ADVANCED ARTIFICIAL NEURAL NETWORKS

BIOE 6306 – SUMMER 2023

SKIN LESION CLASSIFICATION USING CNN AND TRANSFER LEARNING

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ABSTRACT:

Skin cancer is one of the most prevalent cancers globally. Early and accurate diagnosis of skin lesions is crucial for effective treatment. This project aims to classify skin cancer into 7 classes using deep learning techniques. The HAM10000 dataset containing dermoscopic images of 7 skin lesion classes is utilized. As a baseline, a custom 17-layer convolutional neural network (CNN)(3 Conv2D layers, 3 blockred blocks (each with 3 internal convolution layers, 3 Dense layers, 1 Flatten, 1 Dropout, 1 Softmax) is designed and trained from scratch. Data preprocessing techniques like normalization and oversampling are applied to improve model training. Further, transfer learning is achieved by fine-tuning pretrained VGG19, EffecientNetB7 and ResNet152V2 models on the dataset. Models are evaluated using accuracy, Precision, confusion matrix. Custom CNN achieves 95% accuracy. Transfer learning models will achieve better performance, with fine tuning reaching 97% accuracy. Overall, the project demonstrates effective utilization of deep CNNs and transfer learning to build high-accuracy skin lesion classifiers from a small dataset. The techniques can be extended to larger datasets and more lesion types in future work.

PROBLEM STATEMENT:

The main objective of this project is to build a deep learning model to classify skin cancer lesions into different classes. To achieve this, we will build a custom CNN and transfer learning model.

INTRODUCTION:

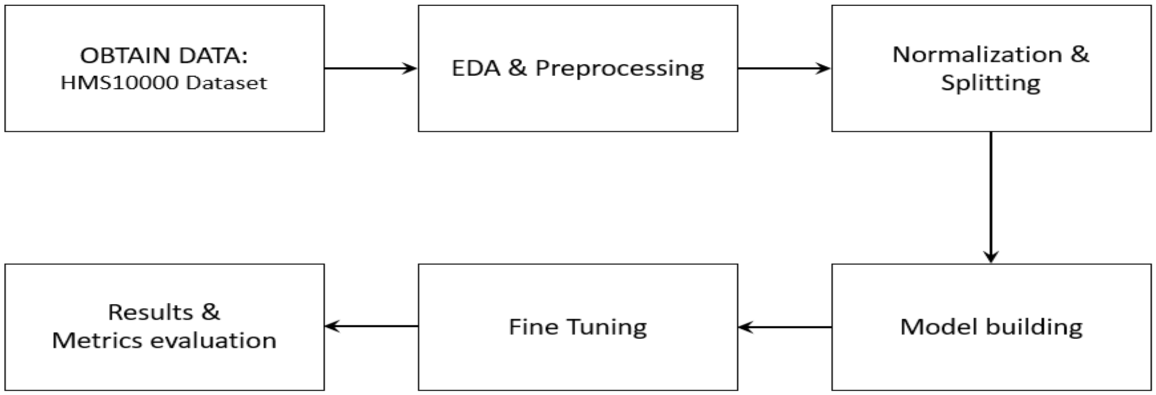
Skin cancer is one of the most prevalent cancers globally, with melanoma accounting for many skin cancer deaths. From 22nd March 2022, North America and Europe has more than 70% skin cancer cases globally. Early diagnosis of skin lesions is critical for timely treatment and improved patient outcomes. However, depending only on a dermatologist's subjective evaluation of dermoscopic images has limitations in accuracy and consistency.

Deep Learning uses number of hidden layers to learn hierarchical data representations. It provides a method for learning a vast volume of data with a little number of hands feature engineering. In recent years, the Deep Learning approach has achieved significant improvements and evolution in Computer Vision. Recent advancments in deep learning have shown potential for building automated computer-aided diagnosis (CAD) systems for skin lesion analysis. Convolutional neural networks (CNNs) have achieved high accuracy in classifying skin lesions from images.

The computer aided skin cancer classification system makes uses of pictures, preprocessing is fed into CNN, features are extracted, and classification is made according to the respective classes. Metrics like accuracy, loss, and confusion matrix are used to evaluate the performance of the custom CNN and transfer learning models. Results show that deep CNNs may be used to categorize skin cancer lesions with high accuracy and in meeting the requirements with clinical diagnosis. In experienced dermatologists may be able to better diagnose the patients using the CAD system used for this study. Through this research, we aim to demonstrate the significance of AI-driven techniques in early detection. ultimately aiding in the fight against skin cancer and improving patient outcomes.

