



Comprehensive and Integrated Deep Learning Approaches-based Intelligent Skin Disease Diagnosis System for Pox Detection

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Abstract: Chickenpox, measles, monkeypox, and smallpox are skin diseases that exhibit very similar signs, making accurate distinction difficult. In this study, an automated deep learning system is developed to classify pox-related skin diseases into six classes, which are Chicken_Pox, Measles, Monkey_Pox, Small_Pox, Normal, and Unknown. The system uses MobileNet to extract features efficiently using a dataset of 4099 training and 1104 evaluation images. The three tested model variants: inception-based CNN, Deep Belief Network, and MobileNet-LSTM-hybrid, Deep Belief Network (DBN) with the SGD optimizer, incurred the best classification accuracy, showing to be more effective at similar tasks to retrieve spatial and temporal features. This will ensure more efficient and quicker detection of the pox, particularly in those regions that do not have specialists in dermatology. Although it is not a replacement for clinical expertise, the system provides a potent instrument in screening and diagnosis of early diseases. The comparative evaluation of these models offers insights into the most effective approach for medical image classification of pox diseases.

Keywords: Pox detection; deep learning; skin disease classification; CNN; medical image analysis.

1. Introduction

Chickenpox [1], measles, monkeypox, and smallpox [2] are viral diseases that, in association with skin manifestations, affect human beings [3]. Viral skin diseases like chicken pox, measles, monkey pox, and smallpox have been major global issues of public health, particularly in developing and underserved areas, where the issue of treating or diagnosing these diseases may economically weigh down authorities. Such infections usually share the same dermatological characteristics, such as rashes, pustules, and blisters, and it can be challenging to diagnose them properly and promptly using clinical examination. These similarities can confuse the basis of diagnosing cases that lead to the delay in effective treatment. Delays result in severe health consequences among individuals, and the spread increases to the whole public. The traditional way of diagnosis is primarily based on clinical judgment and physical examinations including laboratory tests, such as PCR test or a biopsy for confirmation if it is possible, but most of the time, these diagnostics and much more proved to be time-consuming, costly, and most of the time inaccessible, particularly in the remote areas of these developing regions. Therefore, there is a requirement to develop an automated and comprehensive skin disease

diagnosis system with the sole aim of detecting contagious diseases like pox. Late diagnosis may cause higher rates of transmission and poor health outcomes.

Recent developments in artificial intelligence (AI), specifically deep learning, have shown a significant potential for automating the analysis of medical images and improving the capabilities of diagnostic methods. CNNs have demonstrated extensive success in identifying complex structures in dermal images, but most of the existing literature has hitherto focused on single disease detection (such as monkeypox) with either standalone CNN architectures or transfer learning techniques. It is in this context that we suggest a multi-class pox disease classification framework using skin images, which is a comprehensive and integrated deep learning model. Novelty in our project. The key novelty of our work lies in the development and application of a hybrid MobileNet + LSTM model designed specifically for the classification of pox diseases with similar dermal characteristics. This approach uniquely integrates MobileNet's lightweight and efficient convolutional layers for spatial feature extraction with LSTM's capability to model sequential dependencies among spatial features. Although dermal images are static, the LSTM component enhances the model's ability to capture subtle variations by learning contextual relationships within the spatial patterns of skin lesions was developed and evaluated. This hybrid architecture balances computational efficiency and classification performance, making it particularly suitable for portable diagnostic systems. We also conduct a comparative analysis of three optimizers, namely Adam, SGD, and RMSprop, on three model types, such as Inception_Net, the proposed hybrid model, and a Deep Belief Network (DBN). This optimizer-sensitive analysis gives a better insight into the training dynamics and model robustness. In comparison to the previous research methods that concentrated on a single skin condition (Monkeypox) or only a few evaluation metrics means those models were not generalizable to the wider range of pox diseases, our design aims at six classes of skin conditions (Chickenpox, Measles, Monkeypox, Smallpox, Normal, and Unknown), which provides a more generalizable and clinically applicable solution. The point is not to substitute clinical judgement, but to provide quick, convenient, and precise pre-screening, particularly in regions with limited availability of specialist dermatologists.

1. Introduction

1.1 Research Background and Contributions

The advances in AI and deep learning have thrown open the gates for automating medical image analysis and building systems that can analyze and report on images with minimal human input. Convolution Neural Networks (CNNs) come with advantages in terms of pattern extraction in medical images; thus, those networks can represent good candidates for the disease detection task. Here, present some of the deep learning classification models of skin conditions being classified into six types, such as Chicken_Pox, Measles, Monkey_Pox, Small_Pox, Normal, and Unknown. The proposed architecture involves MobileNet as a lightweight and real-time feature extractor suitable for dermal images. Also, three deep learning models are designed and compared: CNN-based Inception Net, spatial-temporal hybrid MobileNet-LSTM that captures both spatial and sequential features, and a Deep Belief Network (DBN) for hierarchical feature learning across the models. All models were trained under the same conditions using three optimizers, Adam, SGD [4], and RMSprop, to provide convergence and performance metrics for the rich models competent in achieving desired classification performance. This research sets out to contribute towards the growing field of AI-assisted medical diagnostics by comparative analysis of the above models in different training scenarios. In the long term, the aim is to develop a simple, inexpensive, scalable, and accurate device for identifying pox diseases for clinical and non-clinical points of care. This is not intended to supersede the expertise of a clinician in the health system, but a tool to enhance the consistency of diagnosis so as to reduce human error and widen access to dermatological care [5].

1.2 Related Works

The rapid globalization of viral skin infections has, in turn, generated the need for reliable tools for their diagnosis. There have been numerous advances in deep learning algorithms, which, by now, have achieved remarkable success in classifying dermatological conditions that share visual symptoms. This makes them a compelling option for image classification, as they autonomously detect and acquire the critical attributes of the given image data. Furthermore, Deep learning approaches offer a pathway to enhanced

performance through the successful mitigation of key factors, such as the computational time involved in image data analysis for detection. These advanced deep learning algorithms can ultimately support dermatologists while they make critical decisions in the treatment of various skin ailments. Mobile Net-based Monkeypox detection was carried out by, who have already shown promise in classifying clinical dermal images. On optimization for model performance, [6] allowed the necessity of optimizations for model performance and put forth a two-stage enhancement pipeline for deep learning methods on medical image classification. The high-performance algorithm designed by distinguished among Mpox lesions and those of others to achieve best-in-class functionality on the big-quantum datasets. Explaining model interpretability and transparency is gaining focus. Explainable AI was fused into transfer learning by allowing clinicians to visualize the prediction logic, and Grad-CAM was used by [7] to say what features delineated Mpox detection lesions. Developing Transformer-Aided architectures is on the rise, as [8] with their research demonstrated an attention mechanism in performing effectively for multi-class skin lesion classification that also included Monkeypox.

Hybrid frameworks have achieved popularity [9] and proposed a hybrid AI model for Mpox detection with increased sensitivity, while [7] fused classical machine learning with CNNs. By demonstrating that merging CNNs with hashing strategies can accelerate processes without compromising accuracy, Zhang et al. [10] contributed to the growing appreciation for hybrid techniques. [11] underscored ensemble algorithms that enhanced combined deep networks to make a robust classifier. [12] created and validated a unique framework for the automatic and precise determination of Mpox illness employing a meticulously gathered Mpox database by going through a diverse range of databases across the internet, and described a unique hybridized known as "Swin-PSO-SVM" that improves the precision and reliability of the discovery of monkeypox. Offers a computer-aided design framework towards the categorization of monkeypox based on an architecture of deep learning comprising numerous steps. [13] presents a complete method towards the identification of monkeypox based on deep learning techniques like ResNet-50, EfficientNetV2, MobileNetV2, and Vision Transformer, along with a combination of critical approaches. Proposed the VGG16-based approach for illness diagnostic generalization and enhancement, utilizing fuzzy expressions to control uncertainties and Principal Component Analysis to minimize dimensions. [14] provided a combined deep learning approach towards the recognition of Mpox by building with the use of deep learning as an attribute acquisition means alongside the classification methods built around the concept of machine learning. Suggested a framework for diagnosis that included the previously trained machine learning classification methods and CNN paradigms alongside the metaheuristic optimizing method. [15] created a novel combination of algorithms by including the capabilities of AlexNet, ResNet50, and Vision Transformers.

