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ENHANCING MONKEYPOX DETECTION THROUGH DEEP LEARNING AND EXPLAINABLE AI: A DATA SCIENCE APPROACH

Masters Thesis – June 2024

Presented by –

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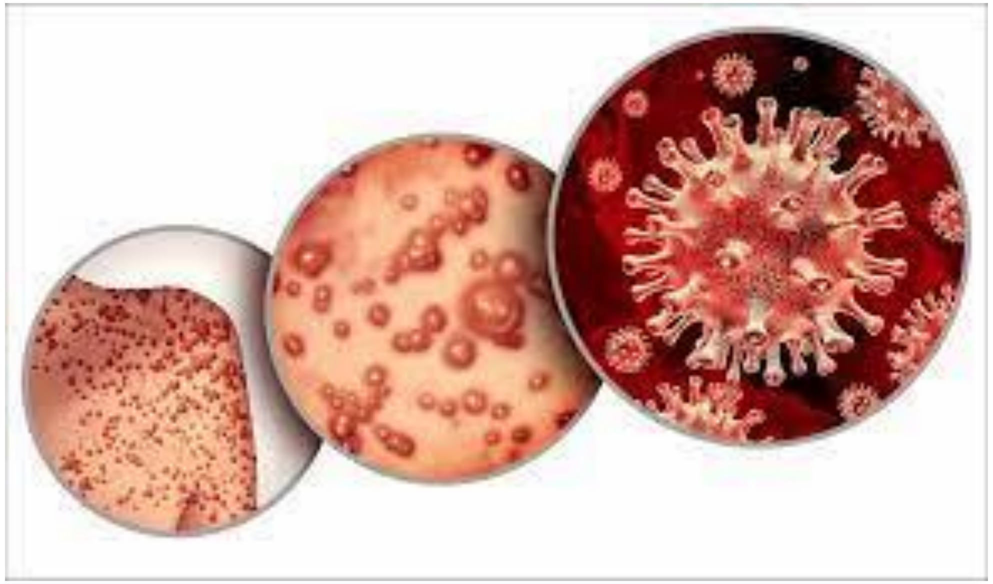
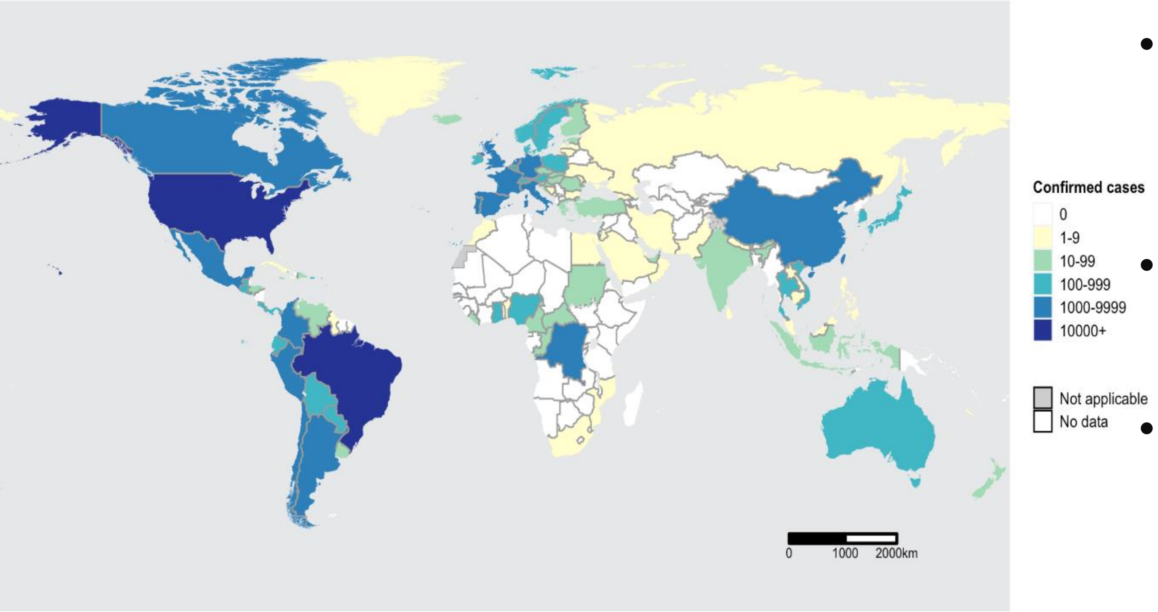
Introduction





- Zoonotic disease caused by the monkeypox virus
- As of January 31, 2024, WHO has received reports of 93,921 confirmed cases
- The global outbreak of mpox was declared a public health emergency of international concern (PHEIC) on 23 of July 2022.
- Laboratory confirmation of mpox is done by testing skin lesion material by PCR
- PCR testing methods are time-consuming and require specialized lab equipment and expertise, which is not always available.
- Our research focuses on harnessing Deep learning methods for faster and more accessible monkeypox disgnosis systems.
- Aim to help in prompt and reliable medical treatment of monkeypox to control outbreaks.

Literature Review

- The integration of data analytics and business into healthcare has led to the emergence of a new sector called, health informatics or health information technology (HIT)

- Deep learning has been increasingly used in medical research to analyze medical images, including skin cancer identification, retinopathy detection, and bone age determination,

- DL models have shown remarkable accuracies in:

✓ COVID19 detection - Ardakani et al. (2020) evaluated ten DL models and got 99% accuracy

✓ Malaria detection- (Dey et al., 2021) used deep Convolutional Neural Network (CNN)-based approaches to automatically detect malaria parasites in blood cell images using ResNet 152 model

✓ Skin disease detection, Velasco et al. utilized MobileNet for smartphone-based skin disease identification, reporting approximately 94.4% accuracy in detecting Chickenpox symptom

✓ Measles detection with ResNet-50, achieving accuracy of 95.2% (Glock et al., n.d.)

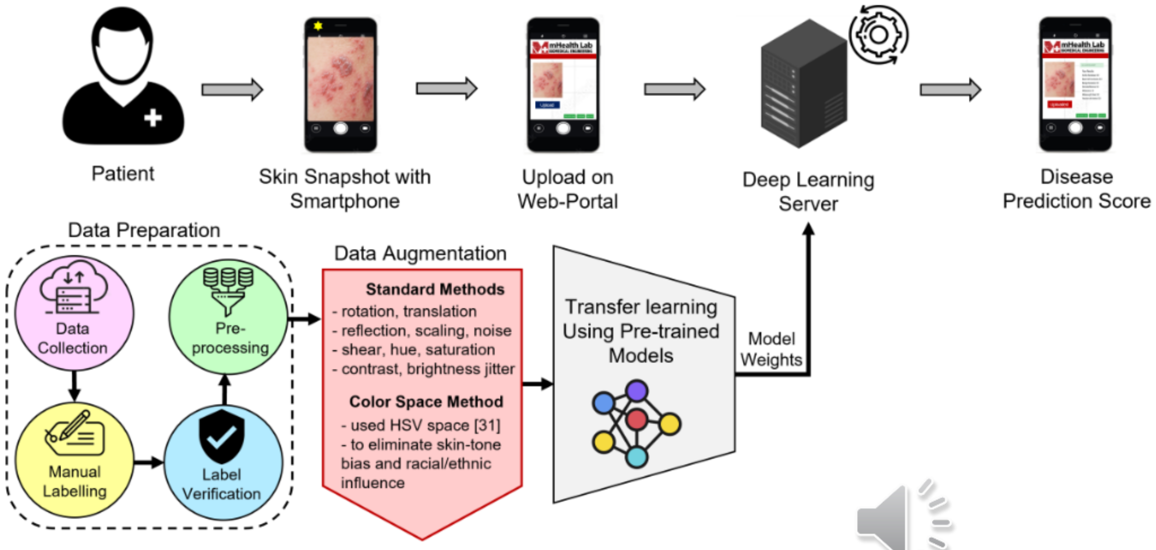
Related works

- "MonkeyNet," for early detection and classification of monkeypox using skin images was proposed by (Bala et al., 2023). Proposed model, "MonkeyNet," is a modified DenseNet-201-based deep CNN. Achieved 93.19% and 98.91% accuracy on original and augmented datasets.

