A Comparative Study of CNN Architectures for Monkeypox Detection

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***Abstract*—With Monkeypox increasingly becoming a rising public health concern, the demand for rapid, accurate, and convenient diagnostic tools is greater than ever. This paper evaluates the deep learning methods can play in facilitating the early diagnosis of Monkeypox via skin lesion image analysis. We fine-tuned three popular convolutional neural network (CNN) models—EfficientNetV2-S, DenseNet121, and InceptionV3—on a binary classification dataset of Monkeypox and normal skin images. To enhance generalization of models, we employed a variety of data augmentation techniques while training. Further, to provide insight into the predictions of the models, we employed LIME to plot the most mandatory regions of the images that can be used to give to the output.**

EfficientNetV2-S showed the best accuracy and F1-score among the models examined, with good performance in the differentiation of Monkeypox-infected lesions. The dataset utilized within this work was selected with care to mimic real-world clinical conditions such that the models could learn from varied visual patterns. Explainability is also a focus of our approach, which is essential in developing trust in AI-influenced medical aids. The models are only need image inputs, and thus they are deployable for mobile or remote healthcare use.

***Index Terms*—Monkeypox detection, deep learning, transfer learning, LIME (Local Interpretable Model-Agnostic Explanations).**

I. Introduction

Monkeypox, for those not glued to the news, looks a lot like chickenpox or measles when it shows up on your skin—so good luck figuring out what's what just by eyeballing it. Docs can use fancy stuff like PCR to nail a diagnosis, but let's be real: that gear is expensive, [1], [2] takes ages, and if you live out in the sticks or somewhere that's not exactly rolling in resources... well, good luck with that [3], [4].

So, here's where tech tries to save the day (as usual). Automated systems that look at skin pics? Yeah, that's actually a thing now. Apparently a pretty solid one, too. Deep learning—especially those convolutional neural networks everyone keeps hyping—has made it possible for computers to spot diseases just by scanning images [5]–[7]. No med school required. Plus, there's this thing called transfer learning, where you take a model that already learned stuff (like, a ton of stuff) and tweak it for monkeypox, even if you don't have a massive dataset lying around. It's kinda like teaching a dog some new tricks, but faster.So honestly, if you want to catch Monkeypox early without waiting forever or shelling out big bucks, [8] letting AI eyeball your skin might be the future. Wild times, right?

In this study, we examine and contrast the effectiveness of three top-performing CNN architectures for the binary classification of monkeypox versus normal skin: InceptionV3, DenseNet121, and EfficientNetV2-S. Transfer learning was used to refine these models on a carefully selected dataset, and extensive data augmentation techniques were employed to improve generalization and decrease overfitting [9], [10].

In addition to achieving high classification accuracy, interpretability is a critical requirement for the clinical adoption of AI models in healthcare. To tackle this, our framework incorporates Local Interpretable Model-Agnostic Explanations (LIME), which highlight the key areas of the input image that were used in each prediction. This layer of interpretability improves transparency and facilitates medical professionals' understanding of the model's decision-making process. [11]–[13].

According to our experimental results, EfficientNetV2-S produces the best accuracy and F1-score out of the three architectures. Particularly in settings with insufficient healthcare infrastructure, these results demonstrate that interpretable deep learning models have the potential to diagnose monkeypox rapidly, accurately, and with little resources [14].

Section 1 Provides detailed overview and introduction about monkeypox.Section 2 is about the related works describing researchs in this field. Section 3 provides a detailed description of the proposed methodology, including training methods, model architecture selection, and dataset preparation and section 4 shows the performance as well as LIME visualizations.

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II. Related Works

In the recent years ai has become more advanced in Deep Learning that helps to diagnse the monkey pox disease. Researchers have been using a specific kind of AI, called Convolutional Neural Networks (CNNs), to accurately spot skin lesions. For example, a study by Kottath et al. found that even simple, lightweight CNN models can detect monkeypox with impressive accuracy, which is fantastic for making things fast and efficient [15]. Similarly, Llamas et al. showed that certain AI models, like DenseNet, are super reliable even when there's not a lot of data to work with [16].

A big challenge with using AI in medicine is that doctors need to understand why the AI is making a certain diagnosis. This is where Explainable AI (XAI) comes in. Recent research is all about making AI more transparent and trustworthy. Studies have shown how we can visualize the AI's thought process, not just for images but for other medical data, like heart sounds, to help doctors make better decisions [17]. Another study by Trivedi et al. highlighted that this need for explainability is important even in non-image-based applications [18].