They were able to increase the effectiveness of monkeypox diagnosis by leveraging the prospects of Graph Convolutional Networks and the capabilities of three algorithms used by them. Modified ResNet50's level-centric structure for recognition of monkeypox. Furthermore, they made use of 4 architectures like Resnet50, AlexNet, VGG16, and GoogleNet to classify and detect, allowing their precision level to increase even more. Described an integrated classification-oriented method towards the identification of monkeypox, concentrating on the initial indicators associated with lesions of the skin, employs an integrated framework that includes LSTM and CNN for evaluating the feelings of individuals around the monkeypox sickness. [16] proposed an amalgamated paradigm for monkeypox categorization in which the attribute was retrieved with the deployment of several CNN architectural compositions. [17] provided an adaptive evaluation and optimum management of an integrated fractionated monkeypox disease paradigm based on outside influences. [18] came up with a novel and hybridized framework known as MonkeypoxHybridNet (i.e., a modified version of CNN), enabling the monkeypox identification using photos, with the primary goal of improving the network's performance. Despite the prospects offered by the aforesaid hybrid deep learning-based studies, there is still a need to improve the systems being built with better digital visualization capabilities.

Web-based platforms are coming into play as well. [19] demonstrated a real-time web system for Mpox skin analysis built upon new-age models, opening the door for mass-scale digital diagnosis. All these studies supported the feasibility and functionality of deep learning in automating the diagnosis of pox-like diseases via image classification.

2. Materials and Methods

2.1 Dataset Description

The data set [20] for this study is made up of high-resolution dermal images that are divided into six classes: Chicken-Pox, Measles, Monkey-Pox, Small-Pox, Normal, and Unknown. Of 4099 total images, 4099 were used for training, and 1104 images were evaluated for model performance. The images were collected from publicly available medical repositories and verified open-access sources. Each image was preprocessed to resize to a uniform dimension and normalized for consistency throughout all models. The nature of this dataset covers a variety of skin tones, lesion patterns, and lighting conditions, successfully simulating real-world scenarios. The labeling process was manually verified to maintain class integrity and to avoid data leakage. The dataset's balanced representation of disease and non-disease cases ensures unbiased training and a robust evaluation. This dataset is the basis for training deep learning models for effective classification of pox diseases and aiding the establishment of scalable AI-based dermatological diagnostic tools. A sample of the image dataset is shown in Figure 1 below.



Figure 1. Dataset Sample Images

2.2 System Design and Models

2.2.1. InceptionNet-Based Model

This is InceptionNet, a deep CNN that uses multiple filter sizes in parallel, so it can capture very detailed features as well as very abstract ones. The changed structure of InceptionNet (as shown in Figure 2 below) was used in this design to classify dermal images into six different classes. It is a network with parallel convolutional branches with 1x1, 3x3, and 5x5 filter cones inside the Inception modules that make possible the analysis of lesion patterns by the model at several scales. A processing structure like this maximizes accuracy yet enables computational efficiency. Also, the model incorporates batch normalization and dropout levels for the prevention of overfitting and to ensure proper generalization. The last dense layer employs a function 'softmax activation' to do the multiclass classification at the end. InceptionNet is most suitable for distinguishing between visually similar skin diseases due to its depth and multi-level feature extraction. This serves as a strong baseline for comparing hybrid and generative models in the research.

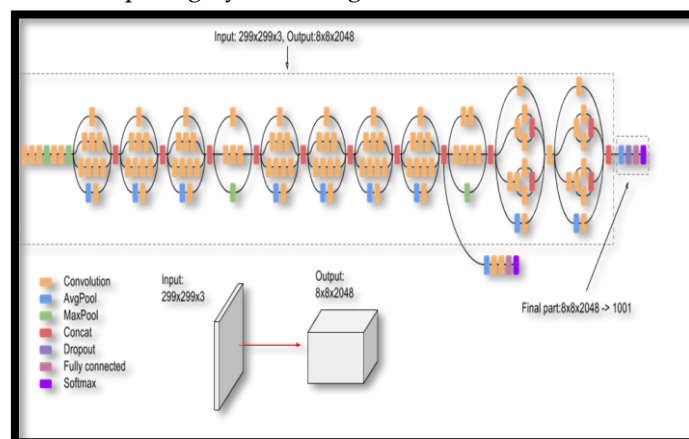


Figure 2. InceptionNet Model

2.2.2. Hybrid MobileNet-LSTM Model

This MobileNet-LSTM fuses the two realms of CNN and a recurrent neural network. Quality image feature extraction on dermal images happens, but at a fraction of its usual computational overhead, using the model called MobileNet. To run in environments with limited hardware support, the model incorporates depthwise-separable convolutions. After extracting feature maps, they are reshaped and passed to LSTM layers that encode temporal patterns or sequential dependencies across the spatial features. While dermal images are not inherently temporal, the LSTM level empowers the paradigm to learn the relationships between localized attributes in the regions of the image, which improves its subtle variation distinction ability. The complete model ends with a fully connected layer and a softmax classifier. That makes this mixed train the best option for portable systems in skin disease detection because it is well balanced on efficiency and performance. It also improves the surrounding meaning of spatial patterns; thus, the ability of the model to draw out lesions specific to pox with a greater accuracy rate.

2.2.3. Deep Belief Network (DBN) Model

DBNs are an artificial neural network composed of RBMs arranged in layers, each of which learns a probabilistic representation of the input. Unlike CNNs that adopt a different training process, the architecture for DBN learns a hierarchically ordered representation of features in the semi-supervised pretraining phase, which is then followed by supervised fine-tuning. With our work, the primary objective of modeling is to analyze the complex skin lesion patterns in the six classes of pox using DBN. Therefore, an input image is first flattened and then passed through multiple RBM layers, whereby the layers learn the more abstract features from the output in the previous layer. The advantage of layer-wise training is that the network is forced to learn robust representations even in the presence of limited or noisy data. This approach is useful throughout the backpropagation fine-tuning, where we refine unsupervised learning results by classifying weights through the softmax layer. Another obvious difference is that DBNs have high generalization and low overfitting characteristics. Probabilistic feature learning is therefore vital for the comparative study of the system. The typical structure of DBN has been shown in Figure 3.

