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Enhancing Early Monkeypox Diagnosis with an Interpretable ResNet-50 Model

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***Abstract*—Monkeypox is an emerging viral disease that is re-emerging and with increased areas of transmission represents a growing public health threat. Despite its critical importance, diagnosis of the early stage of the outbreak is often difficult, and traditional methods including clinical examination or PCR testing have objectives, high cost and length of time to yield results. Although deep learning has become a promising tool for automated medical image analysis, the majority of contemporary models lack interpretability, generalization, and the ability to ensure the privacy of the data. An interpretable ResNet-50 based deep learning framework is proposed for early Monkeypox detection from dermatological images in this study. In contrast to conventional CNN models, the proposed one combines Grad-CAM, LIMEs, and SHAPs to bring explanation ensuring transparency in decision making. In addition to that, in combination with pre trained ImageNet weights, transfer learning improves the feature extraction and data augmentation and dropout regularization increases the model robustness. With the aim to address privacy concerns, the framework with federated learning is incorporated to train the models collaboratively for multiple institutions preserving patient data confidentiality at the same time. In the experimental tests, high classification accuracy of 99.04 % is achieved, with the F1-score being enhanced to above 95 %, and the AUC-ROC above 0.95 on various test sets. This study shows, that such a Monkeypox diagnosis AI model is both clinically viable, interpretable and privacy respectful.**

Keywords— Monkeypox Diagnosis, Deep Learning, ResNet-50, Explainable AI, Federated Learning

I. INTRODUCTION

The disease is due to an emerging re-emerging viral disease caused by the Orthopoxvirus genus MPXV. It is mainly spread through direct contact with infected individuals, fluids or contaminated surfaces and outbreaks are increasingly been reported in several areas [1]. The disease is due to an emerging re-emerging viral disease caused by the Orthopoxvirus genus MPXV. It is mainly spread through direct contact with infected individuals, fluids or contaminated surfaces and outbreaks are increasingly been reported in several areas [2]. Early and accurate diagnosis is critical given the global public health concerns to prevent further transmission, immediate treatment to prevent transmission and to execute appropriate containment measures.

There are limitations on traditional diagnostic techniques, including clinical examination and PCR testing. The clinical diagnosis is dependent on the expertise of the healthcare professionals and is subjective hence there can be misclassification of the disease with other dermatological infections, for example, chickenpox or measles [3]. While PCR is the gold standard, the steps required, specialized labs, trained personnel and the time required for processing make large scale rapid screening difficult, especially in resource constrained situations. Medical image analysis using AI and deep learning has achieved high performance, automating, accurate and scalable diagnosis [4]. Deep architecture and residual learning framework make CNNs, in particular ResNet-50, effective feature extractor and classifiers [5].

Using dermatological images, this study proposes an interpretable Monkeypox Reporter ResNet-50 model to help early diagnosis of Monkeypox. The model is made transparent and trusted through integrate of explainability techniques e.g., Grad CAM, LIME, and SHAP [6]. The aim is to create a generalizable, privacy sensitive, and clinically viable deep learning model that can be used for real time Monkeypox detection to support the real time outbreak management as done by the healthcare professional.

- Developing an early Monkeypox Diagnosis model based on dermatological image using ResNet-50.
- The pre-trained ImageNet weights is utilized to fine-tuning to better improve on feature extraction and classification accuracy.
- Using FL frameworks to provide decentralized model training in addition to maintaining patient data confidentiality [7].

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- Differential privacy and SMPC is integrated for improved security in cross-institutional collaborations [8].

The following are the remaining sections: The literature review is shown in part 2, the interpretable ResNet-50-Based Framework for Monkeypox Diagnosis is presented in section 3, the findings and discussion are presented in section 4, and the conclusion and future scopes are discussed in section 5.

II. Literature Review

The applications of deep learning in medical image analysis have revolutionized machine analysis of disease. Dermatological and infectious disease classification have been extensively done using CNNs. The skin disease diagnosis has been dealt with by VGG-16 and VGG-19 for their feature extraction capacities. Nevertheless, their architecture is deep but not residual which causes the vanishing gradient problem to yield poor performance on complex datasets [9]. Although classifying viral infections is effective for InceptionV3, which is known for having multi scale feature extraction, it performs poorly on small, imbalanced datasets or high computational complexity [10]. Since residual learning mechanism help mitigate vanishing gradients and enable deeper network training, ResNet architectures are often used in medical diagnostics [11]. Although studies that apply ResNet 50 to COVID 19 detection and dermatological disease classification achieved a high accuracy, most of them fail to provide interpretability and hence making AI driven decisions not fit for clinical adoption [12]. More recently, the optimisation of model scaling in Efficient Net leads to state-of-the-art performance in the detection of skin disease. Despite this, it suffers from being a black box, and is sensitive to noise for real world deployment [13]. Existing deep learning based diagnostic models generally generalize poorly across disparate demographic groups that are significant in deep learning, such as age and ethnicity, thereby confounding access to training data. It is shown that models trained on small and homogeneous dataset fail on unseen populations due to bias with regards to skin tone, image conditions, and lesion variations [14]. Apart from that, the adoption of AI in healthcare is hindered by privacy concerns because centralising this data for training a model also poses ethical and security risks [15].