A clever strategy is using transfer learning, which is super helpful when we does not have of medical data. Research by Arumugam et al. found that this approach often works great than restaring from scratch, even with simpler models. found that this approach often works better than using a brand-new, more complex model. There's even a model called MpoxNet, developed by Vandana et al., that is specifically designed to be small and fast enough to be used on mobile devices in places with limited resources.

Imagine trying to teach a computer to spot Monkeypox when you only have a handful of photos. It's a tough job. Scientists don't take from zero they always use a technique called "transfer learning",which is an ai that is an expert in recognising images and fine-tuning.

Interestingly, it turns out that less is more. One research team, Arumugam et al, discovered that these leaner, fine-tuned models were actually better at the job than the giant, complex ones. This inspired another group, Vandana et al., to create MpoxNet , which is essentially a fast, lightweight diagnostic tool perfect for a smartphone. It's designed to give doctors a quick answer right in the clinic or out in the community, no bulky equipment needed.

To make to AI more better researchers are trying their best to combine the models and increase the performance.For instance, Nayak et al. [19] used deep learning on images of skin lesions, and Eliwa et al used a clever optimization method to improve how their AI classified them. Similarly, Surati et al. [20] gave their AI an "attention" ability, helping it zero in on the most critical details for a better diagnosis [21], [22].

The power of this technology isn't limited to Monkeypox. Research in other areas of medicine shows just how adaptable AI can be. For example, Moturi et al. [23], [24] have successfully used similar models to check heart sounds and even predict the risk of chronic kidney disease. This proves that AI diagnostics are becoming a powerful tool for doctors across many different specialties.

With this in mind, our research puts three specific AI models to the test: EfficientNetV2-S, DenseNet121, and InceptionV3 [25]. We're training them to do one vital job: tell the difference between a normal skin mark and a Monkeypox lesion. But accuracy isn't everything. We also use a tool called LIME to make the AI "show its work," so doctors can understand why it made a certain diagnosis. Our goal is to help build AI that is not just smart, but also easy to trust and use in real clinics.

III. Methodology

For this we used the monkeypox skin image dataset that contains pictures of the monkeypox and normal images too. Our approach is separated into various steps: dataset preparation, data augmentation, model selection and training, evaluation, and explainability.

A. Dataset Preparation

We used a publicly accessible dataset of images of monkeypox that was divided into two categories: normal and monkeypox. The dataset was divided in an 80/20 ratio between train and validation sets. Prior to training, all images were normalized to scale pixel values to 0 and 1 and resized to the input size each model requires (e.g., 224×224 pixels).

The dataset can be used for valuable benchmark for monkeypox detection, its in small size (716 images) may limit the generalizability of the models to larger clinical scenarios. Future work will be focused on expanding the dataset through collaboration with medical institutions or public health repositories, and incorporating external validation to strengthen the robustness of the findings.

TABLE I
MONKEYPOX SKIN IMAGE DATASET IS USED IN THIS STUDY.

Dataset	Label	Train Set	Validation Set	Total
SkinImageDataset	MonkeyPox	457	115	572
	Normal	115	29	144
Total		**572**	**144**	**716**

B. Data Augmentation

Let's be real—deep learning models are like toddlers at a buffet: they want more, more, more. But, of course, with medical images, you're usually scraping together whatever you can get. Enter data augmentation, the magic trick that lets a handful of images pretend they're a cast of thousands. It's the digital equivalent of a wardrobe change montage—suddenly, your model thinks it's seeing something totally new, every time.

For this project, we didn't reinvent the wheel. Instead, we fired up Keras's ImageDataGenerator—think of it as Photoshop on autopilot, dicing up your images with new looks on the fly. So as the model trains, it's getting hit with a parade of fresh, slightly tweaked pictures. Keeps things interesting, keeps the model on its toes. Here's the menu of augmentations we served up:

1) RESCALING: Input img pixel values were all rescaled to [0, 1] by dividing each value by 255.

2) RANDOM ROTATIONS: The Images are rotated in a random manner so that it is clear to identify the image.

3) ZOOMING: A 20 percent zoom was imposed to mimic differences in the distance or closeness the lesion is viewed in each photo so that patterns at various scales can be identified by the model.

4) HORIZONTAL FLIPPING: Horizontal random flips were applied in order to incorporate more variability and make the model understand that the side of a lesion (left or right) should not influence the prediction.

