -15 to 15 degrees, allowing the model to learn from variations in object orientation. This technique ensures that the model is not overly reliant on a specific alignment of lesion features. **Scaling:** Zoom-in and zoom-out transformations were applied to simulate different distances from the camera. This scaling variability helps the model generalize across lesions of varying sizes and positions within the frame. **Flipping:** Horizontal and vertical flips were incorporated to create new perspectives of the lesions, effectively doubling the training data without introducing new images. **Brightness and Contrast Adjustment:** Random adjustments to brightness and contrast were implemented to mimic different lighting conditions, ensuring the model learns features resilient to varying image exposures. **Gaussian Noise:** Random Gaussian noise was added to some images to increase robustness. This technique helps prevent overfitting by encouraging the model to focus on meaningful lesion features rather than noise-free patterns in the dataset. **Gaussian Blurring:** Blurring was applied to reduce high-frequency noise and simulate imaging artifacts, further improving the model's ability to generalize.

2.2.3 Transfer Learning

Transfer learning techniques will be used by fine-tuning pre-trained models, such as those trained on ImageNet, to adapt them to the Mpox dataset. Transfer learning is particularly effective when working with smaller datasets, as it allows the model to leverage features learned from large-scale image classification tasks [14].

These strategies combined offer a balanced approach to improving the classification accuracy, f1 score and generalizability of the models, especially in the context of limited and potentially noisy data.

2.3 Approach

2.3.1 Dataset Preprocessing

The Mpox skin lesion dataset from Kaggle was preprocessed to ensure it is in a suitable format for training. This includes resizing all images to a uniform size (e.g., 224x224 pixels) and normalization of pixel values to scale the inputs into a consistent range.

Data augmentation techniques were applied to increase the size of the training set. These augmentations include random

rotations, flipping, zooming, changing contrast and hue values and brightness adjustments. These transformations simulate different angles and lighting conditions, helping the model generalize better.

2.3.2 Model Implementation

DenseNet-121: DenseNet is characterized by its dense connections between layers, where each layer receives input from all preceding layers. This architecture improves feature reuse and alleviates the vanishing gradient problem, which is crucial for deeper networks. DenseNet has been shown to achieve state-of-the-art performance on various image classification tasks. For this project, DenseNet121 will be used, which is known for its ability to learn rich feature representations while maintaining manageable computational cost. DenseNet-121 V2 is an enhanced version with updated hyperparameters: batch size of 32, 224x224 input dimensions, 1e-3 learning rate with cosine decay, and 30 training epochs. Data preprocessing includes train-validation-test splits, autotuned prefetching, and pixel normalization (0–1).

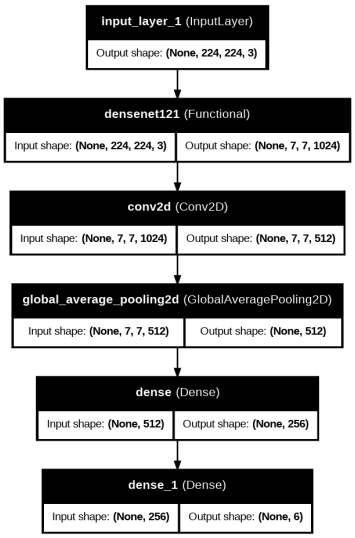

Fig 1: DenseNet-121 Model Architecture

ResNet-50: ResNet-50 is a deep CNN model from the ResNet (Residual Networks) family designed for effective image classification. It uses residual learning, where residual blocks with skip connections enable the network to bypass some convolutional layers, allowing gradients to flow directly through the network and mitigating the vanishing gradient problem. This architecture, with 50 layers, is organized into stages, each containing convolutional and residual blocks that progressively increase in filter size, making it possible to train very deep networks successfully. ResNet-50's structure and depth allow it to perform well in complex image classification tasks, especially when enhanced with transfer learning.