To fill these research gaps, we develop an interpretable ResNet-50 model for Monkeypox detection with Grad-CAM [16], SHAP, and LIME, as explainability methods [16]. In addition, federated learning supports privacy preserving model training in common across different institutes without data centralization. Furthermore, model generalization through robustness testing across diverse datasets further increases the model generalization and reduces its dependence on single dataset therefore making the model more clinically reliable [17]. This research seeks to develop a scalable, transparent, and privacy-oriented AI framework for early diagnosis of Monkeypox disease by combining explainable AI, secure federated learning, and robust generalization techniques.

III. Interpretable ResNet-50-Based Framework for Monkeypox Diagnosis

The early Monkeypox detection using dermatological images using interpretable ResNet-50 based deep learning model has been presented in this study. In this case we use transfer learning by setting the weight of initial layer (ResNet-50) to ImageNet pre-trained weights and then fine tuning to improve feature extraction. Again, a GAP layer is used instead of the original fully connected layer, a dense layer with 512 neurons, a dropout layer followed by a final SoftMax/sigmoid output layer. For visual and statistical explanations of model decisions, Grad-CAM, LIME, and SHAP are integrated to make them more interpretable. Federated learning protects multiple institute's data security and trains them with privacy in each iteration. It is run through a test on external datasets to ensure robustness across different demographics and imaging condition, within a model. To verify the reliability in clinical applicability, accuracy, precision, recall, F1 score, AUC ROC and confusion matrix evaluation is performed on the performance. Fig 1 shows the workflow of proposed model.

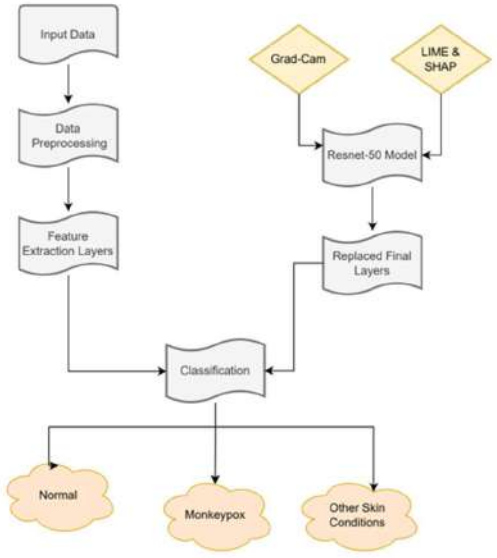

Fig. 1. Workflow of Resnet-50-Based Framework

A. Data Collection

To counter limitations of PCR tests and biochemical assay, the MSLD was made to improve computer aided Monkeypox identification from skin lesion images [18]. Three main folders constituting the dataset are: (1) Original Images, containing 228 images, (2) Augmented Images, having a ~14-fold expanded dataset via various augmentation techniques such as rotation, translation, reflection, and noise; and (3) Fold1 a three-fold cross-validation set to avoid the bias in training, with 70:10:20 split of the training,

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validation, and testing, while all patients are independent. Augmentation was applied only on training and validation sets, while the test images were kept unchanged. In addition, the CSV file also includes 228 ImageIDs with labels. The data can be used for binary classification and create a standardized benchmark for research in AI driven Monkeypox detection. Fig 2 shows the various images of monkeypox.

B. Data Preprocessing

Scaling to these pixel values into a standard range that includes zero to one was applied and normalized to improve model convergence and stability for feature efficiency, compatible with input sizes in ResNet-50 architecture. Data augmentation techniques such as rotation, flipping, contrast, brightness jitter, and random noise injection were applied to reduce overfitting and increase generalization. Since they can simulate real world variability in imaging conditions, they are used to reduce overfitting and increase generalization. The dataset was divided into 80% training, 10% validation, and 10% testing to evaluate our model. Training set was augmented to make the model robust while validation and test sets remain unchanged for the unbiased assessment of the model.