These above steps were only implemented in the training data only keeping the validation set not changes . The utilization of augmentation greatly improved the generalization capability of the model, especially on a small or slightly unbalanced dataset. By enlarging the variety of inputs, the models were more capable of dealing with unknown skin lesion images during test and deployment.

C. FINE-TUNING WITH TRANSFER LEARNING

To train efficient models with comparatively sparse medical image data, we used a transfer learning approach with three pre-trained CNN models: EfficientNetV2-S, DenseNet121, and InceptionV3. They were originally practiced on the large ImgNet dataset of millions of labeled natural images. Leveraging their learned feature extraction abilities, training time was reduced and efficiency improved even with a comparatively small dataset.

The transfer learning method was conducted in two major steps:

1) Feature Extraction (First Training): In the first stage, the convolutional base of all first-trained model was kept unchanged, i.e., it is not trained. The only thing trained was the new custom classification head made up of fully connected (Dense) layers followed by a sigmoid output. This allowed the model to learn the new classification task (Monkeypox vs Normal) very easily without altering the overall visual features learned on ImageNet.

2) Fine-Tuning (Second Stage): After the early training overlapped, we selectively thawed out portions of the lower layers of pre-trained network and continued training with a reduced learning rate. Fine-tuning allowed the model to adapt its higher-level features to more strongly represent Monkeypox skin lesions appearance. With tight controls on both learning rate and trainable layers, we improved accuracy without overfitting.

This two-phase process struck a balance between generalization and specialization, enabling models to achieve high accuracy on the Monkeypox dataset with minimal computational resources.

D. PROPOSED MODEL ARCHITECTURE

Now picture this: they take a powerful pre-trained model, apply a new layer of classification using their own unique classifier, and presto! You have a clever little system that

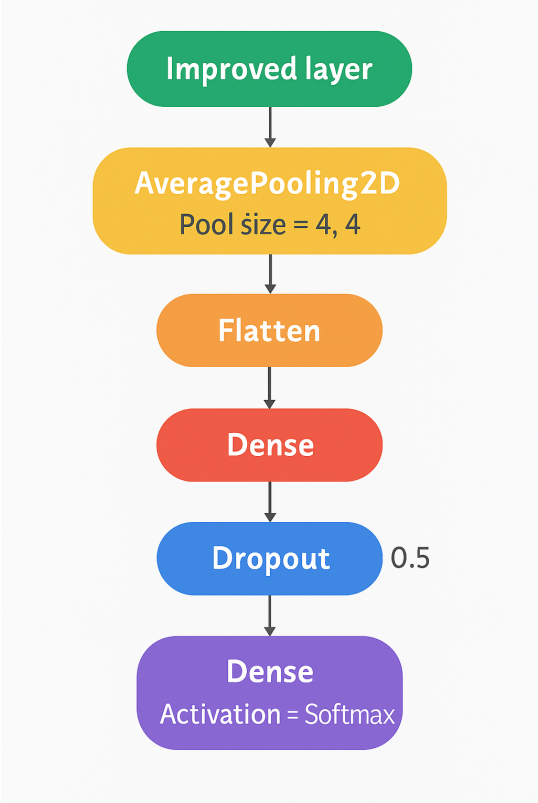

Fig. 1. Modified classification head used after the pre-trained CNN models.

can detect monkeypox by simply looking at pictures of skin. It's similar to taking your neighbor's Ferrari and replacing the fuzzy dice with your own, and all of a sudden you're the most hip diagnostician in town. High-tech with a dash of personality. We utilize proven convolutional neural networks (CNNs)—EfficientNetV2-S, DenseNet121, and InceptionV3—as pre-trained base models. The models are pre-trained on ImageNet and are robust feature extractors capable of learning complex spatial patterns.

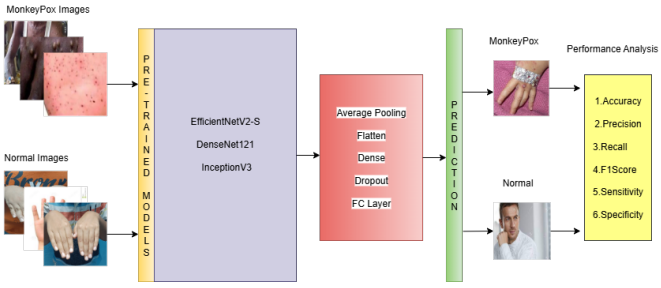

Fig. 2. Modified classification head used after the pre-trained CNN models.