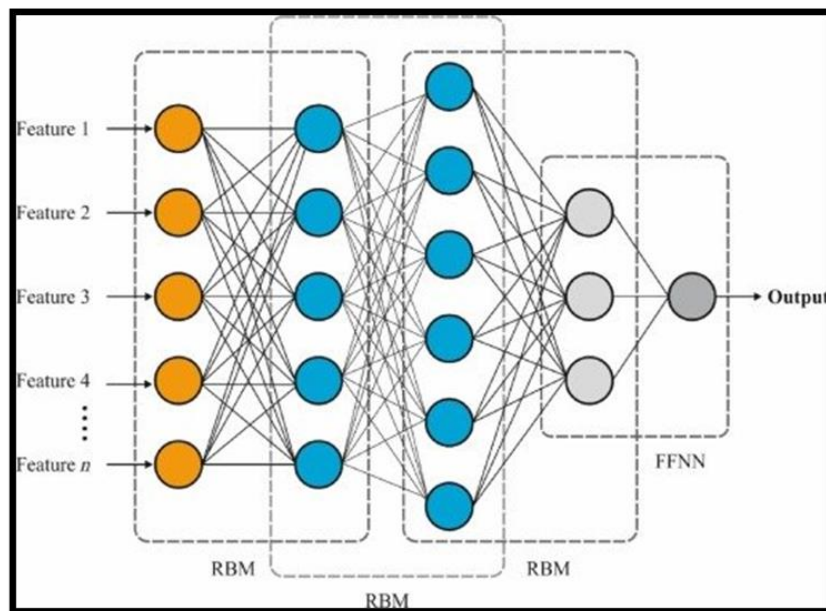


Figure 3. DBN Architecture

2.3 Proposed Methodology

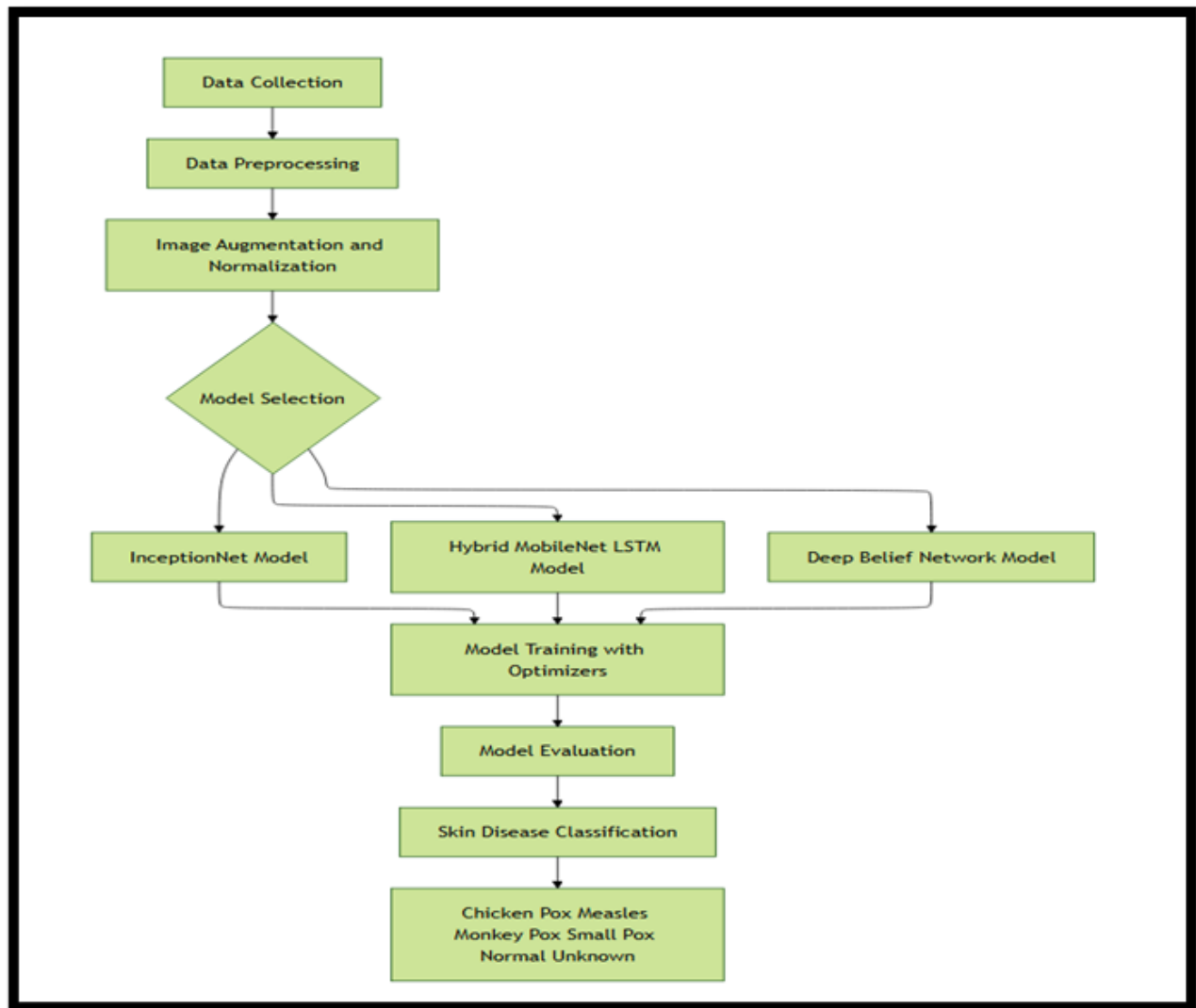


Figure 4. Proposed Workflow

The study methodology depicted in the above Figure 4 centers around formulating an automated deep learning framework that classifies pox-associated skin lesions based on image data acquired through dermoscopy. The procedure can be partitioned into 5 significant steps, namely, dataset preparation, preprocessing, model selection, training with optimizers, and evaluation.

2.3.1. Data preparation and Preprocessing

The dataset consists of 5203 images, out of which 4099 were assigned to training and 1104 were assigned to evaluation. The images were classified into different categories, namely Chicken_Pox, Measles, Monkey_Pox, Small_Pox, Normal, and Unknown. All images were resized to a common size and normalized to a pixel value of [0,1] for better learning and uniformity. To make the model robust and counter the class imbalance, data boost approaches like zooming, flipping, and rotation were incorporated.

2.3.2. Model Architecture

Three distinct model architectures were designed for evaluating the efficacy of pox detection.

- InceptionNet: a convolutional architecture having multi-scale feature extraction by Inception modules.
- MobileNet-LSTM: This model combines MobileNet with LSTM to augment its spatial feature analysis with LSTM extracting deeper dependencies among the feature maps.

- Deep Belief Network (DBN): This is a probabilistic model that learns hierarchical, abstract features via the application of stacked Restricted Boltzmann Machines.

These were developed considering the computational power needed for processing, as well as ensuring that the model takes into consideration the visual similarity that exists among the various pox diseases.

2.3.3. Optimizer Selection and Training

Their influence on training dynamics was studied for each model using the three most popular optimizers, namely Adam [7], SGD [8], and RMSprop [9], to analyze the effectiveness of the optimization methods. These optimizers differ in terms of learning rate adaptation, convergence speed, and model stability. Cross-entropy loss was used in these models as it is suitable for multi-class classification problems. To further counter overfitting, early stopping and dropout layers were included.

2.3.4. Model Evaluation

All models were evaluated against the test set with standard measures of precision, accuracy, F1-score, and recall. The formalization of confusion matrices was done to analyze the classification performance of the different classes. Besides, training and validation loss curves were plotted to study convergence behavior. Thus, this entire approach can serve as a detailed comparative measure of the different deep learning models in creating an understanding of the architecture and training strategy most appropriate to the automatic pox detection from skin images.

3. Results and Discussion

3.1 Inception Model

This utilized Inception Model has been optimized with 3 optimizers like RMSprop, SGD, and Adam. The confusion matrix, accuracy, and loss curves are given separately for each optimizer in the following figures 5, 6, 7, 8, 9, and 10. Using Adam, the InceptionNet achieved very good classification accuracy across all six classes, even hitting 100% decent accuracy in the identification of the "Unknown" class. It converged early and stabilized, as witnessed by the smooth decay in the loss and steady rise in accuracy throughout the training epochs (Figures 5 and 6). The model converged slowly with SGD, where small fluctuations in accuracy were observed, indicating training instability (Figures 7 and 8). RMSprop had convergence speed in between but led to a slight increase in misclassifications, mainly in confusing Small_Pox with Monkey_Pox (Figures 9 and 10). Thus, the InceptionNet retained its ability to majorly distinguish among very similar classes, thereby giving a strong notion of robustness along with Adam.

3.1.1 InceptionNet Model - Adam Optimizer

The Adam optimizer shows excellent performance with a decent classification for all classes. Misclassifications are very less, with only a few errors occurring between closely related classes, such as Measles (1 misclassified as Chicken_Pox) and Monkey_Pox (2 misclassified as Small_Pox). The "Unknown" class is perfectly classified with no errors, highlighting strong model confidence and stability using Adam.

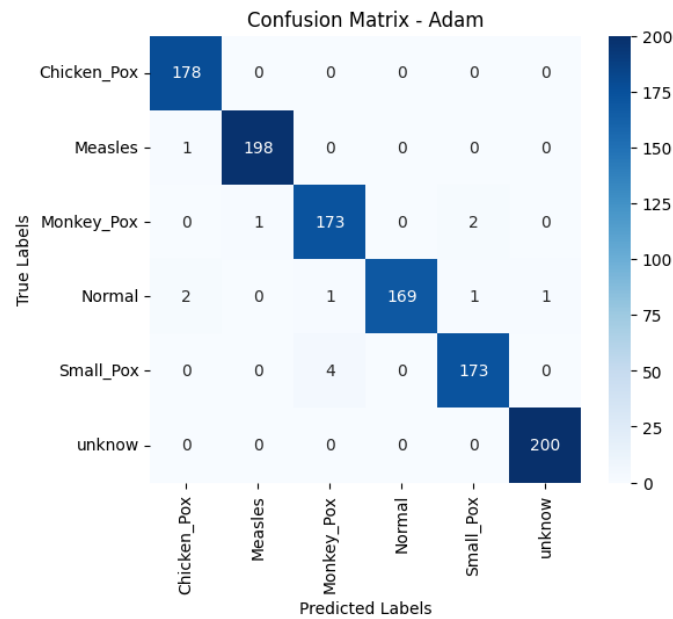


Figure 5. Confusion Matrix of the InceptionNet Model with Adam optimizer across 6 labels.