- Investigating into federated learning, to address privacy concerns in relation to medical imaging, (Ahsan et al., 2024) focus on improving Monkeypox diagnosis using modified transfer learning, ViT, and federated learning

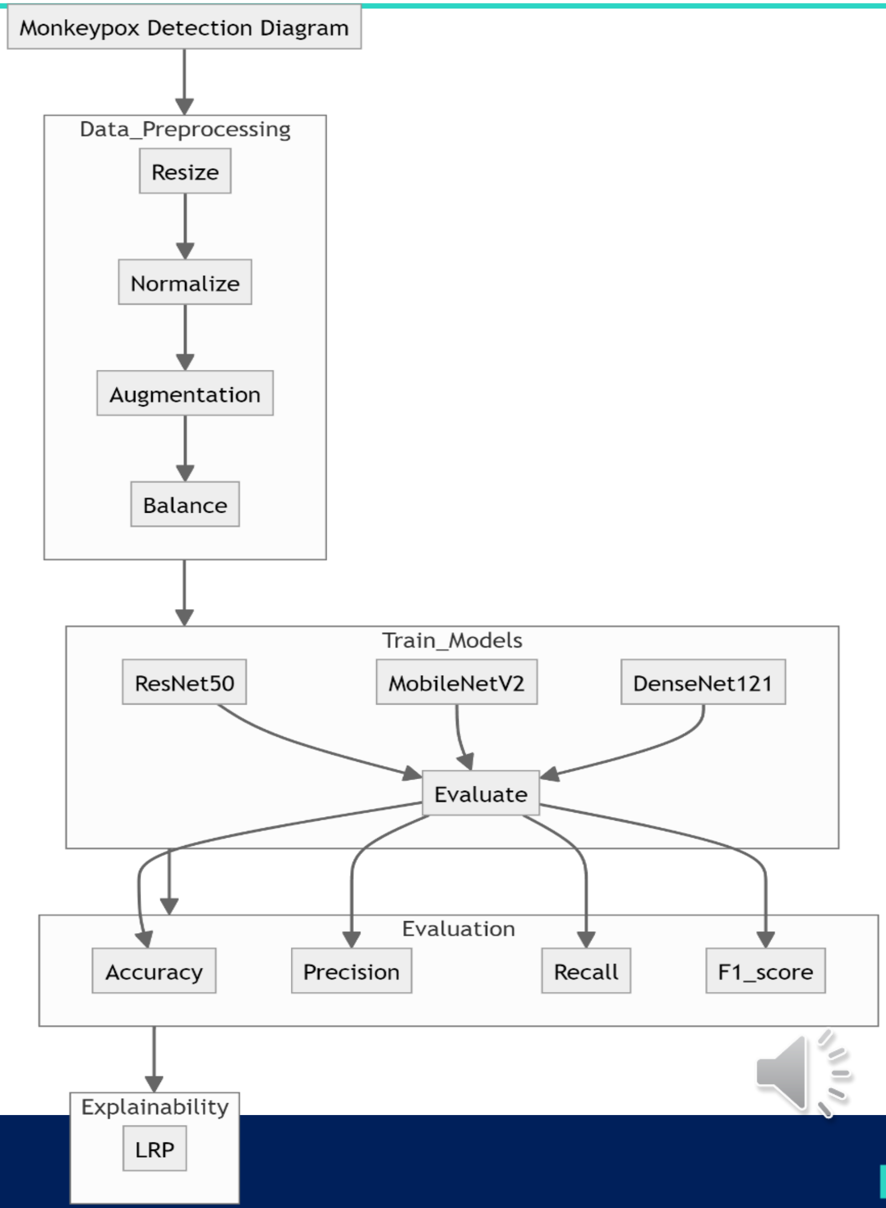
- Nayak et al., 2023) have aimed to utilize the advanced capabilities of smartphone sensors and dedicated high-performance hardware to detect monkeypox infection effectively to offer a low-cost, reliable alternative to PCR testing.

- (Ali et al., 2023) introduced a web-based system for detecting Monkeypox using deep learning models. DenseNet121 achieving an overall accuracy of 82.26%. The models are integrated into a prototype web application for skin image analysis emphasizing the importance of the web application for public health screening



Research Methodology

- Data loaded and normalized using keras class of ImageDataGenertor()
- Images and labels loaded, resizing and augmentation done by flow_from_directory(), which is a method offered by ImageDataGenenrator() in Keras
- Train, test and Validation folders created
- Augmentation techniques performed: horizontal and vertical shifting, zooming in and out, horizontal flipping, rotating, shearing, and filling in new pixels with the nearest possible value



Dataset description

'HFMD' -1526,

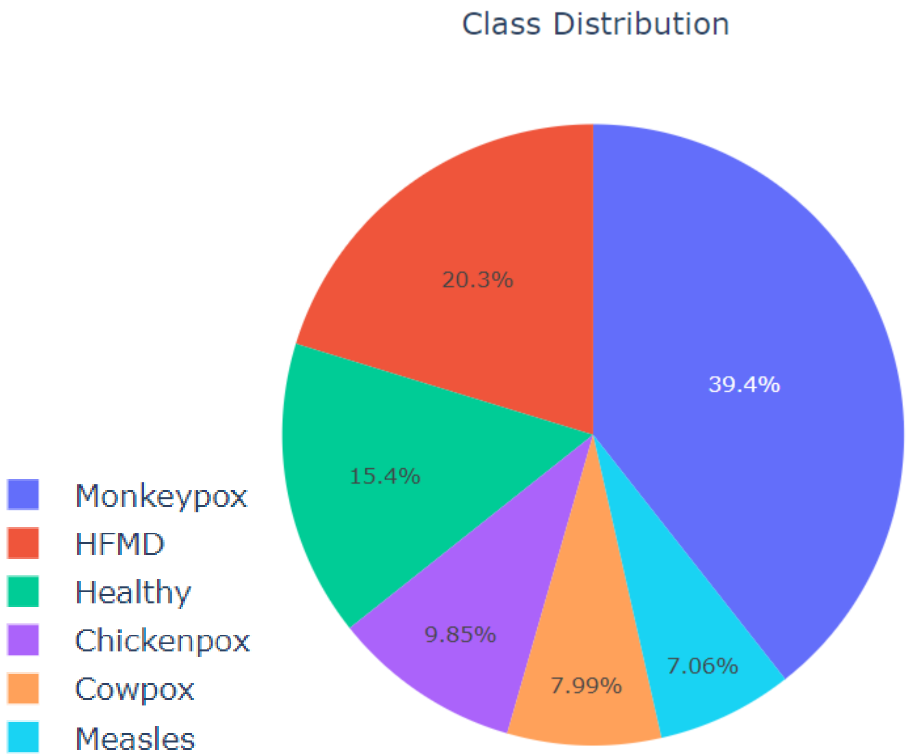
'Chickenpox' – 742

'Monkeypox' – 2968

'Measles' – 532

'Healthy' - 1162

'Cowpox' - 602 images

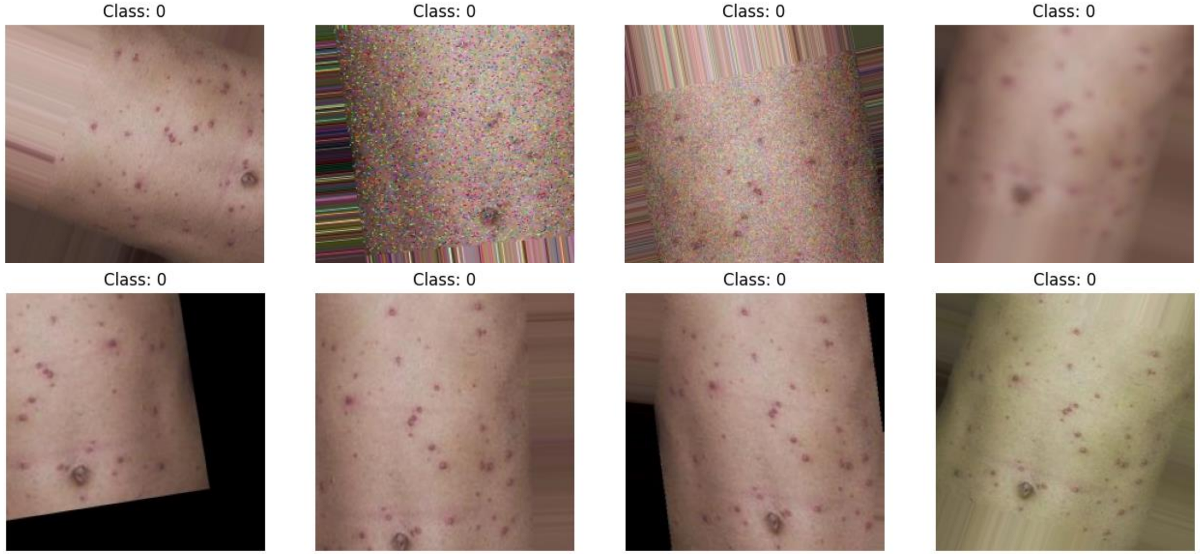


Unbalanced data

Class Balancing

Random Oversampling (ROS)