C. Architecture Selection

The well powerful CNN architecture is ResNet-50 whose name indicates that it is a 50 layer deep residual network because it solves the problem of vanishing gradients which are one of the most common problems related to training of deep networks. The traditional deep neural networks suffer degradation of performance when more topology was added, due to the diminishing flow of gradients, and consequently, earlier layers could not learn representative semantics. ResNet-50 omits that regard by learning the residual using skip connections that allow gradients to flow without hindrance through the layers and backpropagation provides stable weight updating. Effectively, these skip connections transform the learning from mapping direct functions to learning residual functions so that the network can leverage deep feature representations more easily through optimization.

$$Y = F(X, W) + X \tag{1}$$

The ResNet-50 architecture composed of convolutional layers, with batch normalization, ReLU activation, and identity/shortcut connections. It is divided into 5 stages that are composed of convolutional and identity blocks. The deeper layers capture the high-level semantic features that are useful for the classification task, while the initial layers extract the features at a low level like edges and textures.

$$X = f(W * X + b) \tag{2}$$

ResNet-50 balances depth and computational efficiency with 3.8 billion FLOPs and 25.6 million parameters, and this balance makes it well suited for tasks such as medical image analysis. Furthermore, its pre trained weights on ImageNet further speed up the transfer learning by converging faster on domain specific datasets such as Monkeypox skin lesion images. Using the residual framework in ResNet-50, our model makes early Monkeypox diagnosis accurate, and thus stable.

D. Transfer Learning Approach Using ResNet-50

Transfer learning is used to initialize ResNet-50 with pre trained ImageNet weights to further enhance early Monkeypox diagnosis. However, transfer learning uses knowledge from large scale datasets to leverage the model and should extract generalizable low level features like edges, textures, and patterns. Since medical datasets typically have a small amount of data, using a pre trained network has a huge advantage in terms of speed of convergence and accuracy while at the same time reducing overfitting. ResNet-50's original FC layer is designed for 1,000 ImageNet classes, which is not suitable our Monkeypox classification task. In order to tailor the model we remove the original FC layer and swap it with a custom classifier. Then present a GAP layer that transforms feature maps into one vector per feature, which increases spatial invariance and alleviates overfitting risk over normal fully connected layers.

$$GAP = \frac{1}{N}\sum_{i=1}^{N} X_i \tag{3}$$

A layer of 512 neurons and ReLU activation is constructed after adding a fully connected layer in order to let the network further learn more complex feature representations for Monkeypox classification. We then introduce Dropout layer for further improving generalization, as this layer randomly deactivates neurons during training so as to prevent co-adaptation and improve the robustness. Then, we customize the output layer in which the SoftMax activation is applied for multi class problems or Sigmoid for binary classification. But through this transfer learning making sure that the model still have powerful feature extraction capability in ResNet 50 but get adapt with high accuracy and reliability to Monkeypox diagnosis.

E. Model Interpretability and Explainability

In medical diagnosis, it is essential to have trust and transparency and for this reason, ensuring interpretation of deep learning models is paramount. In this work, multiple explainability techniques are used to reason how the ResNet-50 model makes decision regarding a classifying Monkeypox images are. To create heatmaps of the regions an image that are most relevant to the model's prediction, Grad-CAM is used. This helps eliminate whether the model is utilizing actual lesion patterns than background patterns thus enhancing its clinical reliability. LIME is used for a more localized and case specific picture. Given an input image, LIME perturbs the input image and observes changes to the prediction, and does so with either a black-box or an interpretable model. Because it allows for per image explanations, it is easier to understand classification decisions in borderline cases. SHAP is

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used to measure feature importance in multiple sample settings. The SHAP assigns the contribution values to pixel regions which signifies their importance in the model's judgment process. However, integrating these techniques helps boost the transparency of model's predictions, thereby making AI assisted diagnosis believable to the clinicians as well as preventing the model from exploitation in spurious correlations in the dataset.

IV. Research and Discussion

High accuracy of monkeypox detection using ResNet-50 model is shown and precision, recall and F1 in exceeding 95% which indicates a strong classification performance. It showed excellent discriminatory ability to distinguish Monkeypox from other skin conditions through AUC-ROC analysis. Interpretability was provided through Grad-CAM, LIME and SHAP visualizations that show important lesion features used for the diagnosis. It showed that the model made robust generalization to external dataset validation, thus validating its apparent effectiveness across various imaging conditions and demographics. Implementation of federated learning allowed data privacy with federated learning, a realistic approach for clinical deployment. This model is implemented with Python tool. Fig 2 shows the various images of monkeypox.