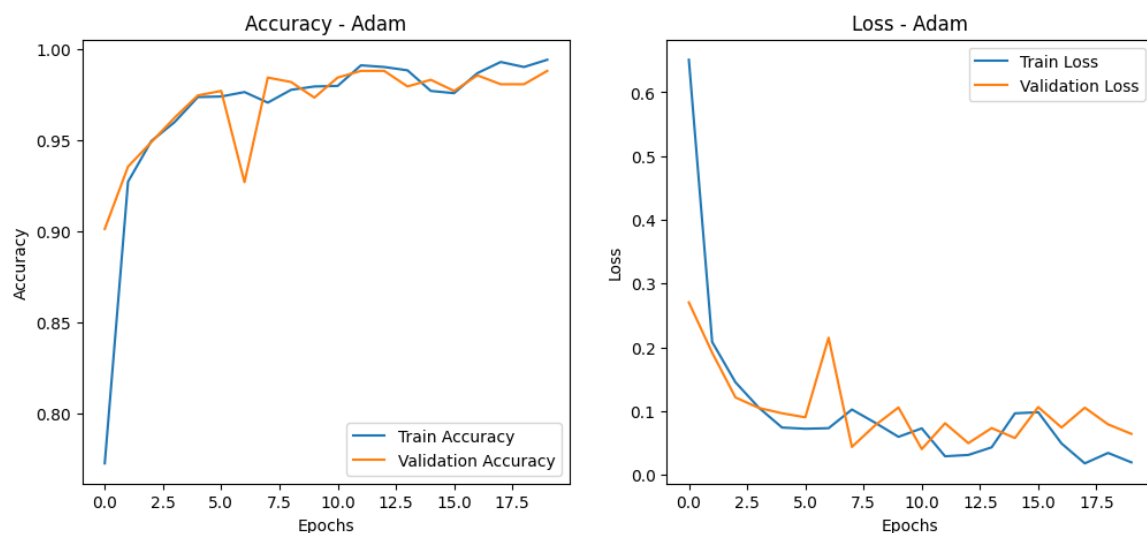


Figure 6. Accuracy and Loss Curves for InceptionNet Model using Adam Optimizer.

The accuracy and loss curves for the Adam optimizer show a rapid increase in both training and validation accuracy during the initial epochs, stabilizing above 0.95 after about the fifth epoch. Both curves maintain high accuracy through later epochs, with only minor fluctuations, indicating effective learning and minimal overfitting. The corresponding loss curves demonstrate a sharp decrease early on, converging to low and stable values for both training and validation sets as epochs progress. This suggests the model achieves good generalization while steadily minimizing errors throughout training.

3.1.2 InceptionNet Model - SGD Optimizer

The SGD optimizer has a bit more misclassifications compared to Adam, especially between Small_Pox and Monkey_Pox, where 11 total misclassifications are there. Chicken_Pox and Measles classes maintain strong precision, but Small_Pox shows some confusion with Chicken_Pox and Monkey_Pox.

Overall accuracy is high, but it shows that SGD might require more tuning or epochs to reach Adam's level of stability.

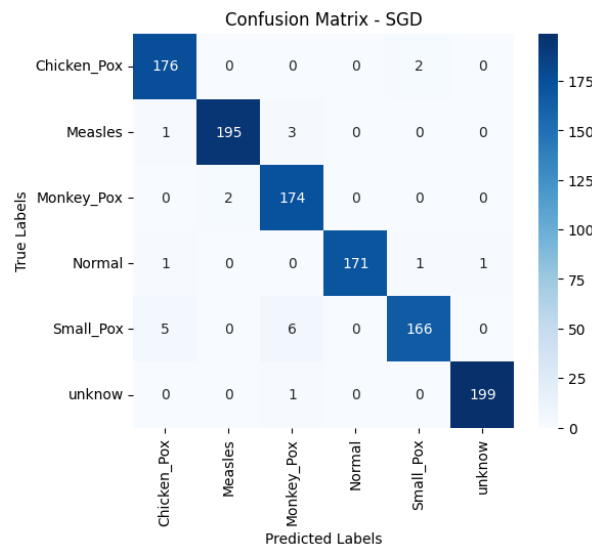


Figure 7. Confusion Matrix of the InceptionNet Model with SGD optimizer across 6 labels.

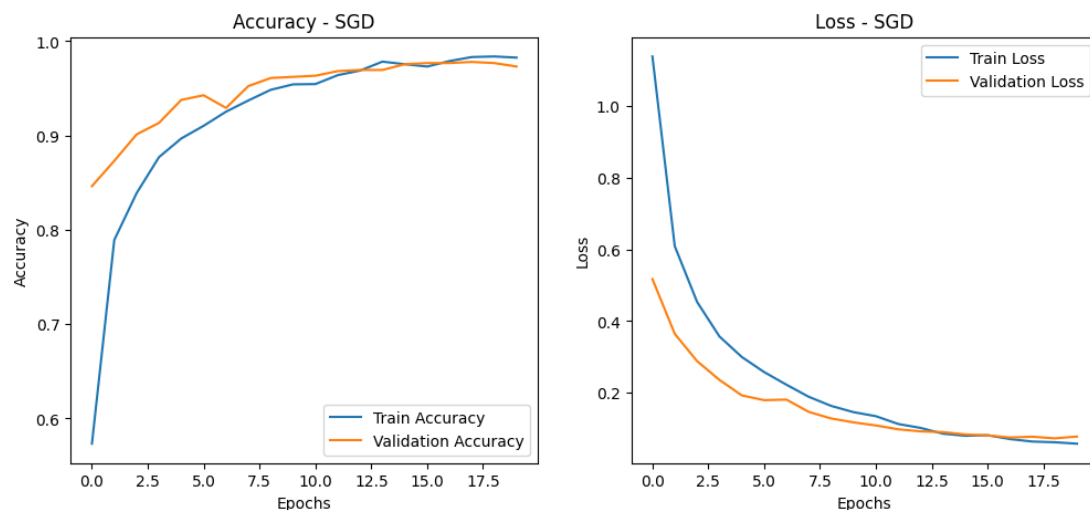


Figure 8. Accuracy and Loss Curves for InceptionNet Model using SGD Optimizer.

The accuracy and loss curves for the SGD model show a typical learning process over multiple training epochs. Both training and validation accuracy increase rapidly during the initial epochs, stabilizing near 0.98, indicating that the model is learning effectively and generalizing well to unseen data. The loss curves for both training and validation decrease steadily, converging towards zero, which further confirms that the model is minimizing errors and is not overfitting or underfitting during training. These trends suggest that the SGD optimizer is successfully finding good parameters, and the model performs consistently across both training and validation datasets.

3.1.3 InceptionNet Model - RMSprop Optimizer

The RMSprop optimizer results show a noticeable increase in misclassifications, especially in Small_Pox with 14 samples wrongly classified, reducing overall precision for that class.

Chicken_Pox, Measles, and Monkey_Pox are generally classified well, but the model struggles slightly more to differentiate Small_Pox from other classes. Unknown class remains perfectly classified, indicating that the model can still reliably detect this category with RMSprop.

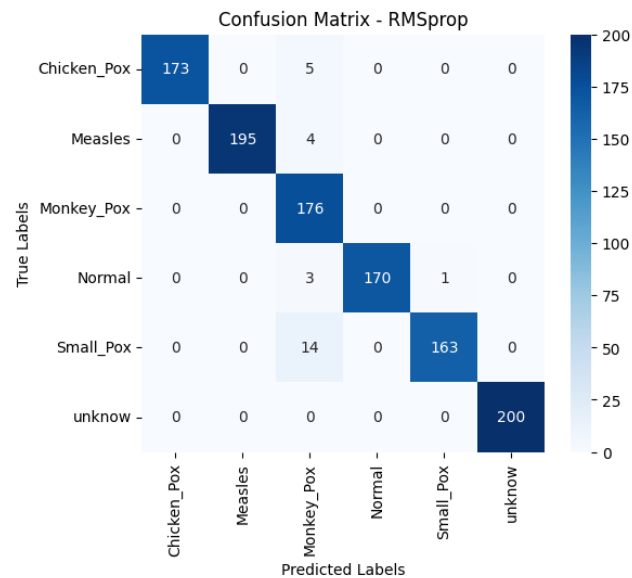


Figure 9. Confusion Matrix of the InceptionNet Model with RMSprop optimizer across 6 labels.