SMOTE (Synthetic Minority Over-sampling Technique)



Hyperparameter Tuning

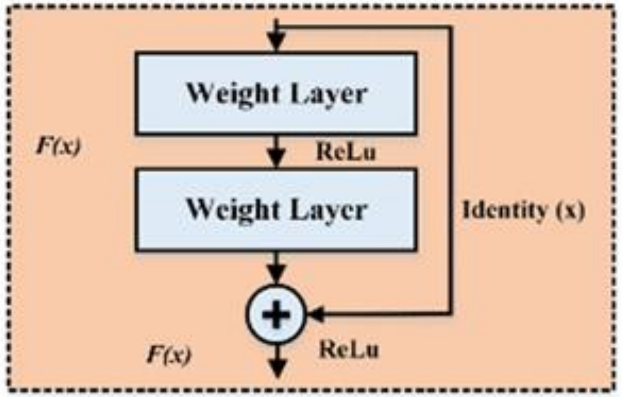
Hyperparameters	Values
Optimizer	Adam
Loss Function	Categorical cross-entropy
Epochs	20, 30, 40
Batch size	16
Learning rate	0.001, 0.0001, .00001

Callbacks: to monitor and control the training process to achieve optimal performance and prevent overfitting

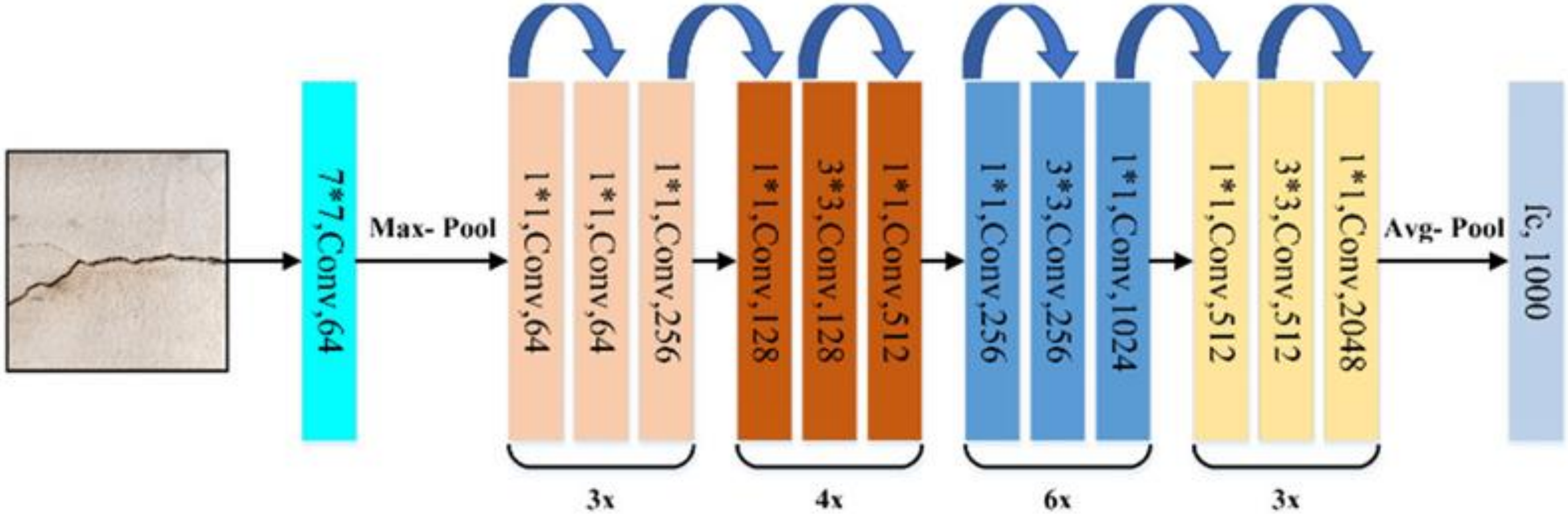
- ModelCheckpoint - saves the model's weights at specified intervals
- ReduceLROnPlateau - reduces the learning rate when the validation loss stops improving
- EarlyStopping - stops training when the validation loss stops improving for a specified number of epochs

ResNet50

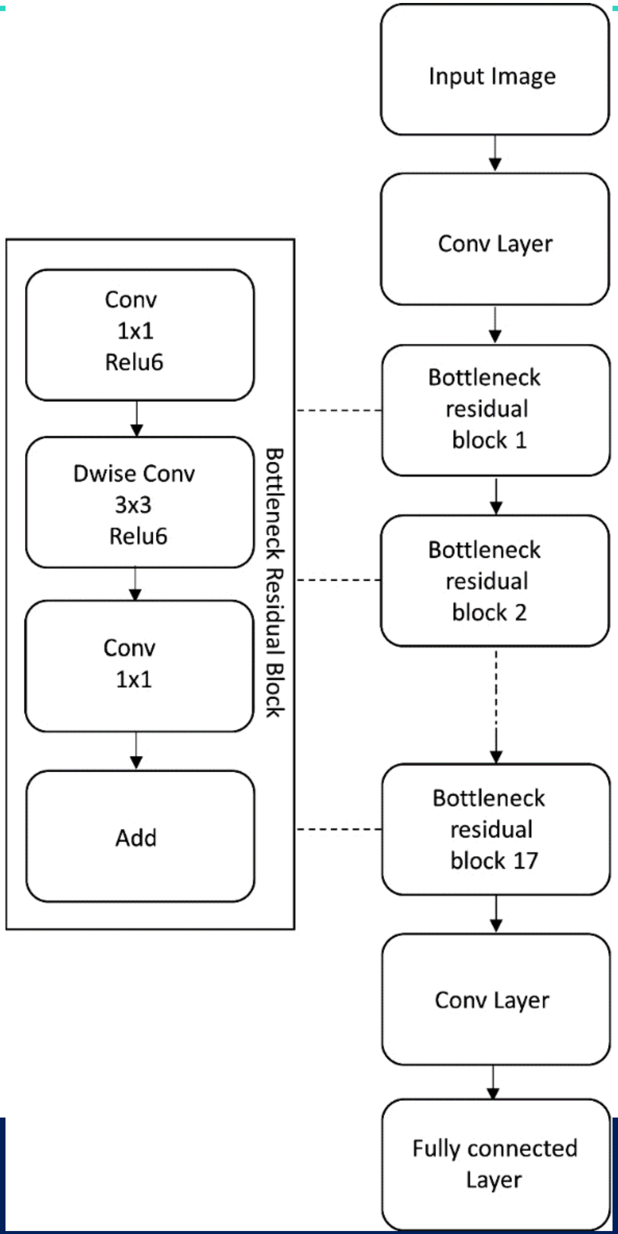
- Deep residual neural network architecture consisting of 50 layers
- ResNet architecture, along with features tries to learn some residuals as well
- Network is constructed by stacking residual blocks, each containing multiple convolutional layers, batch normalization, and ReLU activation.
- Skip connections, also known as identity connections, are a key feature of ResNet-50 which allow for the preservation of information from previous layers, which helps the network to learn better representations of the input data.
- Skip connections are implemented by adding the output of an earlier layer to the output of a later layer preventing the vanishing gradient problem leading to convergence