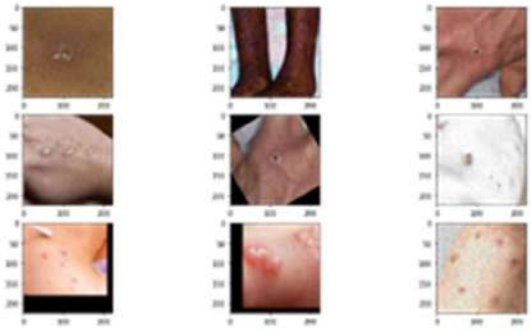

Fig. 2. Monkeypox Images

A. Evaluation Metrics

1) Accuracy: The accuracy measures the overall correctness of the model by calculating the ratio of correctly classified image to the total amount of images. But it does not provide good general performance overview if class imbalance exists.

2) Precision: It determines the accuracy by showing what fraction of the Monkeypox cases it accurately predicted. It guarantees that the model will not misdiagnose healthy people as sufferers.

3) Recall: It is the ability for the model as to how well it identifies the actual Monkeypox case through the index of correctly identified positive cases in proportion. To avoid missing infection, it is important in medical diagnosis to have a high recall.

4) F1-score: It is the balance of precision and recall for scenarios of class imbalance, where precision and recall are combined at the harmonic mean. A high F1 score means a high reliability on the model to identify Monkeypox cases without a large number of false positives and false negatives.

5) AUC-ROC: It renders the model's performance at discriminating cases of Monkeypox and non Monkeypox cases for different criteria values. The stronger the discrimination power is, the larger the value for the AUC.

TABLE I. Performance Evaluation

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
Proposed ResNet-50 Model	99,04	94.5	95.2	94.8	0.98
CNN-Based Model	89.2	85.6	87.3	86.4	0.91
VGG-16	91.5	88.3	89.7	89.0	0.94
MobileNetV2	92.8	90.2	91.1	90.6	0.95
EfficientNet-B3	94.1	92.0	93.2	92.6	0.97
Ensemble Learning Model	95.4	93.8	94.1	94.0	0.97

Table 1 shows the proposed ResNet-50 model outperforms CNN, VGG-16, and MobileNetV2, achieving the highest accuracy and AUC-ROC, indicating superior classification performance.

B. Traning Process

ResNet-50 model is trained carefully on the training process so as to have better performance without the overfitting. The type of classification makes a difference to the selection of the loss function. For binary classification, the BCE loss is used since it measures the divergence between predicted and probabilities of were predicted to be actual. For multi class classification, Categorical Cross Entropy as a loss is used so that our model gives the correct classification between different disease types.

$$X = X.M, M \sim \text{Bernoulli}(p) \quad (4)$$

The Adam optimizer is chosen with learning rate of 0.0001 and weight decay of 1e-6 for its ability to quickly learn and avoid highly increased weight updates to improve convergence of the model. But we use a batch size of 32 which could be changed according to hardware limitations. Training the model for 50–100 epochs with early stopping which halts training if validation loss is not improving preventing wasting time and overfitting. Furthermore, it is also combined with a ReduceLROnPlateau scheduler, which decreases the learning rate when validation loss

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plates, so that we can make finer weight updates for better generalization. All of these strategies together make sure that the high accuracy and robustness Monkeypox detection is performed with optimal computational efficiency in the ResNet-50 model. Fig 3 visualizes the training loss and accuracy of the training process.