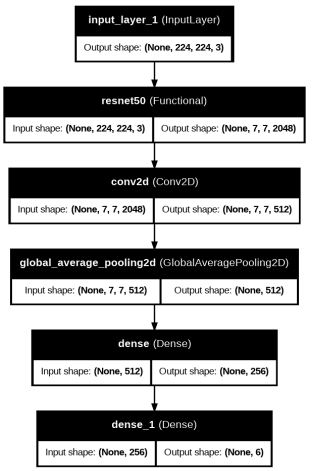

Fig 2: ResNet-50 Model Architecture

Xception: Xception is a deep convolutional architecture that uses depth wise separable convolutions to reduce the number of parameters while maintaining model performance. Xception is an extension of the Inception model that replaces traditional convolutions with depthwise separable convolutions, allowing the model to be more efficient in terms of computation while still achieving high accuracy. This makes it particularly well-suited for tasks that require learning complex patterns without excessive computational cost. The Xception model will be employed here to evaluate how it performs with augmented data.

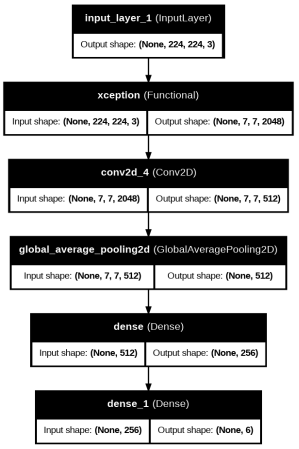

Fig 3: Xception Model Architecture

CNN + SVM Hybrid: The CNN model is used for feature extraction, and the features learned by the CNN are then passed to an SVM classifier, which finds the optimal decision boundary for classification and classification strength. This hybrid approach leverages the strengths of both methods, where CNNs excel at feature extraction, and SVMs excel in creating boundaries for high-dimensional spaces.

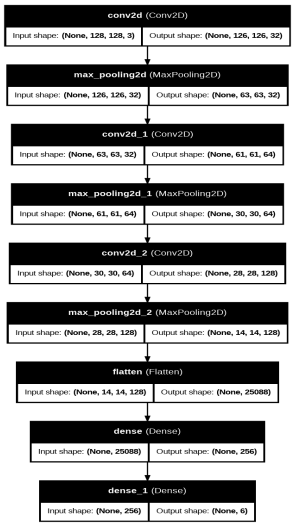

Fig 4: CNN+SVM Model Architecture

2.3.3 Training

To ensure robustness, k-fold cross-validation was employed to evaluate the performance of the models on different subsets of the data. Hyperparameters such as the learning rate, batch size, and number of epochs were tuned to find the optimal configuration for each model.Each model was trained using the Adam optimizer with a learning rate of 0.0001 and a batch size of 32 images. Early stopping was employed to monitor the model's performance on the validation set and prevent overfitting[15]. The models were trained for a maximum of 50 epochs or until validation loss stops improving for 5 consecutive epochs. Regularization techniques such as dropout (set to 0.5) were applied to further reduce the risk of overfitting.

2.3.4 Evaluation

The models will be evaluated using standard classification metrics, including accuracy, precision, recall, F1-score and training time. These metrics provide a comprehensive view of each model's ability to correctly classify the Mpox lesions, with a focus on balancing sensitivity and specificity.

Comparative analysis will be performed to evaluate which model benefits the most from data augmentation and transfer learning, and to identify which model performs best in terms of f1 score, training time and robustness. F1 score is a crucial metric as the dataset is imbalanced which makes accuracy a less significant metric for evaluation.

Moreover, the validation accuracy is the metric to check to determine the early stopping while training the models. If the validation loss does not improve for certain number epochs, the training can stop and prevent overfitting.

3. Plan and Experiment

3.1 Dataset

The dataset used in this project is the Mpox Skin Lesion Dataset, which is publicly available on Kaggle. The dataset consists of images of Mpox lesions, which are visually distinct and require careful classification in medical settings. This dataset serves as a critical resource for developing models aimed at detecting and classifying Mpox lesions from images.

The dataset primarily consists of image data, so the features are pixel values (with each image having a resolution of 224x224 pixels, typically represented by 3 color channels—RGB). The number of features is therefore determined by the dimensions of the image: 224 x 224 x 3, which results in a feature space of 150,528 dimensions for each image.