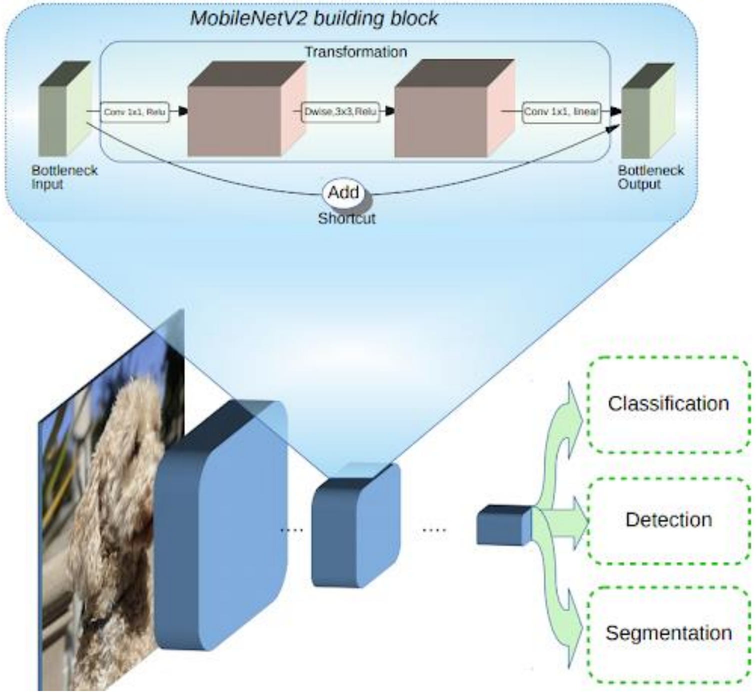
Residual Learning Block



MobileNetV2

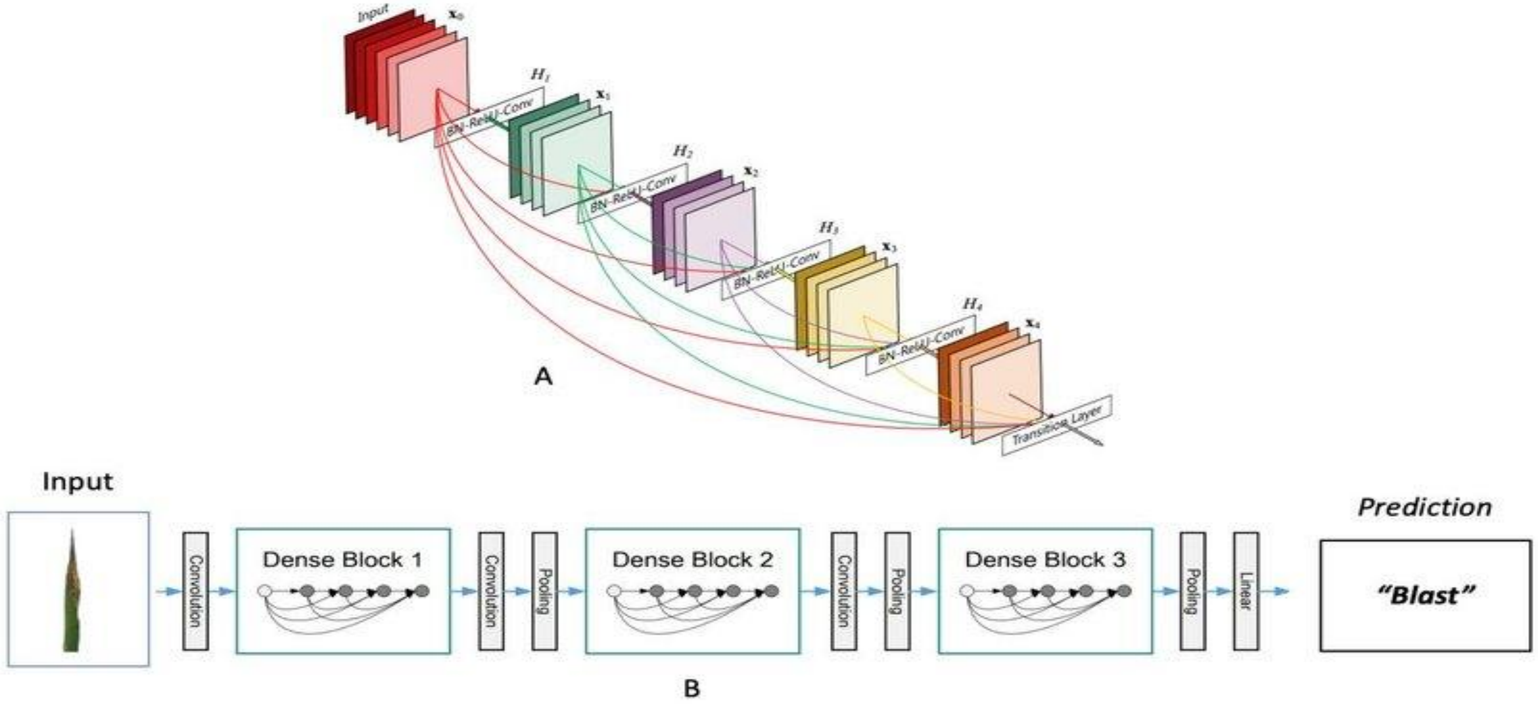


- Deep learning model designed for mobile and edge devices with limited computational capacities
- MobileNetV1 applies 3x3 depth-wise convolutions followed by 1x1 pointwise convolutions across 13 blocks, using batch normalization and ReLU activation, without pooling layers, and includes a global average pooling layer at the end.
- Inspired by ResNet, MobileNetV2 enhances this by incorporating linear bottlenecks and inverted residuals for better gradient propagation and memory efficiency.
- V2 introduces two new features to the architecture: 1) linear bottlenecks between the layers, and 2) shortcut connections between the bottlenecks
- Optimized for smartphone CPUs using hardware-aware Network Architecture Search (NAS)

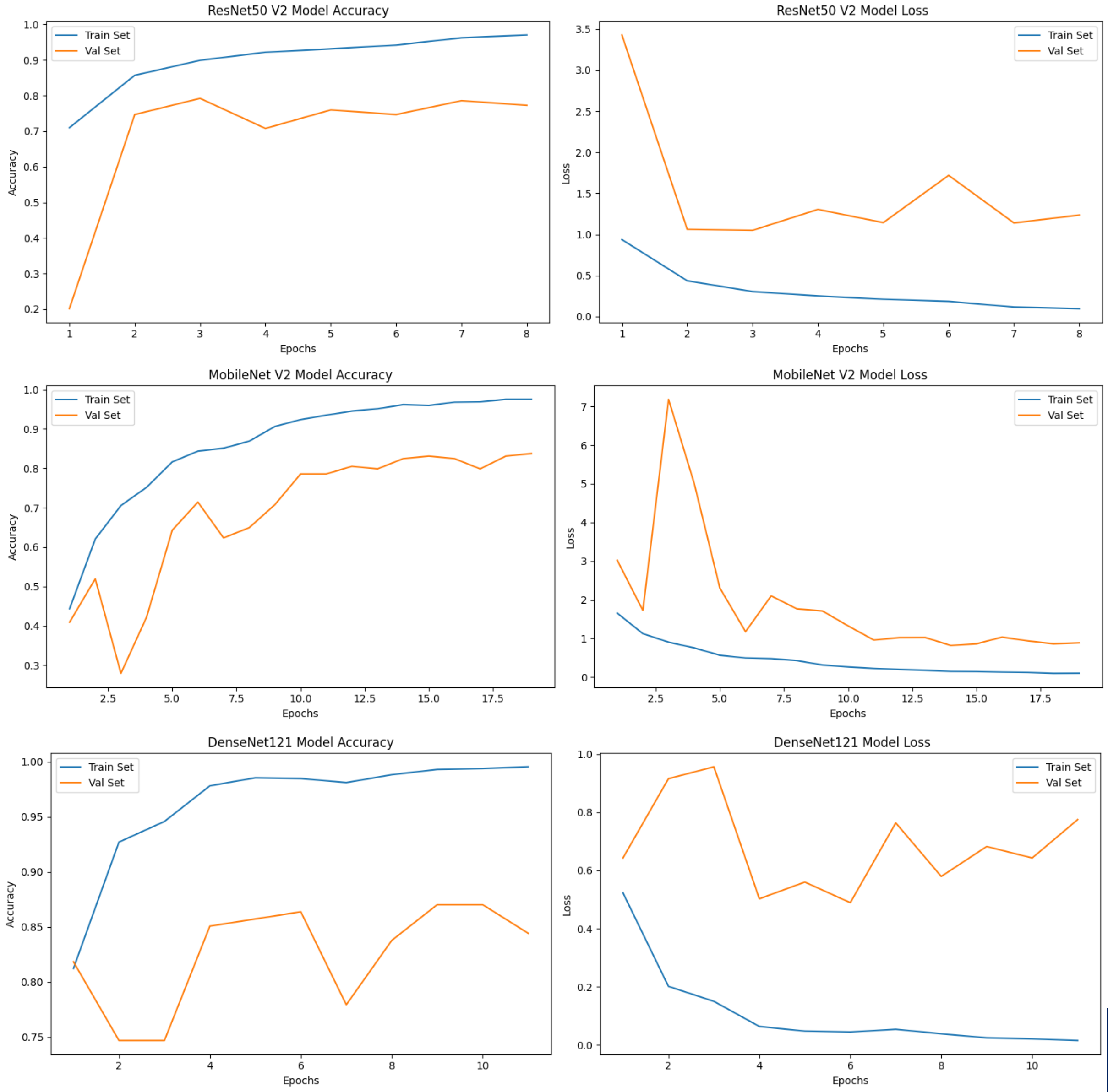


DenseNet121

- Establishes direct connections between all layers
- Solves the vanishing-gradient problem, reinforcing feature propagation, promoting feature reuse, and significantly reducing the number of parameters
- Architecture does not suffer from overfitting or the optimization difficulties faced by residual networks
- offers an approach to expanding deep CNNs without running into common issues like vanishing or exploding gradients.
- every layer is directly connected to all successive layers, which allows for maximum information and gradient flow.