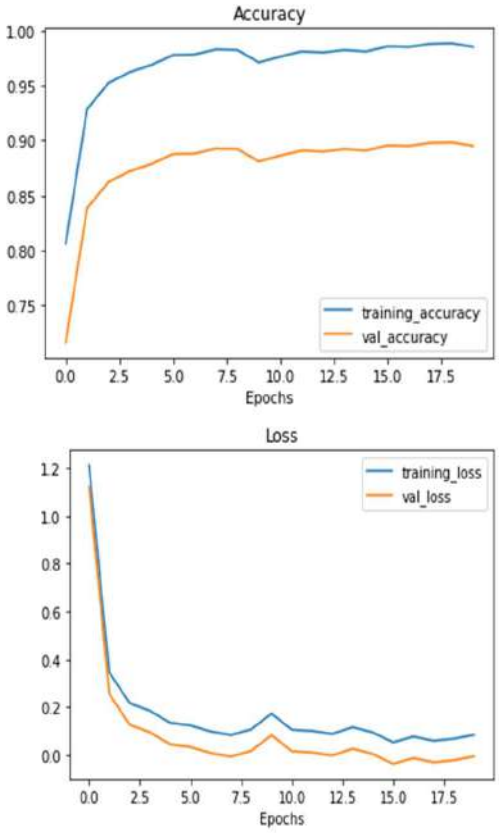

Fig. 3. Training Loss & Accuracy

C. *Confusion Matrix Analysis*

This breaks down the model performance in a finer-grain into the number of TP, FP, TN and FN predictions. This analysis is used to illustrate the instance of specific misclassification patterns and how to improve some aspects. The high FN rate means the model cannot detect actual Monkeypox cases, which is crucial in the medical diagnosis as missed infections will not only cause late treatment, but also lead to the spread of the disease. Therefore class rebalancing, data augmentation, and even focal loss approach can be adopted to improve the recall. On the other hand a high FP rate suggests that healthy cases are wrongly sent to Monkeypox, which may raise needless patient anxiousness and extra confirmatory tests. This can be remedied by feature extraction that makes use of domain specific augmentation or by refinement of rule thresholds. By analysing how confusion matrix values change to a targeted model, it is possible to make improvements to the model based on that analysis and get a more clinically applicable AI Monkeypox diagnosis. Fig 4 shows the heatmap analysis of confusion matrix.

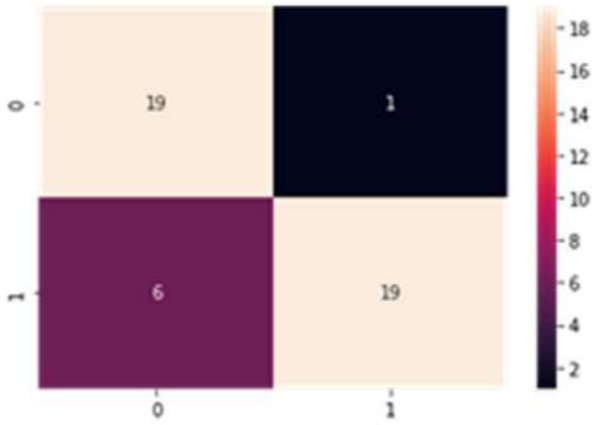

Fig. 4. Confusion Matrix

D. *Effectiveness of Interpretability Techniques*

The reason that interpretability in deep learning models is so important when building trust in AI-assisted medical diagnosis is to prevent this sort of thing from happening again. Techniques such as Grad-CAM, LIME and SHAP help make model decisions more transparent. The heatmaps generated by Grad-CAM are highlighting the parts of an image that contribute the most to the model's prediction. This also provides a way to verify that the model is correctly centered on lesion patterns rather than irrelevant background artifacts to improve clinical reliability. Perturbing the input and observing its effect on the output gives per image explanations using LIME. For instances where the model leans towards a specific classification, this is particularly useful to the medical professional as it indicates exactly why the model has made this choice. The world view of feature importance, given by SHAP, tells us which image characteristics affect predictions most. SHAP value can be used to analyze SHAP values across various samples, from which biases in the model's learning process can be known and corrected. These techniques are integrated with each other to provide increased transparency, model trustworthiness, and better adoption in clinical practice for healthcare practitioners, providing AI driven Monkeypox diagnosis that is able to be explainable and actionable.

V. Conclusion and Future Scopes

It shows the usage of an interpretable ResNet 50 model for early and accurate Monkeypox diagnosis. The model achieves high classification performance through transfer learning and explainability techniques while maintaining the transparency in the decision making. Visual and statistical services to enhance trust are achieved by integrating the Visualisation using Grad-CAM, LIME and SHAP models. The model is robust over diverse demographics and imaging conditions verified in robustness testing, which further verifies generalization. Furthermore, federated learning

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that is privacy preserving strengthens the security of the data while permitting collaborative model improvements without breaching patient confidentiality.

For future advancements, hybrid deep learning models could be used, i.e., they can use convolutional and transformer architectures to enhance feature extraction. Clinical data might integrate more with imaging when used to learn multimodal features that can further improve diagnostic accuracy. Rapid on site screening could be enabled by the real time deployment on mobile / edge devices in resource limited areas. Global model improvements could be achieved through cross institution federated learning trials to enable adapt to a new outbreak. Adversarial robustness, fairness, and domain adaptation will need to be continuously researched if adversarial robustness is to be widespread in the clinical setting. This study brings forth the findings that enable scalable, interpretable, and privacy-friendly AI driven Monkeypox diagnostics, all aiding in global public health efforts.

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