The dataset contains 7777 labeled images, with each image representing a lesion from a patient who has been diagnosed with Mpox. The images are labeled with the corresponding class of the lesion, which represents the severity or stage of the disease.

3.1.1 Pre-processing Procedure

Image Resizing: All images will be resized to a uniform resolution of 224x224 pixels to match the input size expected by the models. **Normalization:** The pixel values will be normalized to the range [0, 1] to improve model convergence during training. **Data Augmentation:** To simulate additional training data and improve the robustness of the model, data augmentation techniques were applied. This step is crucial to ensure that the model generalizes well, especially given the relatively small size of the dataset.

Imbalance in the Dataset: A notable challenge with this dataset is the imbalance in class distributions. Certain classes, such as those representing more common or visually distinctive stages of Mpox, have a disproportionately higher number of samples compared to rarer classes. This imbalance can bias the model towards predicting the majority classes while underperforming on minority classes, resulting in poor generalization. We've addressed this issue by using f1 score as a metric.

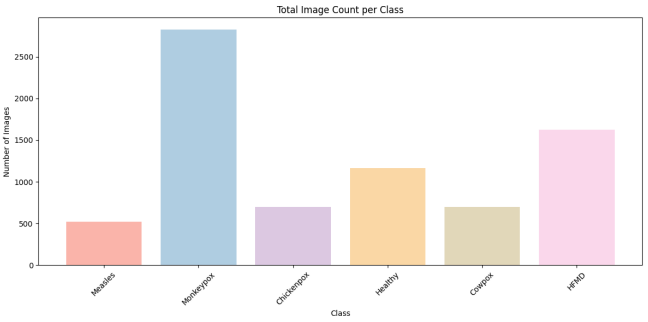

Fig 5: Visualization of images in the dataset

The dataset is split into training, validation, and test sets, with a 70-20-10 ratio. This ensures that the model is trained on a sufficiently large portion of the dataset while retaining separate data for validation and testing to assess its performance.

3.2 Hypothesis

The hypothesis driving this project is that deep learning models (DenseNet-121, ResNet-50, Xception) will perform

better than the CNN+SVM hybrid model on the Mpox dataset, due to the following reasoning:

Deep learning models such as DenseNet, ResNet, and Xception are specifically designed to learn high-level features from raw image data. These models are capable of handling complex hierarchical features and have shown great success in medical image classification tasks, particularly when trained with large, varied datasets. Since the Mpox dataset is relatively small, data augmentation and transfer learning will be used to help these models generalize better. *CNN+SVM hybrid:* While CNNs are powerful feature extractors, combining them with an SVM classifier may not always outperform deep learning models for image classification tasks, especially when the dataset is small and unbalanced. SVMs are more effective in high-dimensional spaces when dealing with small datasets, but the feature extraction capabilities of deep CNN architectures may surpass those of CNN+SVM, especially in this context. Thus, the expected result is that the deep learning models will show superior classification accuracy and generalizability compared to the CNN+SVM hybrid, particularly when trained on augmented data.

3.3 Experimental Design

The experimental design is structured to evaluate the performance of each model on the Mpox dataset under different configurations. The experiments are designed to answer the following research questions:
How do the different architectures (DenseNet-121, ResNet-50, Xception, and CNN+SVM) perform on the Mpox dataset?
How does data augmentation influence model performance?
How well do the models generalize to unseen data after training on augmented and non-augmented datasets?

3.3.1 Experimental Setup

Training-Testing Split: The dataset will be split into training, validation, and test sets in a 70-20-10 ratio. This split ensures that the training process is based on a sufficiently large portion of the data, while the validation and test sets will allow for unbiased evaluation of the model's performance.