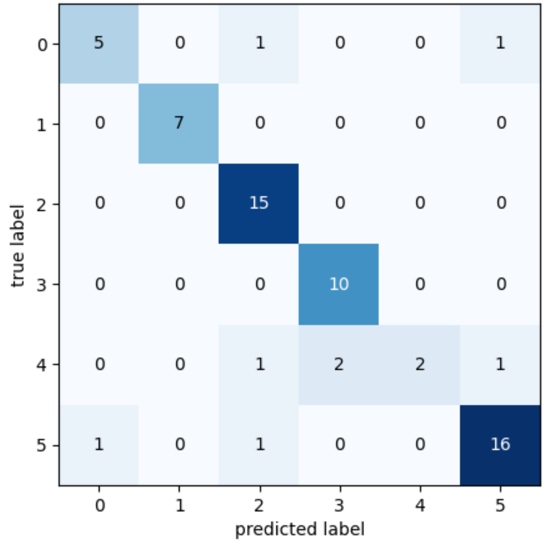
Case 1: Initial results with standard augmentation



Training and validation Accuracy and Loss graphs

Model	Validation accuracy(%)	Test accuracy(%)	Precision	Recall	F1-score
ResNet50	79.2	71.4	0.731	0.644	0.649
MobileNet V2	83.7	85.7	0.898	0.816	0.837
DenseNet 121	87	87.3	0.898	0.823	0.829

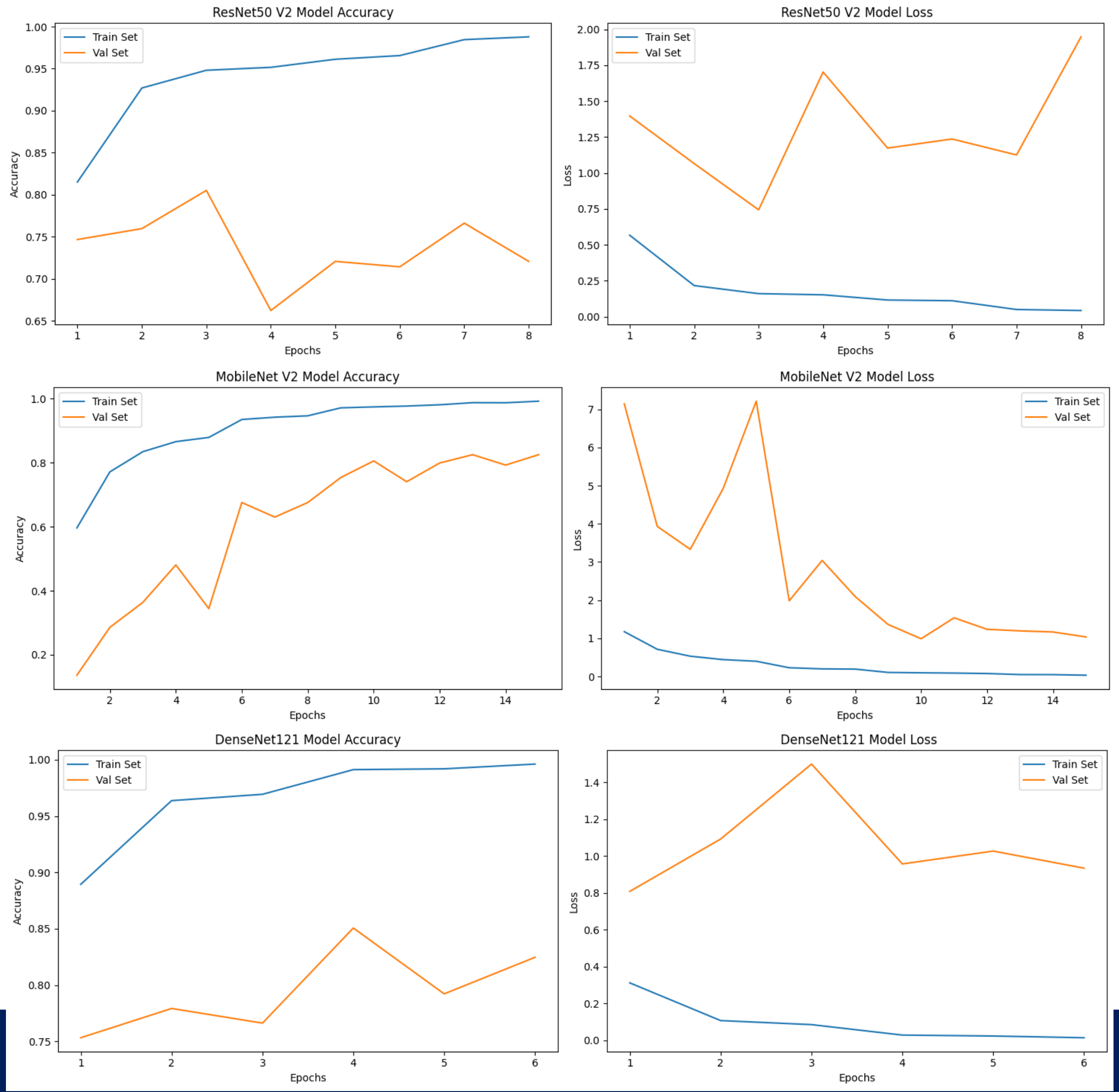
Evaluation metrics



Confusion matrix of DenseNet121

Models pre-trained on ImageNet source dataset

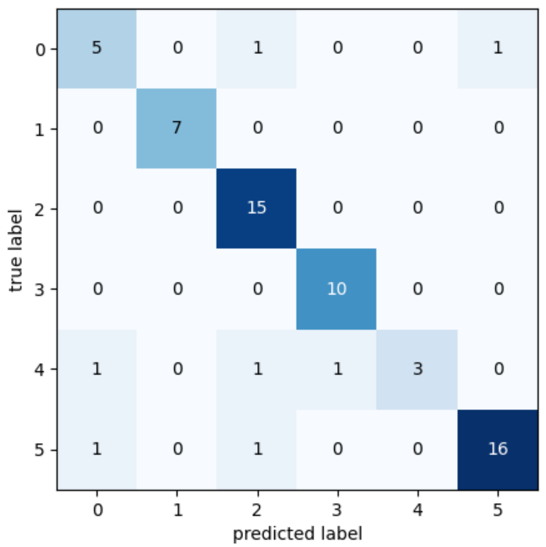
Case 2: Results after applying Random oversampling



Training and validation Accuracy and Loss graphs

Model	Validation accuracy(%)	Test accuracy (%)	Precision	Recall	F1-score
ResNet50	80.5	87.3	0.901	0.839	0.849
MobileNetV2	82.4	87.3	0.906	0.831	0.855
DenseNet121	85	88.9	0.900	0.851	0.859