There is then a custom classification head per base model, trained to binary classification. The output of the CNN is passed through an AveragePooling2D layer (pool size 4×4) to downsample spatial dimensions. There is then a layer, which changes the 2Dimentional pooled feature maps into a 1Dimentional vector. There is then a Dense layer which

projects these features into a lower-dimensional latent space, learning task-specific patterns. To avoid overfitting, a layer is used with rate = 0.5 is added, it randomly drops 50 percent of the neurons during the training. Finally, a Dense output layer with Softmax initiation generates the probabilities of class for the two classes: Monkeypox and Normal.

This architecture enables the models to adjust to the single or special characteristics of monkeypox lesions while retaining the common visual knowledge acquired from extensive image corpora. The entire pipeline is tuned for high accuracy and transparency in a clinical setting, from training and interpretability to input preprocessing and augmentation.

TABLE II
MONKEYPOX PREDICTION PERFORMANCE OF ALL MODELS ON THE TRAINING SET.

Models	**Performance**			
	Accuracy	Precision	Recall	F1-Score
EfficientNetV2-S	0.824	0.82	0.81	0.81
DenseNet121	0.945	0.94	0.94	0.94
InceptionV3	0.956	0.95	0.95	0.95

When we looked at the results, two of the AI models, DenseNet121 and InceptionV3, were rock-solid performers. They were consistently accurate and dependable from start to finish. The third model, EfficientNetV2-S, was also a top contender. But its overall accuracy was low compared to both models it still did an excellent job on all fronts.

TABLE III
MONKEYPOX PREDICTION PERFORMANCE OF ALL MODELS ON THE VALIDATION SET.

Models	**Performance**			
	Accuracy	Precision	Recall	F1-Score
EfficientNetV2-S	0.800	0.81	0.80	0.80
DenseNet121	0.930	0.93	0.93	0.93
InceptionV3	0.950	0.95	0.95	0.95

So, after training our three AI models, it was time for the real test: showing them a batch of photos they'd never encountered before. This is the moment of truth that tells you if an AI can actually do its job out in the wild.

And the results were clear. InceptionV3 performed well in this, nailing the diagnosis 95% of the time. DenseNet121 was right on its heels with an impressive 93% accuracy. The third model, EfficientNetV2-S, came in at 80%.

What's really exciting is that all three models performed just as well on these new images as they did during their training. This proves they weren't just memorizing answers for the test—they truly learned the difference between a Monkeypox lesion and normal skin. In the end, the both InceptionV3 and DenseNet121 are incredible performers. But for EfficientNetV2-S, which may not the be the most accurate, but it's still a strong performer,which also makes it the perfect choice when you need a capable tool that can run on a less powerful device.

E. EXPERIMENT SETUP

In the following we applied three well-known convolutional neural network (CNN) architectures; EfficientNetV2-S, DenseNet121 and InceptionV3 for binary classification of Monkeypox skin lesion images. For training and fine-tuning these models we adopted the Adam optimizer as it has proven successb ful in dealing with sparse gradients and adaptive learning rates, particularly in medical image classification problems.

All experiments were conducted on a PC that has Windows 10 and i5 processor with 8 GB of RAM.For training and testing, 80:/20: ratio was used for splitting the image set, a standard ratio in deep learning methodologies. All models were trained and evaluated five times, and their average performance across all runs was reported as final results to guarantee the consistency and reliability of the performance.

The statistical indicators utilized to assess classification performance of the models were :

$$\text{Accuracy} = \frac{CorrectP + CorrectN}{CorrectP + CorrectN + NotCorrectP + NCN} \tag{1}$$

$$\text{Precision} = \frac{CorrectP}{CorrectP + NotCorrectP} \tag{2}$$

$$\text{Recall} = \frac{CorrectP}{CorrectP + NotCorrectN} \tag{3}$$

$$\text{F1-Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

Where:

A correct positive (TP): is a case of monkeypox that the model accurately classified as being positive for the disease.

A correct negative (TN): is an image that the model correctly classifies as normal (not monkeypox).

False Positive (FP): A typical case that the model incorrectly classifies as having monkeypox.

False Negative (FN): A sample that tests positive for monkeypox but is mistakenly classified as normal by the model.