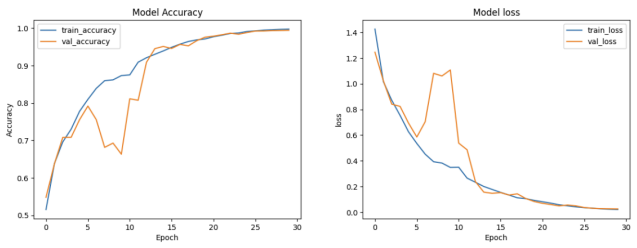

Fig 6: Accuracy and Loss curves of DenseNet-121 model training

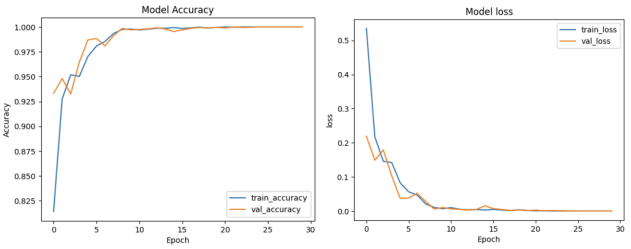

Fig 7: Accuracy and Loss curves of ResNet-50 model training

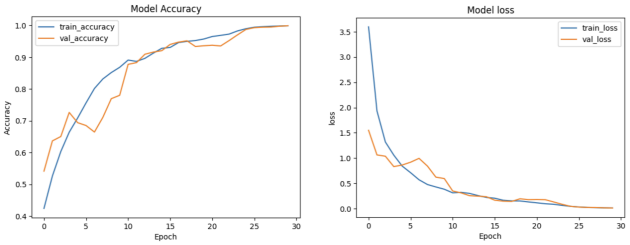

Fig 8: Accuracy and Loss curves of Xception model training

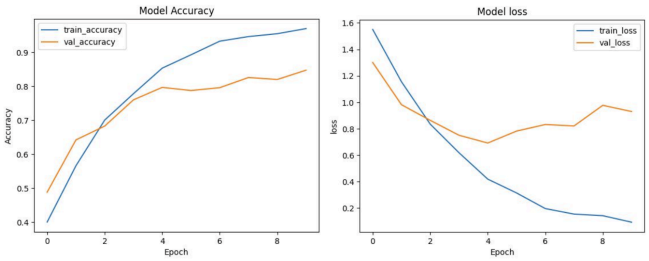

Fig 9: Accuracy and Loss curves of CNN+SVM model training

Cross-validation: K-fold cross-validation will be implemented to mitigate the risk of overfitting and ensure that the results are not dependent on a particular training/validation split. The models will be trained multiple times on different subsets of the data to assess their stability and generalizability.

Hyperparameter Tuning: Hyperparameter optimization will be performed using a combination of grid search and random search methods to identify the best values for parameters such as learning rate, batch size, number of epochs, and regularization techniques. A validation set will be used to tune hyperparameters, ensuring that the model avoids overfitting.

Fine-tuning: Fine-tuning involves taking a model pre-trained on a large dataset, and then training it further on a smaller, task-specific dataset to help it adapt its learned features to a particular task.For transfer learning, we used a pre-trained **ResNet50** model (`weights='imagenet'`) without its top layers, adapting it for six-class classification by adding custom layers: a convolutional layer, `GlobalAveragePooling2D`, and dense layers for feature extraction and prediction. Initially, the ResNet50 base was frozen to retain pre-trained weights, leveraging features learned from ImageNet, with fine-tuning later by unfreezing some layers for better dataset adaptation. Similarly, for

DenseNet-121, the model input was defined for 224x224x3 images, using the pre-trained base for feature extraction while freezing its weights (`training=False`). Custom layers were added, including a Conv2D layer (512 filters, ReLU), `GlobalAveragePooling2D` for dimensionality reduction, a Dense layer (256 units, ReLU), and a final Dense(6) layer for class logits.For the **Xception model**, input images of size 224x224x3 were used, with the pre-trained Xception base frozen for feature extraction. Custom layers included a Conv2D layer (512 filters, ReLU), GlobalAveragePooling2D for dimensionality reduction, a Dense layer (256 units, ReLU), and a final Dense(6) layer for class logits. For the **CNN+SVM** model, input images of size 128x128x3 were processed through a custom CNN with Conv2D, MaxPooling2D, and Flatten layers, followed by a Dense(256) layer for feature extraction. The extracted features were then classified using an SVM for the 6-class task.