Evaluation metrics



Confusion matrix of DenseNet121

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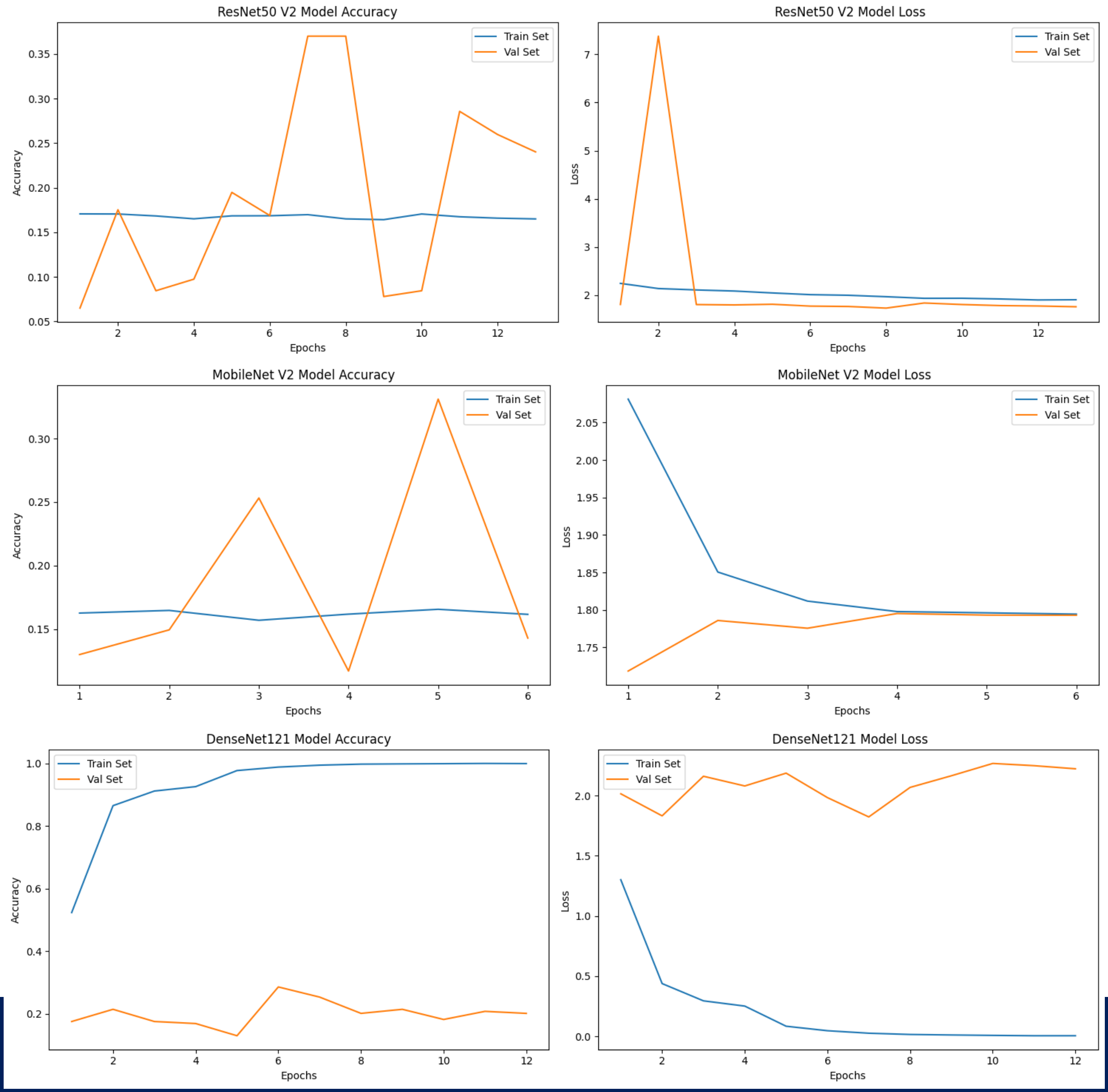
Models pre-trained on ImageNet source dataset

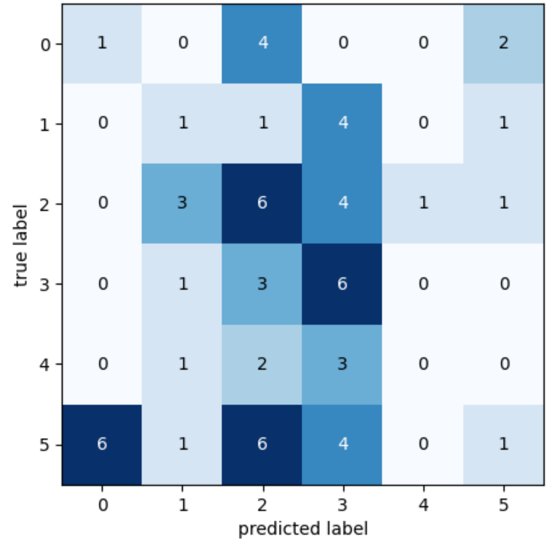
Case 3: Results after applying SMOTE



Training and validation Accuracy and Loss graphs

Model	Validation accuracy(%)	Test accuracy(%)	Precision	Recall	F1-score
ResNet50	37	30.1	0.134	0.180	0.112
MobileNet V2	33.1	31.7	0.146	0.205	0.150
DenseNet 121	28.5	23.8	0.174	0.224	0.181

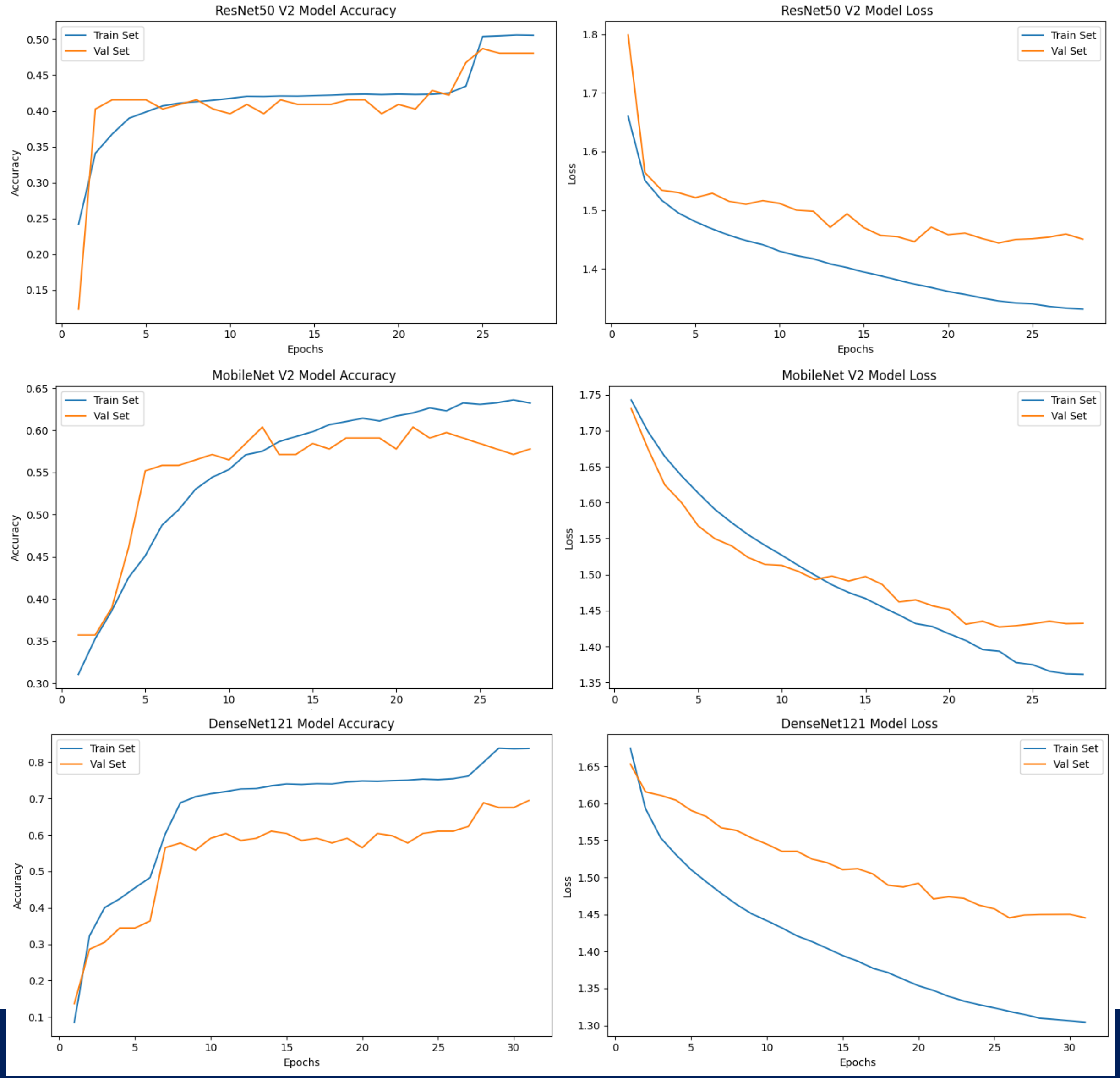
Evaluation metrics



Confusion matrix of DenseNet121

Models pre-trained on HAM10000 source dataset

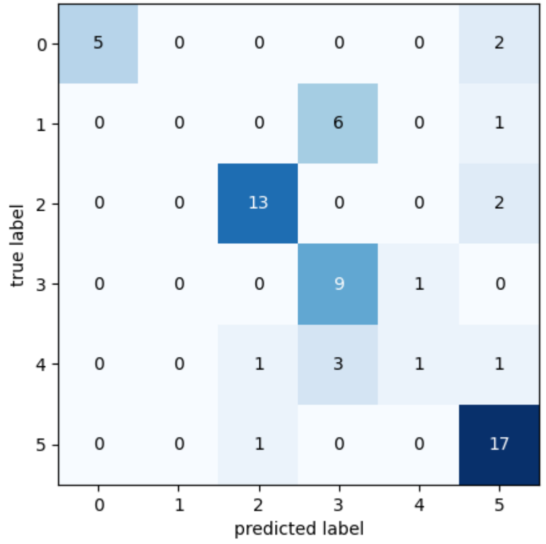
Case 1: Initial results with standard augmentation