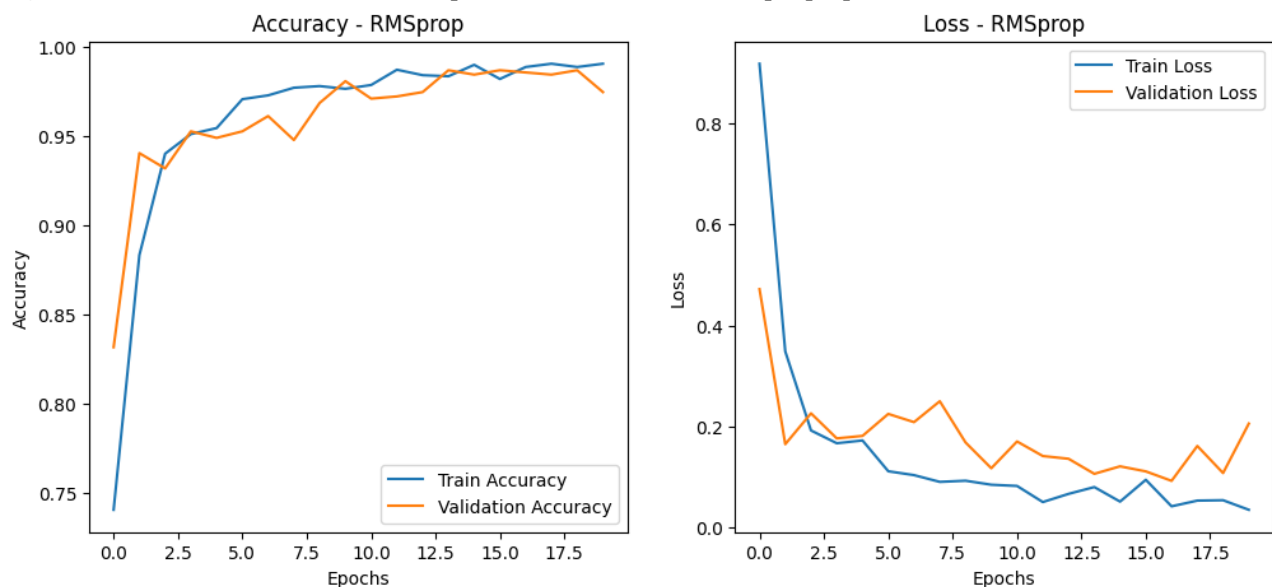


Figure 10. Accuracy and Loss Curves for InceptionNet Model using RMSprop Optimizer.

The accuracy and loss curves for the RMSprop optimizer show that the model performs well and learns efficiently over the training epochs. Both the training and validation accuracy curves rise sharply, exceeding 95% within a few epochs, and gradually plateau close to 100%, indicating effective and consistent learning with minimal overfitting. The loss curves for both training and validation quickly decrease, demonstrating that the model's prediction errors are rapidly minimized and remain low throughout the remaining epochs. These trends reflect a stable and good-performing model with a good fit on both the train and validation datasets.

3.2 Hybrid Model

The Hybrid Model is optimized with three different optimizers, such as Adam, SGD, and RMSprop. The confusion matrix, accuracy, and loss curves are given separately for each optimizer in the following figures 11, 12, 13, 14, 15, and 16. This model captured both spatial and temporal features, but convergence was slower across all optimizers than with the InceptionNet (Figures 11–16). According to Figures 11 and 12, Adam had an excellent compromise between speed and stability, with accuracy increasing steadily without any

major oscillation in loss. With SGD optimization, convergence was the slowest and most variable and had the worst misclassification rate, especially for Measles and Chicken_Pox (Figures 13 and 14). RMSprop provided moderate convergence but was less stable with respect to loss, thus indicating some overfitting potential (Figures 15 and 16). Hence, the prime power of the hybrid model comes from its temporal feature extraction; nonetheless, its performance depends too much on what optimizers are considered.

3.2.1 Hybrid Model - Adam Optimizer

Adam leads to steady gains in accuracy with stable loss reduction, while SGD and RMSprop display slower convergence and greater variability, corresponding with higher misclassification rates between visually similar disease classes. The Adam-based model demonstrates good performance, particularly for Chicken_Pox, Measles, and Normal categories. However, Small_Pox exhibits vulnerability to misclassification, suggesting potential overlap in feature representation with Chicken_Pox and Normal.

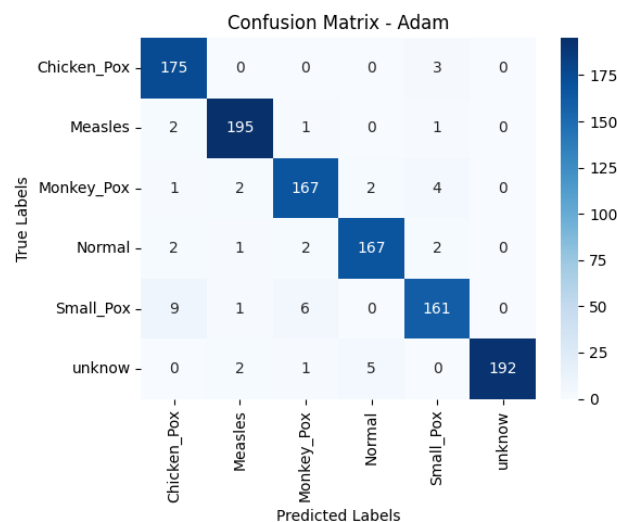


Figure 11. Confusion Matrix of the Hybrid Model with Adam optimizer across 6 labels.

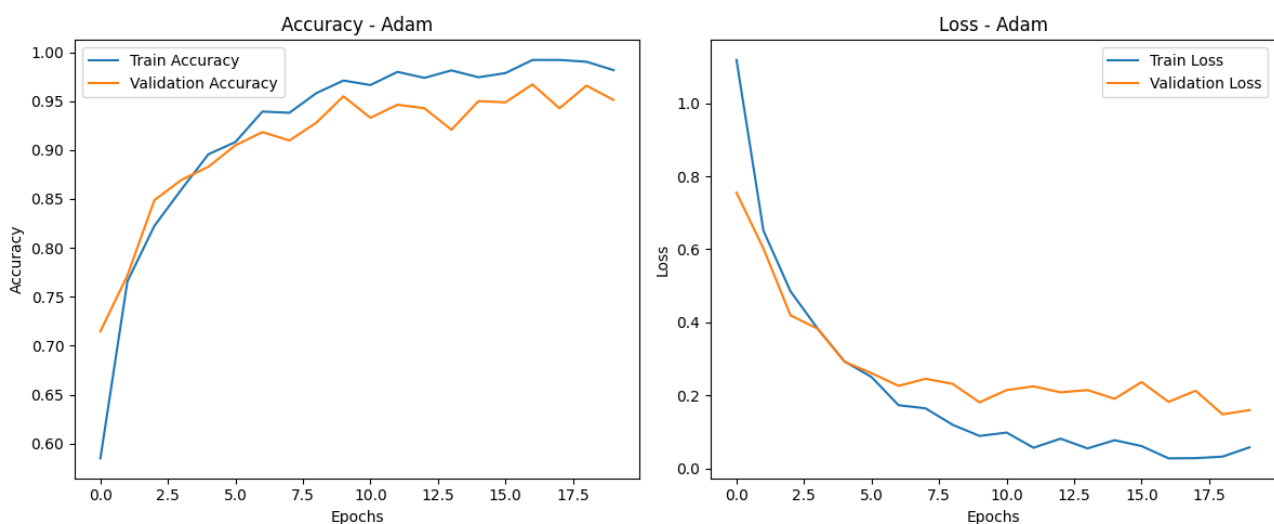


Figure 12. Accuracy and Loss Curves for Hybrid Model using Adam Optimizer.

The accuracy and loss curves for the Adam optimizer demonstrate effective model training. Both the training and validation accuracy show a steady increase, reaching values above 95% as epochs progress. Simultaneously, the training and validation losses exhibit a downward trend, indicating improved model fit and reduced error. The close alignment of validation accuracy and loss with their training counterparts

suggests good generalization and minimal overfitting. These results indicate that the model is learning efficiently and can generalize well with unseen data.

3.2.2 Hybrid Model - SGD Optimizer

The SGD-based model struggles with inter-class separability, particularly among pox-related diseases. The high misclassification of Monkey_Pox and Small_Pox suggests that the model may benefit from enhanced feature discrimination or regularization.

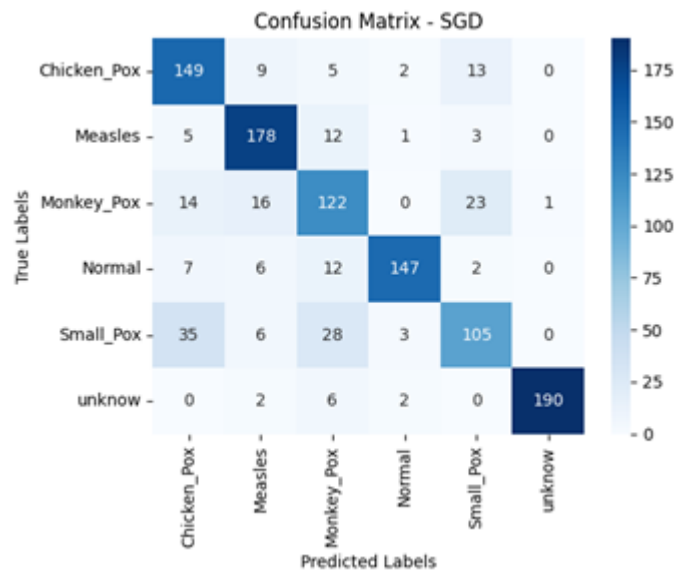


Figure 13. Confusion Matrix of the Hybrid Model with SGD optimizer across 6 labels.