4. Results and Discussion

Model	Precision	Recall	F1-Score	Support
DenseNet-121	0.87	0.84	0.83	154
Resnet-50	0.93	0.90	0.91	154
Xception	0.83	0.84	0.83	154
CNN + NB	0.46	0.49	0.49	1504
CNN + SVM	0.88	0.87	0.87	1504
CNN + KNN	0.77	0.73	0.74	1504
CNN + RF	0.90	0.70	0.76	1504

Table 1: Comparison of Models on basis of Macro Average

Table1 compares the performance of various models on an unbalanced dataset on the basis of Macro average, with the F1-score used as the primary metric to balance precision and recall. ResNet-50 stands out as the top-performing model, achieving the highest F1-score of 0.91 on a smaller support set of 154 samples, indicating exceptional performance for this subset of data. Other deep learning models like DenseNet-121 and Xception achieve slightly lower F1-scores of 0.83, demonstrating comparable but less robust performance. For the larger dataset (1504 samples), CNN + SVM achieves the best F1-score of 0.87, outperforming other hybrid approaches such as CNN + NB (0.49), CNN + KNN (0.74), and CNN + RF (0.76). In summary, ResNet-50 is the best choice for tasks involving the smaller class, while CNN + SVM performs better for the larger dataset providing higher generalizability, with DenseNet-121 and Xception providing solid alternative options in the smaller subset.

Model	Precision	Recall	F1-Score	Support
DenseNet-121	0.87	0.84	0.83	154
Resnet-50	0.93	0.90	0.91	154
Xception	0.85	0.86	0.85	154
CNN + NB	0.46	0.49	0.49	1504
CNN + SVM	0.88	0.87	0.87	1504
CNN + KNN	0.77	0.73	0.74	1504
CNN + RF	0.90	0.70	0.76	1504

Table 2: Comparison of Models on basis of Weighted Average

The Table2 evaluates the performance of several models on an unbalanced dataset, using the weighted average F1-score as the primary metric due to its ability to balance precision and recall across classes. Among the deep learning models, ResNet-50 achieves the highest F1-score of 0.91 on a smaller support set (154 samples), making it the best-performing model for this subset. DenseNet-121 and Xception follow closely with F1-scores of 0.85, showing consistent but slightly lower performance. For the larger dataset (1504 samples), CNN + SVM achieves the highest F1-score of 0.88, demonstrating strong generalizability across the unbalanced data. Comparatively, other hybrid models like CNN + KNN (0.77) and CNN + RF (0.80) perform moderately well, while CNN + NB lags significantly with an F1-score of 0.47. Overall, ResNet-50 is the best model for tasks involving smaller support sets, while CNN + SVM emerges as the most robust model for handling the unbalanced larger dataset.

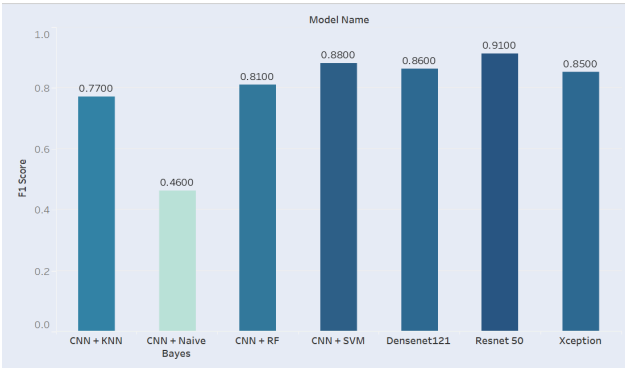

Fig 10: Visualization of F1 score of various models trained

The above figure compares the F1-scores of various models for a classification task, highlighting their performance. ResNet-50 achieves the highest F1-score of 0.91, emerging as the best-performing model. It is closely followed by CNN + SVM (0.88) and DenseNet-121 (0.86), which also demonstrate strong performance. The Xception model performs the same, with an F1-score of 0.86. Among hybrid

models, CNN + RF achieves a moderate F1-score of 0.81, while CNN + KNN has a lower score of 0.77. The CNN + Naive Bayes model performs the worst, with a significantly low F1-score of 0.46. Based on this analysis, ResNet-50 is the most suitable model for this task, particularly in scenarios where balanced precision and recall are crucial.