Training and validation Accuracy and Loss graphs

Model	Validation accuracy(%)	Test accuracy(%)	Precision	Recall	F1-score
ResNet50	48.7	49.2	0.462	0.492	0.417
MobileNet V2	60.3	55.5	0.315	0.410	0.341
DenseNet 121	69.7	71.4	0.601	0.599	0.570

Evaluation metrics



Confusion matrix of DenseNet121

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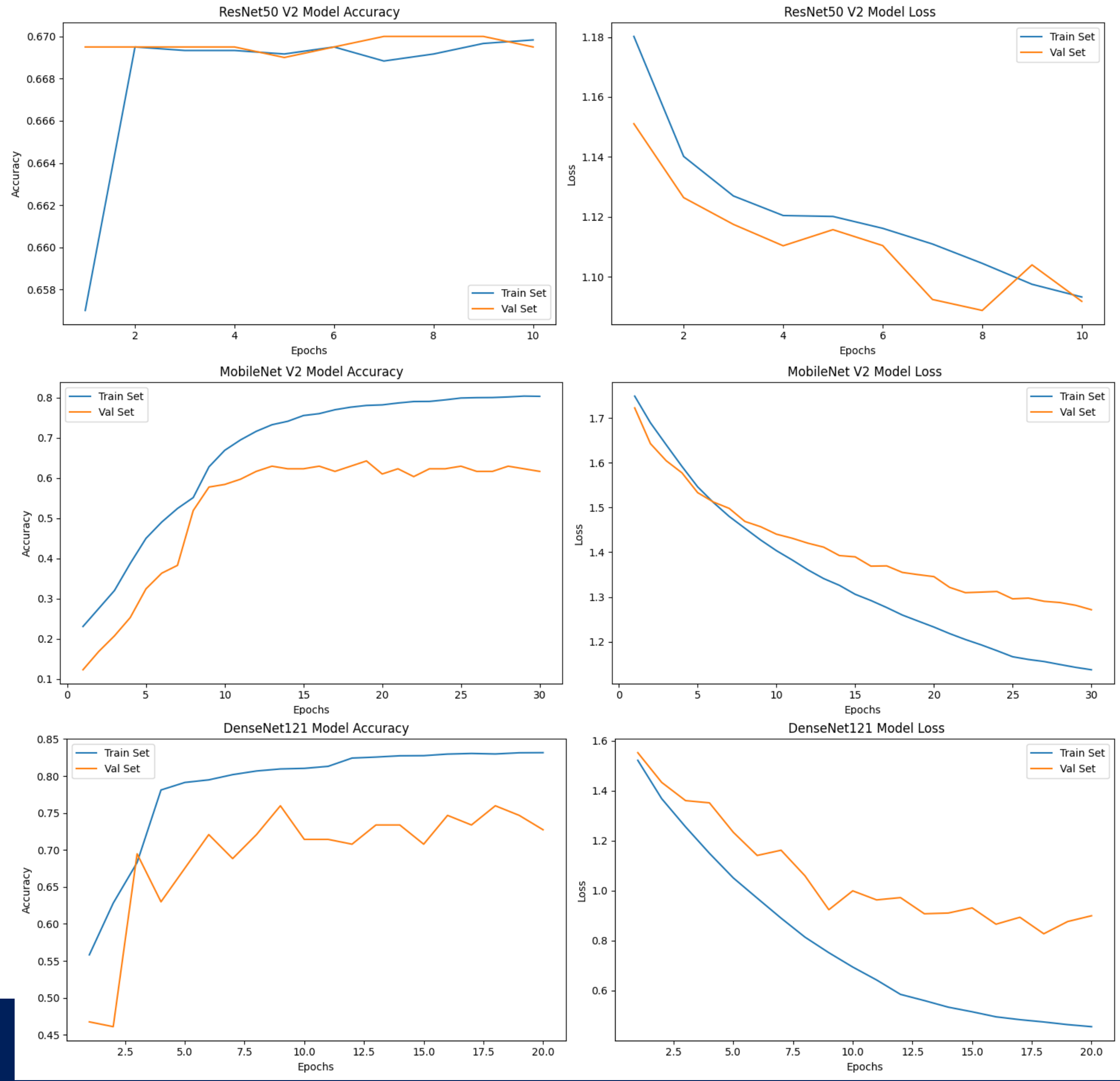
Models pre-trained on HAM10000 source dataset

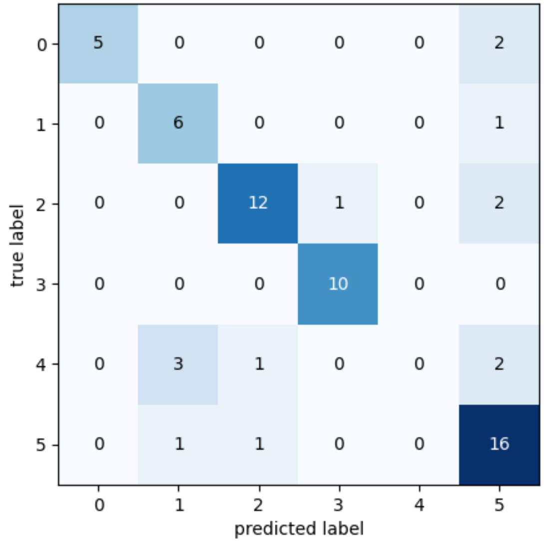
Case 2: Results after applying Random oversampling



Training and validation Accuracy and Loss graphs

Model	Validation accuracy(%)	Test accuracy(%)	Precision	Recall	F1-score
ResNet50	70.1	60.3	0.461	0.479	0.442
MobileNet V2	64.2	69.8	0.778	0.787	0.714
DenseNet 121	75.9	77.7	0.677	0.710	0.683