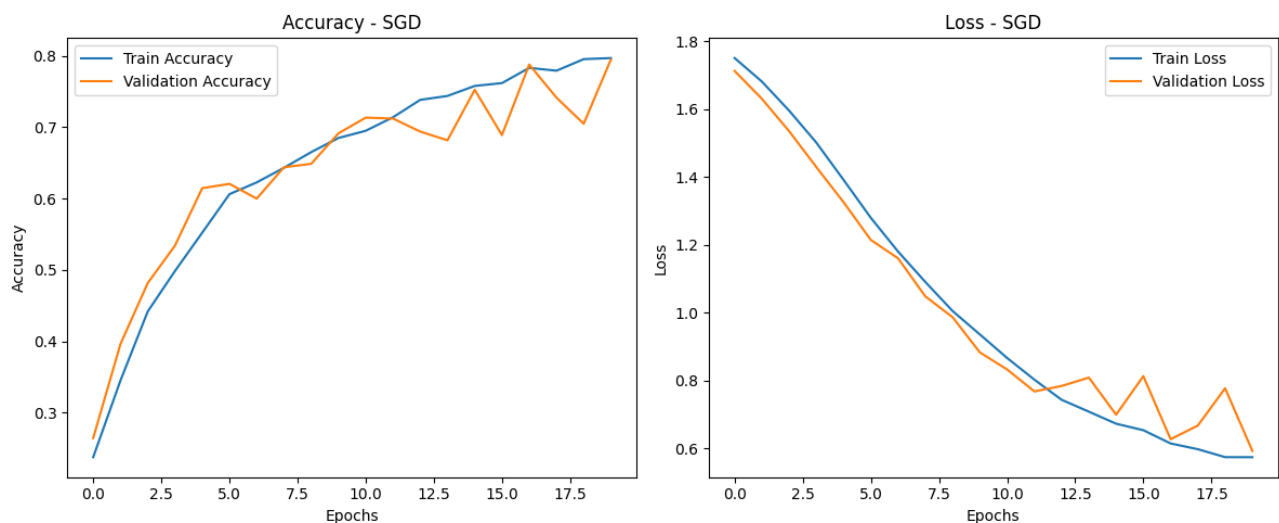


Figure 14. Accuracy and Loss Curves for Hybrid Model using SGD Optimizer.

The accuracy and loss curves for the SGD model show the typical learning behavior over 20 epochs. Both train and validation accuracy steadily increase, reaching around 0.8 by the final epoch, indicating good model improvement. Similarly, the loss curves for both train and validation data decrease consistently, reflecting effective learning and minimizing errors across epochs. Validation performance closely follows training trends, suggesting minimal overfitting and a well-generalized model.

3.2.3 Hybrid Model - RMSprop Optimizer

The RMSprop-optimized model achieves strong classification accuracy overall, but the confusion matrix reveals sensitivity in distinguishing similar pox variants. Specifically, a consistent pattern of misclassifying

Small_Pox as Monkey_Pox suggests the model over-relies on coarse morphology, highlighting the critical need for enhanced feature discrimination.

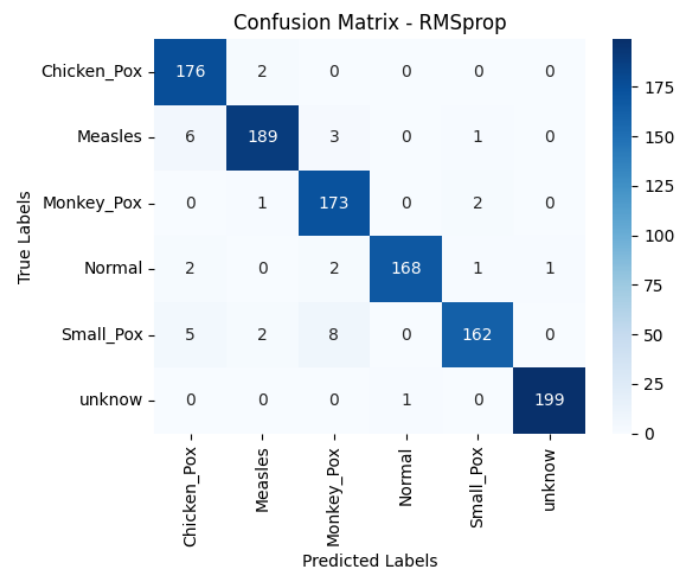


Figure 15. Confusion Matrix of the Hybrid Model with RMSprop optimizer across 6 labels.

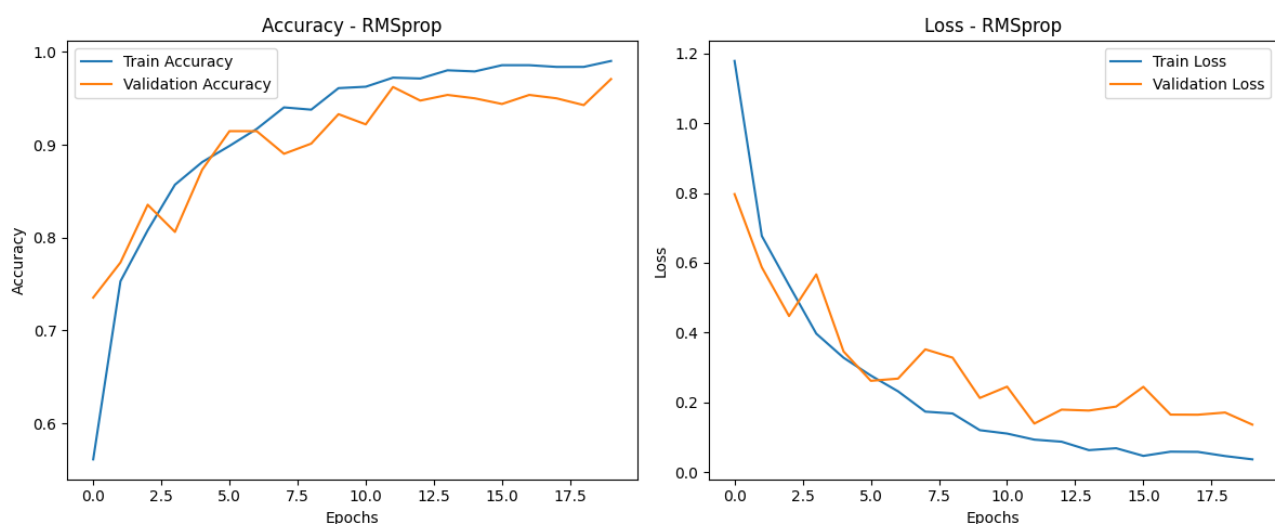


Figure 16. Accuracy and Loss Curves for Hybrid Model using RMSprop Optimizer.

The accuracy and loss curves for the RMSprop optimizer show that both training and validation accuracy steadily increase with each epoch, approaching nearly 1.0, which indicates strong model performance and generalization. The loss curves reveal a rapid decline in both training and validation loss, with validation loss stabilizing and remaining low, further supporting effective learning and minimal overfitting throughout the epochs.

3.3 Deep Belief Network

The Deep Belief Network is optimized with three different optimizers, such as Adam, SGD, and RMSprop. The confusion matrix, accuracy, and loss curves are given separately for each optimizer in the following figures 17, 18, 19, 20, 21, and 22. DBN models demonstrated strong hierarchical feature learning, yielding classification accuracies comparable to or surpassing InceptionNet in some categories (Figures 17–22). Under Adam optimization, the DBN converged quickly and showed stable training with minimal loss fluctuations (Figures 17 and 18). SGD optimization led to slower convergence and more inconsistent accuracy trends, causing misclassifications predominantly in the Small_Pox and Monkey_Pox classes (Figures 19 and

20). RMSprop's performance was moderate, with stable but slower convergence and slightly higher confusion among similar classes (Figures 21 and 22). DBN's simpler architecture offers effective generalization, particularly with Adam, making it a promising alternative for pox disease classification.

3.3.1 DBN Model - Adam Optimizer

SGD optimization slows convergence and increases classification errors, while RMSprop provides intermediate performance, confirming DBN's capability as a lightweight yet effective model. The DBN model trained with the Adam optimizer shows great generalization and class separation. The minimal confusion between Monkey_Pox and Normal suggests a slight overlap in feature space, but overall, the model is highly reliable.