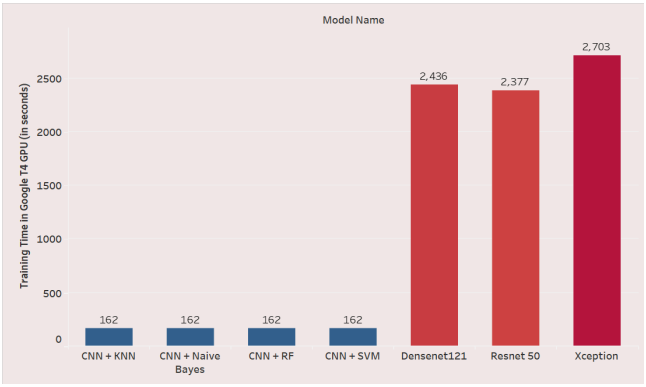

Fig 11: Visualization of training time of various models trained

The bar chart illustrates the training times (in seconds) for different models on a Google T4 GPU. The hybrid models—CNN + KNN, CNN + Naive Bayes, CNN + RF, and CNN + SVM—have significantly shorter training times of 162 seconds each, making them highly efficient in terms of computational cost. In contrast, deep learning models like DenseNet-121, ResNet-50, and Xception require substantially more training time, with DenseNet-121 and ResNet-50 taking 2,436 seconds and 2,377 seconds, respectively, while Xception takes the longest at 2,703 seconds. Considering both F1-score and training time, ResNet-50 stands out as the best model, as it achieves the highest F1-score (0.91) with a reasonable training time among the deep learning models. For tasks prioritizing speed, hybrid models like CNN + SVM may be preferable despite their slightly lower F1-scores.

Conclusion

This study highlights the potential of machine learning, particularly deep learning architectures, to address the critical challenge of automated classification of Mpox lesions. By leveraging state-of-the-art models such as DenseNet-121, ResNet-50, Xception, and a hybrid CNN+SVM approach, we evaluated their effectiveness on the Mpox Skin Lesion Dataset. The application of extensive data augmentation techniques, including rotation, flipping, brightness adjustment, and noise injection, significantly enhanced the robustness and generalizability of the models.

Among the evaluated models, ResNet-50 demonstrated superior performance, benefiting from its deep residual connections that enable efficient feature learning and better generalization. DenseNet-121 and Xception also performed well, showcasing their strengths in feature reuse and computational efficiency, respectively. In contrast, the hybrid CNN+SVM model, while effective in certain contexts, struggled to match the depth and complexity handling capabilities of the deep learning architectures.

Our results underscore the importance of combining transfer learning, data augmentation, and advanced model architectures to overcome the challenges of limited and imbalanced datasets, such as those encountered in medical imaging. The insights gained from this study offer a pathway for developing robust diagnostic frameworks that can assist healthcare professionals in the early detection of Mpox and other dermatological conditions. Future work should focus on expanding the dataset to include more diverse lesion types, exploring ensemble methods, and integrating multimodal data, such as patient demographics and clinical metadata, to further enhance diagnostic accuracy.

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CSC 522 002 - GROUP 21

Meeting Attendance

Date and Day	Location	Time	Type	Parth	Mrudani	Abhinav	Yuvraj
10/20 - Sun	GMeet	2:00pm-4:00 pm	Virtual	✓	✓	✓	✓
10/24-Thurs	GMeet	2:00pm-5:00 pm	Virtual	✓	✓	✓	✓
10/27-Sun	Hunt library	2:00pm-5:30 pm	In-person	✓	✓	✓	✓
11/05-Tue	Hunt library	3:00pm - 6:00pm	In-person	✓	✓	✓	✓
11/06 - Wed	Hill library	2:00pm-6:00 pm	In-person	✓	✓	✓	✓
11/12 - Tue	Hunt library	3:00pm - 6:30pm	In-person	✓	✓	✓	✓
11/16 - Sat	University Commons	2:00pm-4:00 pm	In-person	✓	✓	✓	✓
11/17-Sun	GMeet	2:45pm-10:00pm	Virtual	✓	✓	✓	✓