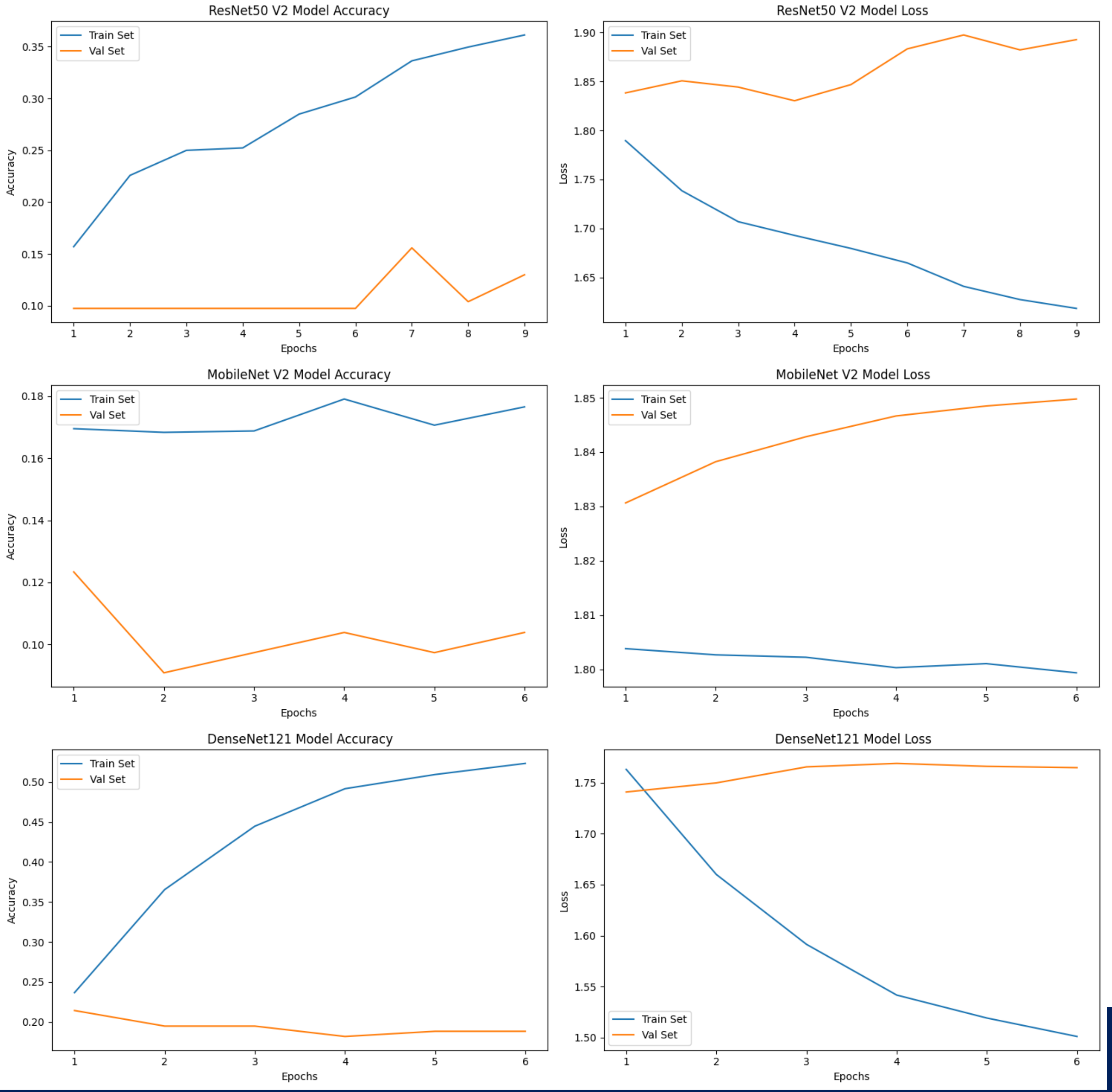
Evaluation metrics



Confusion matrix of DenseNet121

Models pre-trained on HAM10000 source dataset

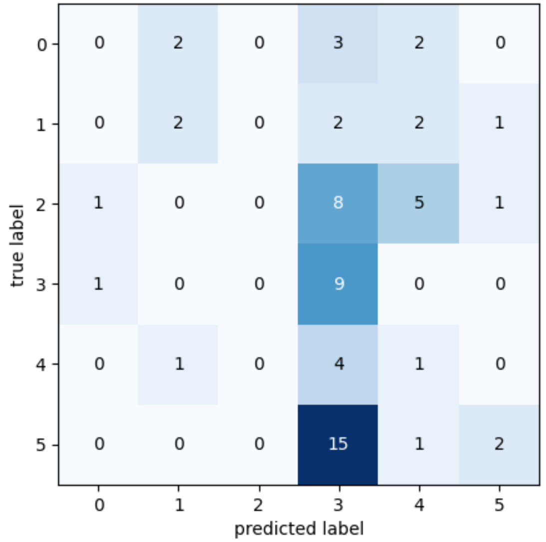
Case 3: Results after applying SMOTE



Training and validation Accuracy and Loss graphs

Model	Validation accuracy(%)	Test accuracy(%)	Precision	Recall	F1-score
ResNet50	15.5	14.2	0.051	0.138	0.071
MobileNet V2	12.3	15.8	0.089	0.254	0.117
DenseNet 121	21.4	22.2	0.202	0.244	0.164

Evaluation metrics



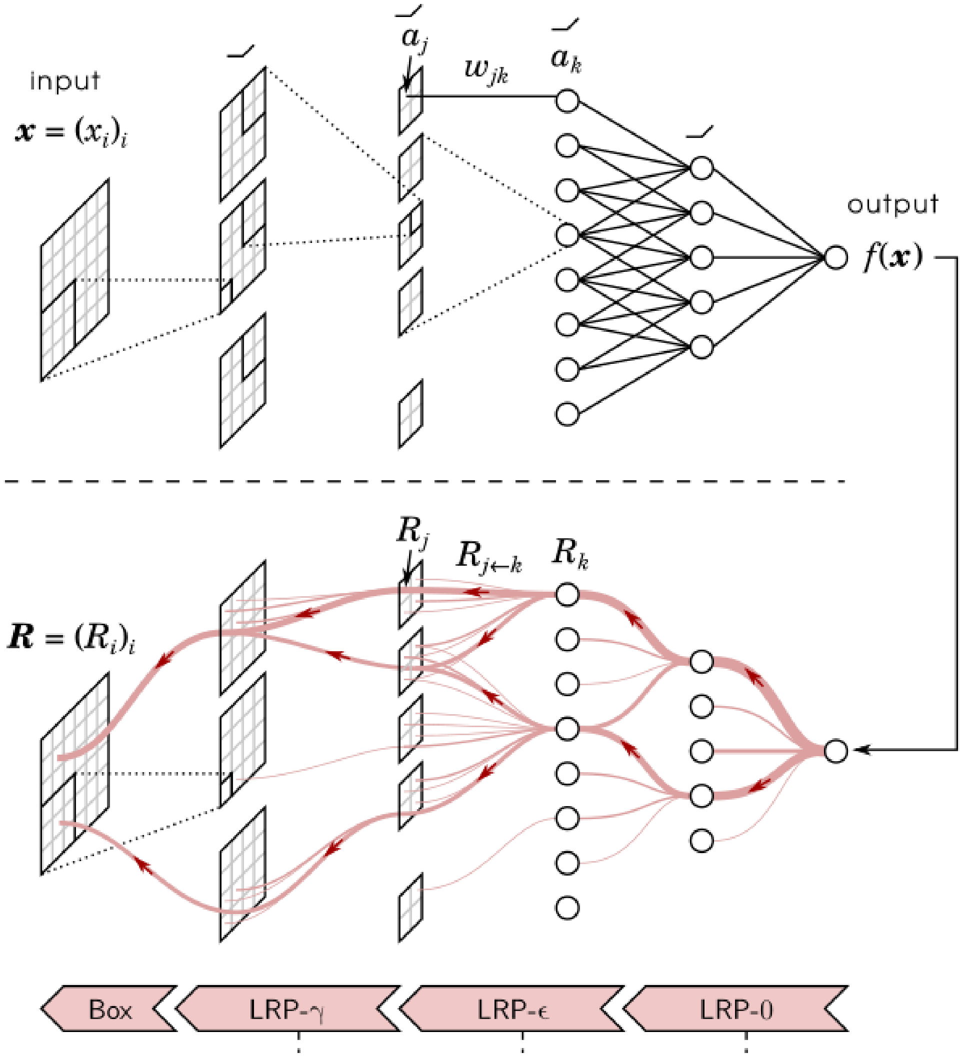
Confusion matrix of DenseNet121

Interpreting the results

- DenseNet121 outperforms the other two models in all cases.
- DenseNet121 is generally more parameter-efficient compared to other architectures, which can lead to better generalization on smaller datasets
- ResNet50 not be as efficient as DenseNet121 in reusing features.
- MobileNetV2’s inverted residuals and linear bottlenecks provide for good efficiency but might not capture as rich features as DenseNet121
- We can observe that model is complex and has memorized the training data learning noise and details specific to the training set rather than learning the underlying patterns
- Models are performing well on dataset balanced using ROS than the dataset that was balanced using SMOTE because synthetic samples might not always represent the true underlying distribution well, especially if the dataset has complex or noisy minority class boundaries like in our case where skin lesion images generally have irregular and fuzzy boundaries, making it difficult to refine contours and define lesion boundaries

eXplainable AI -LRP

- Promotes transparency, understandability, and interpretability of AI models in order to boost user confidence in their predictions
- LRP works by decomposing the output of a neural network backward through the layers to the input, assigning relevance scores to each input feature.
- Its **process highlights** the features that contribute most significantly to the network's decision, allowing researchers to understand the model's behaviour better.
- LRP involves *two processes*.
  - Firstly, a **forward pass** that computes activations at each layer of the neural network until the output layer is reached and here the activation score in the output layer represents the prediction.
  - Secondly, a **reverse propagation** that applies a backward pass where the output score is redistributed layer by layer back to the input layer.



eXplainable AI – LRP heatmaps

Heatmap generated of a Monkeypox image by DenseNet121 model after balancing with ROS

Heatmap generated of a Chickenpox image by DenseNet121 model after balancing with ROS

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References

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