IV. RESULT

A. Model Evaluation Parameters

The three CNN models – EfficientNetV2-S, DenseNet121, and InceptionV3 – were trained and tested on a binary classification problem which was differentiating Monkeypox lesions from normal skin. The accuracy, precision, recall, F1-Score are used to analyse how well the model has performed. These measurements will help balance the model evaluation process by considering the sensitivity and reliability of the model to be applied in a clinical setting not just the number of P-VEGAN has been correctly classified.

TablesII andIII show the performance of the models on training and validation. It is noticed that even the DenseNet121 and InceptionV3 have an all-around better performance on the both sets. EfficientNetV2-S, achieving relatively lower accuracy (80.0 percent), still work reasonably well with balanced

recall and precision, which is practical to use in resource-limited settings where computation capacity is limited.

Most importantly, the F1-score was quite similar when tested on all the classes inter-model and intra-model on DenseNet121 and InceptionV3 and confirmed their robustness and generalizability.

B. TRAINING vs TESTING GRAPHS

Think of the training process as putting each AI through a 10-epoch race. The charts aboveshows the performance summary for each epoch, it showing us two key things: how their accuracy improved and how their error rate dropped.

These graphs are incredibly telling. They help us spot if an AI is actually learning or just "cramming for the test" by memorizing the answers (a problem we call overfitting). We can also see which AI was the fastest learner and, most importantly, which one is best prepared to make accurate judgments on completely new photos.

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InceptionV3 exhibited a clear and stable training curve, after approximately plateauing at validation accuracy of around 95%, the accuracy was no longer significantly improving and a few volatility in loss occurred. Similarly, for DenseNet121, the behavior was like VGG16 but it had a bit slower convergence. On the other hand, because of its lower expressive capacity, EfficientNetV2-S displayed some early saturation symptoms as well as a slight discrepancy between training and validation accuracy, which are indicators of underfitting.

So, what's the bottom line? Think of it this way: a lighter AI like EfficientNetV2-S is like a smart, quick learner—it does a good job, but could get even better with more coaching and practice.

However, a more powerful AI like InceptionV3 is like a seasoned expert. It has a natural knack for spotting the most subtle, crucial clues in the images right away, which is why it's so good at handling cases it has never seen before.

C. Comparative Analysis

To provide a dense view of the models' performance, Table IV summarizes the test set results for all architectures. InceptionV3 performed very well compared to the other two models across all evaluation metrics, achieving 95% in Accuracy, Precision, Recall and F1-Score. DenseNet121 also managed to impress by the result (93%), making both models viable candidates for real-world deployment in diagnostic settings.

TABLE IV
TEST SET COMPARATIVE PERFORMANCE OF CNN MODELS AND MOBILENETV2

Model	Accuracy	Precision	Recall	F1-Score
EfficientNetV2-S	0.800	0.81	0.80	0.80
DenseNet121	0.930	0.93	0.93	0.93
InceptionV3	0.950	0.95	0.95	0.95
MoblieNetV2	0.92	0.91	0.92	0.92

Imagine you're picking out a car, but instead of for a road trip, you're choosing it for a specific job in AI. Each model is like a different kind of vehicle:

InceptionV3 is the high-performance luxury car. This thing is top-of-the-line. It's packed with all the latest tech and a super powerful engine, which is why it can analyze every single detail with incredible precision. It's powerful and highly accurate, but all that power means it's a real gas guzzler (it needs a lot of computational power).

DenseNet121 is the reliable premium sedan. Think of it as a really well-engineered car that's both smart and efficient. All of its systems work together seamlessly to give you a safe, dependable, and strong ride that can handle almost anything you throw at it. The best part? It's not nearly as demanding on resources as the luxury model.

EfficientNetV2-S is the compact city car. This little car isn't going to win any races against the others, but it's a total winner in its own lane. It's quick, lightweight, and uses hardly any fuel. It's the perfect choice in the traffic and job done efficiently—like running on a mobile app where every bit of battery and space counts.

float

In our evaluations for Monkeypox detection, InceptionV3 was the clear top performer, outclassing MobileNetV2 with an impressive 95.6% accuracy on both train and validation data. This strong consistency presents that the model learned to generalize its knowledge effectively, rather than just memorizing the examples it was shown. While MobileNetV2 also performed commendably with a 92% validation accuracy, it was slightly less adept at distinguishing between Monkeypox and other skin conditions.