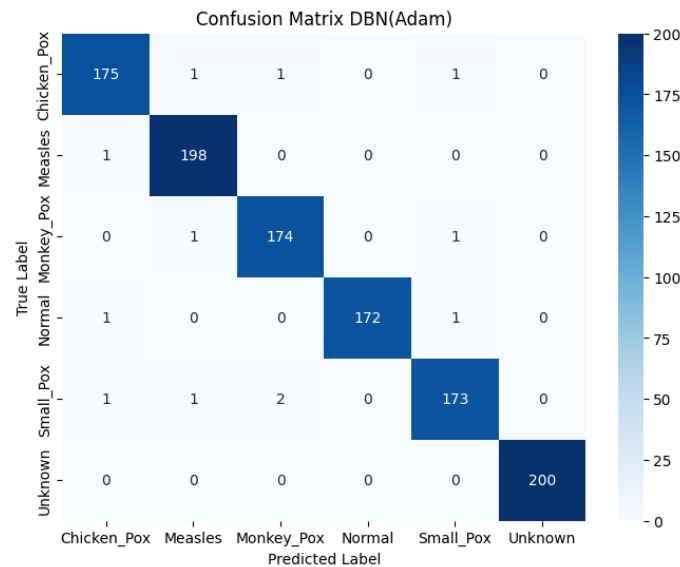


Figure 17. Confusion Matrix of the Deep Belief Network with Adam optimizer across 6 labels.



Figure 18. Accuracy and Loss Curves for Deep Belief Network (DBN) using Adam Optimizer.

The training and validation loss curves demonstrate a rapid initial decrease within the first few epochs, indicating effective learning by the model from the data. Both losses gradually stabilize and maintain low values, suggesting that overfitting is minimal and the model generalizes well. The validation accuracy curve consistently rises and reaches above 98%, confirming the model's robust performance and high predictive reliability throughout the training process.

3.3.2 DBN Model - SGD Optimizer

The Deep Belief Network (DBN) combined with the SGD optimizer achieved the highest test accuracy of 99.09% and perfect specificity (1.00), positioning it as the most effective model for pox disease classification. This superior performance is rooted in DBN's architecture, which inherently supports probabilistic, hierarchical feature learning through semi-supervised pretraining, enabling the extraction of highly robust

and generalized representations from complex dermal images. Crucially, the model's negligible misclassification rate, despite utilizing the generally noisier SGD optimizer, suggests DBN's inherent structural robustness minimizes convergence variability. This synergy between the deep feature extraction capability of the DBN and the effective optimization by SGD confirms its suitability for precise classification of visually similar pox-related skin conditions.

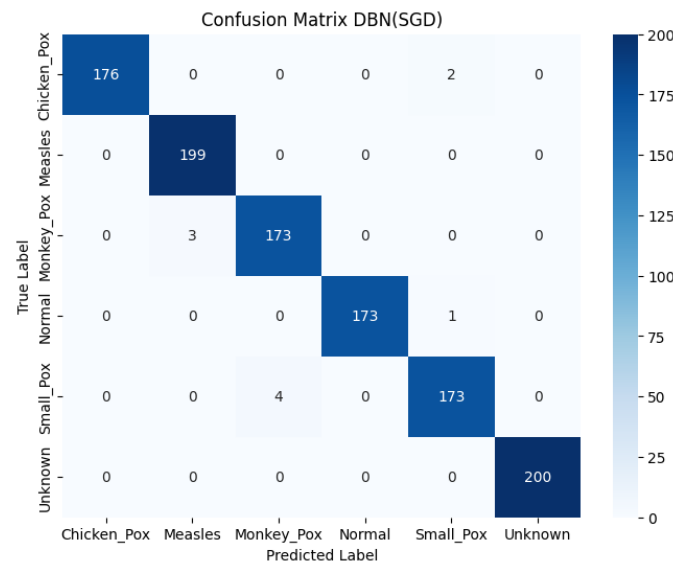


Figure 19. Confusion Matrix of the Deep Belief Network with SGD optimizer across 6 labels.

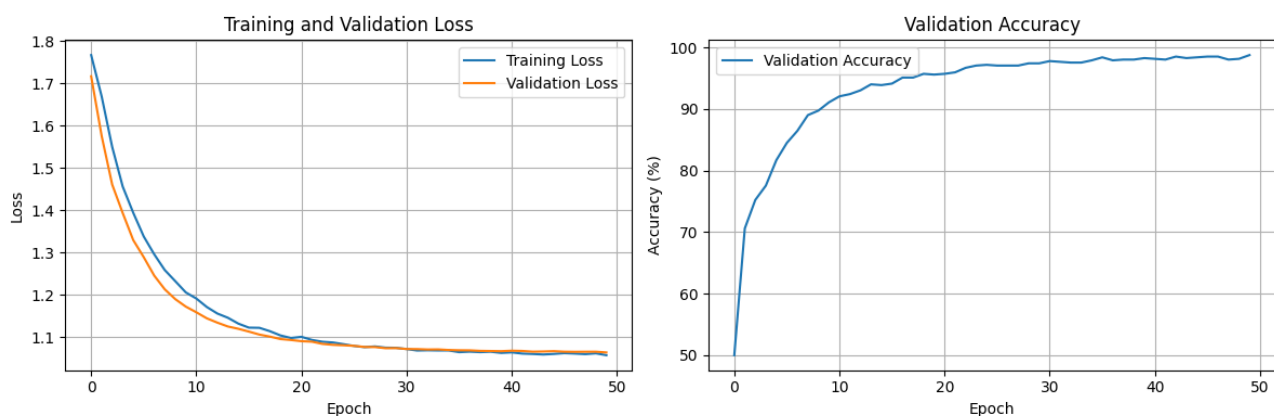


Figure 20. Accuracy and Loss Curves for Deep Belief Network (DBN) using SGD Optimizer.

The training and validation loss curves show a steady decline over the epoch, starting from around 1.75 and gradually approaching just above 1.1. Both curves follow similar trajectories, which indicates that the model is learning effectively without significant overfitting. The validation accuracy curve rises sharply in the initial epochs, then gradually levels off, maintaining a value close to 98–99% after approximately 20 epochs. This behavior suggests that the model is generalizing well to the validation data and achieving high accuracy as learning progresses.

3.3.3 DBN Model - RMSprop Optimizer

The DBN-RMSprop model performs well but shows slightly more confusion between Normal and Small_Pox, which may reflect shared visual features or insufficient feature separation. Nonetheless, the model maintains strong overall reliability.

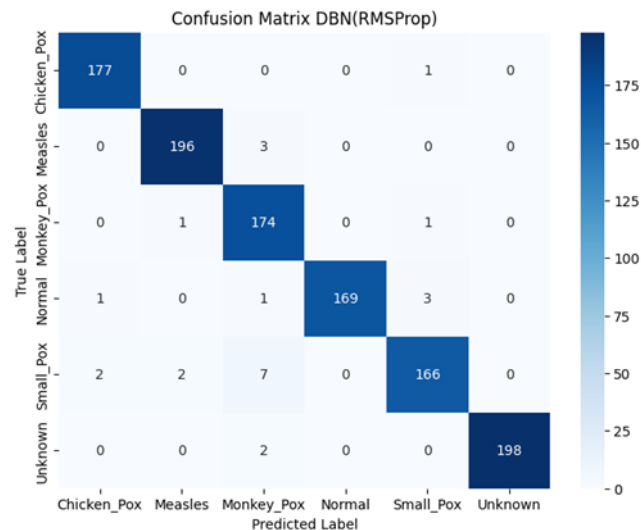


Figure 21. Confusion Matrix of the Deep Belief Network with RMSprop optimizer across 6 labels.

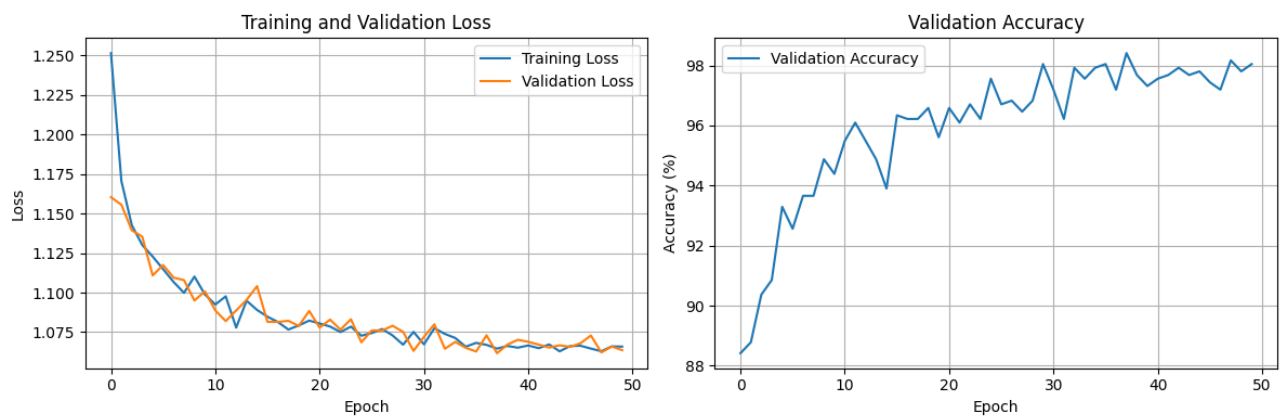


Figure 22. Accuracy and Loss Curves for Deep Belief Network (DBN) using RMSprop Optimizer.