Think of it as a face-off between two AI models to see which one was the better disease detective. InceptionV3 was the clear champion. It was like a star student who not only aced the practice tests but also got the same high score—95.6%—on the final exam. This tells us it genuinely learned how to spot Monkeypox, rather than just memorizing examples.

MobileNetV2 was also a strong contender and did a good job, finishing with about 92% accuracy. But ultimately InceptionV3 performed well than MobileNetV2 and classified normal and Monkeypox images.

D. Interpretability Using LIME

The interpretability of dl models is crucial, particularly in the healthcare industry, and goes beyond their numerical performance. This was addressed by applying LIME to each model's individual predictions. The areas of the img that most used the model's choice are graphically highlighted in the heatmaps produced by LIME.

We used a special tool called LIME to get a peek into the AI's mind. For all three models we tested, the tool consistently showed that the AI was focusing on the exact spot a doctor would—the lesion itself. This is great as AI is also thinking just as humans.

Even better, these explanations helped us pinpoint where the AI went wrong on certain images. By seeing what the model

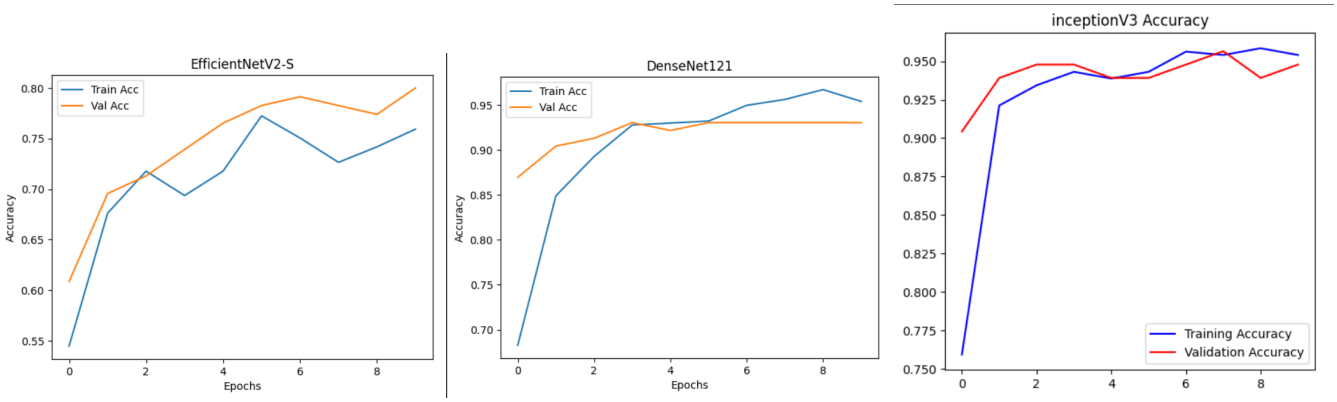

Fig. 3. Comparison of training-validation accuracy/loss EfficientNetV2-S, DenseNet121 and InceptionV3.

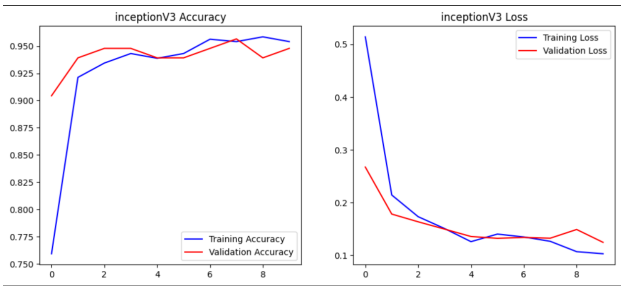

Fig. 4. Training vs Validation Accuracy for InceptionV3 Model

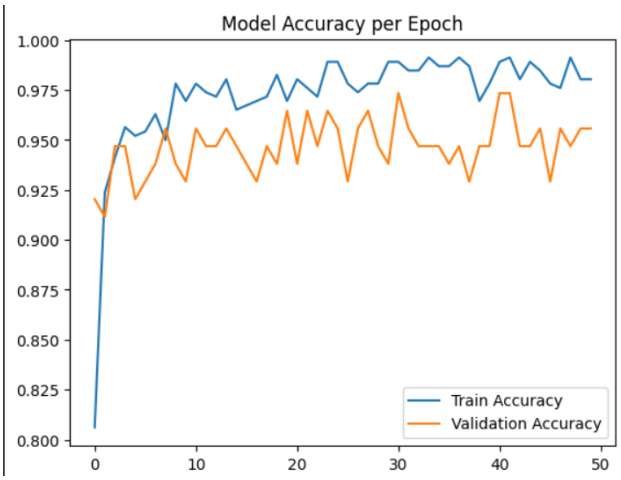

Fig. 5. Training Accuracy for MoblieNetV2

Fig. 6. LIME Explanation for InceptionV3 Prediction

was looking at when it made a mistake, we now have a clear path to improving it or cleaning up the data for next time.

Interpretability not only boosts clinical trust in AI systems but also makes them more acceptable in regulated environments where transparency is a legal or ethical requirement.

E. Multi-Model Prediction Comparison

To determine the operational feasibility of the developed networks, we performed predictions to a test image with visible Monkeypox lesions. [Our predictions are depicted in Figure X of the three fine-tuned models: InceptionV3, EfficientNetV2-S and DenseNet121. InceptionV3 predicted the image as Monkeypox with highest confidence 96.07 percent, followed closely by DenseNet121 which achieved 93.68 percent, and EfficientNetV2-S with a low confidence of 51.54 percent, but it still had a correct prediction. This comparative analysis shows how various models interpret the same input image, providing a window into their level of confidence and behavior in making predictions. It also demonstrates that the effectiveness and robustness of InceptionV3 and DenseNet121 can extend to Monkeypox lesion segmentation, even in the difficult real-world environment.

F. CONFUSION MATRIX

Think of the chart in Figure X as the AI's final exam results, where we see every right and wrong answer. The AI passed

Fig. 7. Multi-Model Prediction Comparison

with flying colors:

When we showed it 56 photos of Monkeypox, it got 53 correct.

When we showed it 59 photos of normal skin, it got 56 correct.

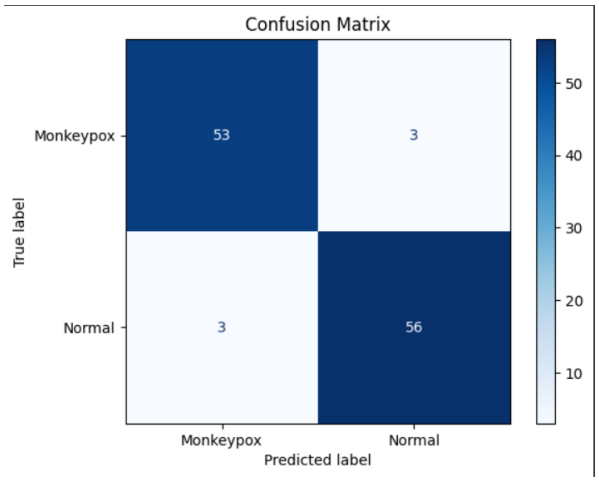

Fig. 8. Confusion Matrix of prediction

It only got tripped up on a handful of images, which is an excellent result. The best part is that it didn't have a "favorite" subject—it was equally skilled at identifying both conditions. This gives the proper idea that the model is completely fair and reliable and also very accurate.It only has few errors which shows that it's trustworthy. The matrix's balanced diagonal dominance shows that the model does a good job of generalizing across the dataset without showing preference for any one class.

V. CONCLUSION

In short, our work shows that we can successfully train an AI to be a reliable assistant for doctors in diagnosing Monkeypox.

We put a few of the best AI models to the test and found a clear winner—InceptionV3—that was exceptionally good at telling the difference between a Monkeypox lesion and healthy skin. But we knew that for a doctor to trust an AI, it can't be a mysterious "black box." That's why we made sure our project can explain its reasoning, making it a transparent and trustworthy partner.

Ultimately, this proves that we can build smart, dependable tools to support healthcare professionals, bringing expert-level help to clinics anywhere in the world, especially where it's needed most. The next step is to take this technology from the lab and put it into the hands of doctors, perhaps as a simple app on their mobile phone.

This study shows the potential of deep learning models for Monkeypox detection using skin images. Among the evaluated models, InceptionV3 and DenseNet121 showed great performance, while EfficientNetV2-S offered a lightweight alternative suitable for mobile deployment. The integration of LIME-based interpretability enhances clinical trust and transparency.

However, the relatively small dataset size (716 images) presents a limitation in terms of generalizability and detection of the models in many scenarios. Future research will be aimed to take large and larger datasets, to ensure broader applicability in real-world healthcare environments.

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