The training and validation loss curves show a consistent decrease over epochs, indicating effective model learning and good convergence without significant overfitting. Both losses nearly overlap, which suggests that the model's performance is stable on both training and validation datasets. In parallel, the validation accuracy curve rises quickly in the initial epochs and then plateaus near 98%, reflecting strong and reliable generalization with minimal signs of accuracy degradation or overfitting across the training process.

3.4 Summary of Results

By confusion matrices optimized with Adam, then evaluating the InceptionNet and Deep Belief Network (DBN) models, it was found that the first run under InceptionNet had great accuracy, being able to classify almost perfectly among the six classes, particularly the "Unknown" class with perfect 100% accuracy. The second InceptionNet run performed well overall, though it had a few more misclassifications than the first run, particularly in Small_Pox and Monkey_Pox classes. The DBN model also provided very high accuracies, equaling or outperforming InceptionNet over several of the categories and showcasing the potential for the deep model to generalize well due to hierarchical feature learning. Hence, both models gave reliable results with very few misclassifications. InceptionNet remained consistent across runs, while DBN proved very effective with a less complex architecture. Hence, this shows yet again the power of deep-learning models when coupled with the Adam optimizer for proper classification of skin conditions associated with pox. The comparative study highlights the significant role of the choice of model architecture and optimization techniques in determining the performance outcome.

Table 1. Accuracy & Key Observations of All Models & Optimizers

Model	Optimizer	Test Accuracy	Key Observations
InceptionNet	Adam	98.8%	High precision & recall across classes; very stable and fast convergence.
	SGD	97.9%	Slightly lower accuracy; slower convergence; minor misclassifications in Small_Pox and Monkey_Pox.
	RMSprop	97.6%	Moderate accuracy; some confusion in Small_Pox and Monkey_Pox.
Hybrid Model (MobileNet + LSTM)	Adam	95.7%	Good accuracy; stable training; balanced precision and recall.
	SGD	80.7%	Lowest accuracy; slow convergence; notable misclassification in multiple classes.
	RMSprop	96.6%	High accuracy; some minor instability.
Deep Belief Network (DBN)	SGD	99.0%	Highest accuracy; excellent precision and recall; stable training.
	RMSprop	98.0%	Slightly lower than Adam; good overall performance.
	Adam	98.8%	High accuracy; well-balanced metrics.

¹SGD – Stochastic Gradient Descent, ²RMSprop – Root Mean Square Propagation

The framework for pox disease detection currently shows immense promise, but there are still several opportunities to improve it. Improving the database for varying skin types, age groups, and disease variations will assist in better generalizing the model and improving prediction accuracy. Having a larger system that incorporates at least six other skin conditions may give the system overall dermatologic classification tasks more versatility. Further studies could then aim to build advanced architecture, such as transformer-based models or ensemble methods, to enhance performance. Incorporating explainable AI features could enhance the model's transparency, thereby helping users understand the basis for its predictions. The framework may be optimized for lightweight deployment, thereby ensuring access across different platforms. Validation with domain experts could further fine-tune the classification's reliability and robustness in diagnosis. This future endeavor will push the system's effectiveness into an operationally sound and credible tool in medical image analysis.

Table 2. Performance Analysis of Each Model & Optimizer

Model	Optimizer	Accuracy	Precision (macro)	Recall (macro)	F1-Score (macro)	Specificity (macro)
InceptionNet	Adam	0.9882	0.99	0.99	0.99	0.9969
	SGD	0.9792	0.98	0.98	0.98	0.9958
	RMSprop	0.9755	0.98	0.97	0.98	0.9908
Hybrid Model (MobileNet + LSTM)	Adam	0.9574	0.96	0.96	0.96	0.99
	SGD	0.8071	0.81	0.80	0.80	0.93
	RMSprop	0.9665	0.97	0.97	0.97	0.99
Deep Belief Network (DBN)	Adam	0.9891	0.99	0.99	0.99	1.00
	SGD	0.9909	0.99	0.99	0.99	1.00
	RMSprop	0.9783	0.98	0.98	0.98	0.99

¹LSTM – Long Short-Term Memory, ²DBN – Deep Belief Network.

Three deep learning models were experimentally evaluated, including InceptionNet, Hybrid MobileNet+LSTM, and Deep Belief Network (DBN) through three optimization algorithms: Adam, SGD, and RMSprop. Out of all possible combinations, the DBN using the SGD optimizer was the most effective, with an accuracy of 99.09 as well as a precision, recall, and F1-score of 0.99. It also exhibited absolute specificity (1.00), meaning that there were no false positives in all classes. The InceptionNet model also exhibited good performance, particularly when using the Adam optimizer, which had an accuracy of 98.82 and balanced precision and recall of 0.99. The Hybrid MobileNet+LSTM model worked well with RMSprop (96.65% accuracy) but was much lower with SGD (80.71% accuracy), which may indicate that it is sensitive to optimizers. In general, DBN was always more accurate and generalized than the other models. The analysis revealed that the model architecture and the choice of the optimizer can be considered important factors in classification performance in pox disease diagnosis. These results confirm the usefulness of deep learning in the classification of medical images and emphasize SGD with DBN as the best combination to provide precise information about the presence of a skin disease.

3.5 Limitations & Future Work

While the proposed model demonstrates high predictive performance, its deployment in diverse real-world clinical settings must acknowledge certain limitations inherent to the study design and dataset. Specifically, the current dataset comprising 4,099 training and 1,104 evaluation images is relatively modest, which may restrict the model's ability to fully generalize across all demographic populations, especially for skin tones or patient groups underrepresented in the source data. Furthermore, consolidating images from various public sources inevitably introduces a degree of variability in image quality, including inconsistent lighting, resolution, and background clutter, which can inherently affect diagnostic robustness. Finally, the current system relies solely on visual dermatological features and does not incorporate essential contextual information such as patient history, concurrent symptoms, or laboratory test results. Future work should therefore focus on enriching the dataset size and diversity, standardizing image quality, and developing a framework capable of integrating these critical biological and contextual data points to enhance clinical utility and reliability.

4. Conclusions

In view of the above points, the present study proposes a framework for deep learning to automatically detect and classify pox-related skin diseases from dermal images. With a comparative study on the three architectures—InceptionNet, MobileNet-LSTM, and Deep Belief Network—it classified a total of six dermatological conditions: Chicken_Pox, Measles, Monkey_Pox, Small_Pox, Normal, and Unknown. The scope for good feature extraction is available with the MobileNet platform, combined with advanced optimizers such as Adam, SGD, and RMSprop for execution of strong cross-architecture training and scaling. The experimentation thus proves that these deep learning models can accurately discriminate between skin lesions and are promising in early and accurate diagnosis. Among the architectures, the mobile fusion of mobile and long short-term memory (LSTM) seemed to be the one that gave such benefits of efficiency and effectiveness, while InceptionNet added better accuracy through multi-scale feature capturing. The DBN offered the possibility of working through another unsupervised framework. This investigation observes the promise of AI-assisted tools for diagnosis as adjuncts to clinical decision-making, particularly in resource-limited environments. Future work may focus on data augmentation, the enhancement of real-time deployment, and the development of some explainability features for clinical trust and adoption. This research provides a firm basis for further innovations toward automated skin disease diagnosis using deep learning.

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Author Contributions:

Padmaja Bodagala led the foundational development of the research framework by overseeing conceptualization, designing the methodology, and preparing the dataset with meticulous preprocessing. She implemented all deep learning models, managed the training phases with a focus on optimization, &

conducted a thorough comparative evaluation of architectures and optimizers. Her responsibilities extended to comprehensive experimental analysis, insightful interpretation of results, and the generation of detailed visual figures. Additionally, she took charge of drafting the original manuscript and played a vital role in refining the scientific narrative, ensuring the study maintained the highest standards of technical rigor throughout.

Naga Malleswari Dubba provided invaluable supervision and strategic oversight across all stages of the research. She significantly enhanced the methodological framework and rigorously validated the experimental findings to guarantee alignment with both clinical relevance and established academic standards. Her expertise was crucial in reviewing and editing the manuscript to improve clarity, technical precision, and structural cohesiveness. Furthermore, she diligently monitored the integrity of the entire research process and offered continuous advisory support during model evaluation, contributing profound insights into the interpretation of key findings.

All authors have thoroughly reviewed and approved the final manuscript.

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