METHODOLOGY:

To build a custom CNN model using transfer learning the following methodology is followed:



DATASET:

In this project, the dataset used is Skin Cancer MNIST: HAM10000 dataset that was downloaded from Kaggle repository using API key that was explained in code. HAM10000("Human Against Machine with 10000 training images") dataset consists of 10015 dermatoscopic images which can serve as a training set. These images encompass the following diagnostic categories: actinic keratosis (akiec), basal cell carcinoma (bcc), benign keratosis (bkl), dermatofibroma (df), melanoma (mel), melanocytic nevi (nv), and vascular lesions (vasc). Different images of dataset are in different resolutions. That needs to be normalized. The dataset includes lesions with multiple images, which can be tracked by the lesion_id-column within the HAM10000_metadata file. Which contains each pixel of image, ID, age, sex and other details.

DATA PREPROCESSING:

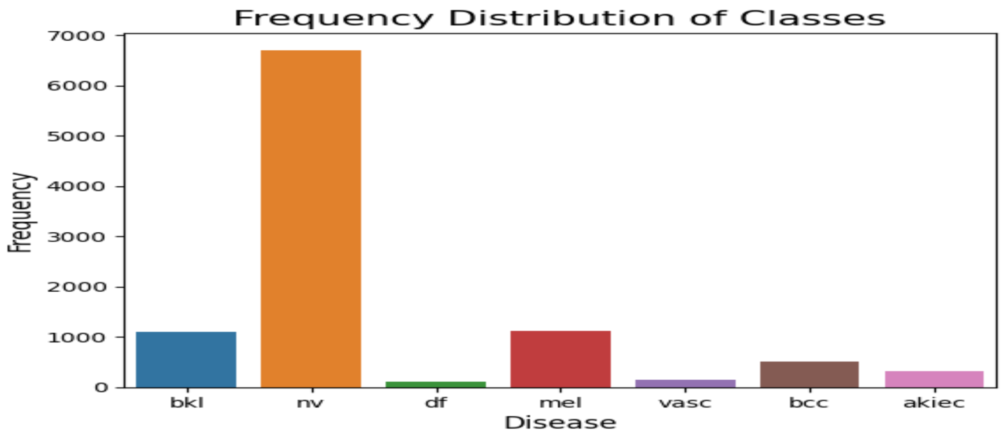
Load the data:

Loading the Skin Cancer MNIST HAM10000 dataset from Kaggle repository after installing all the necessary libraries and packages. Unzip the folder and load the metadata csv file.

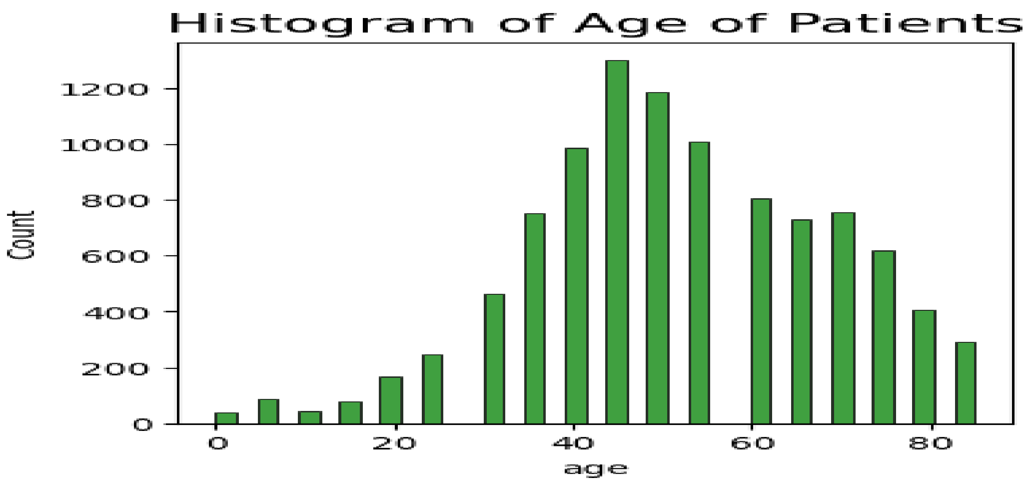
	pixel0000	pixel0001	pixel0002	pixel0003	pixel0004	pixel0005	pixel0006	pixel0007	pixel0008	pixe
0	192	153	193	195	155	192	197	154	185	
1	25	14	30	68	48	75	123	93	126	
2	192	138	153	200	145	163	201	142	160	
3	38	19	30	95	59	72	143	103	119	
4	158	113	139	194	144	174	215	162	191	

Exploratory Data Analysis:

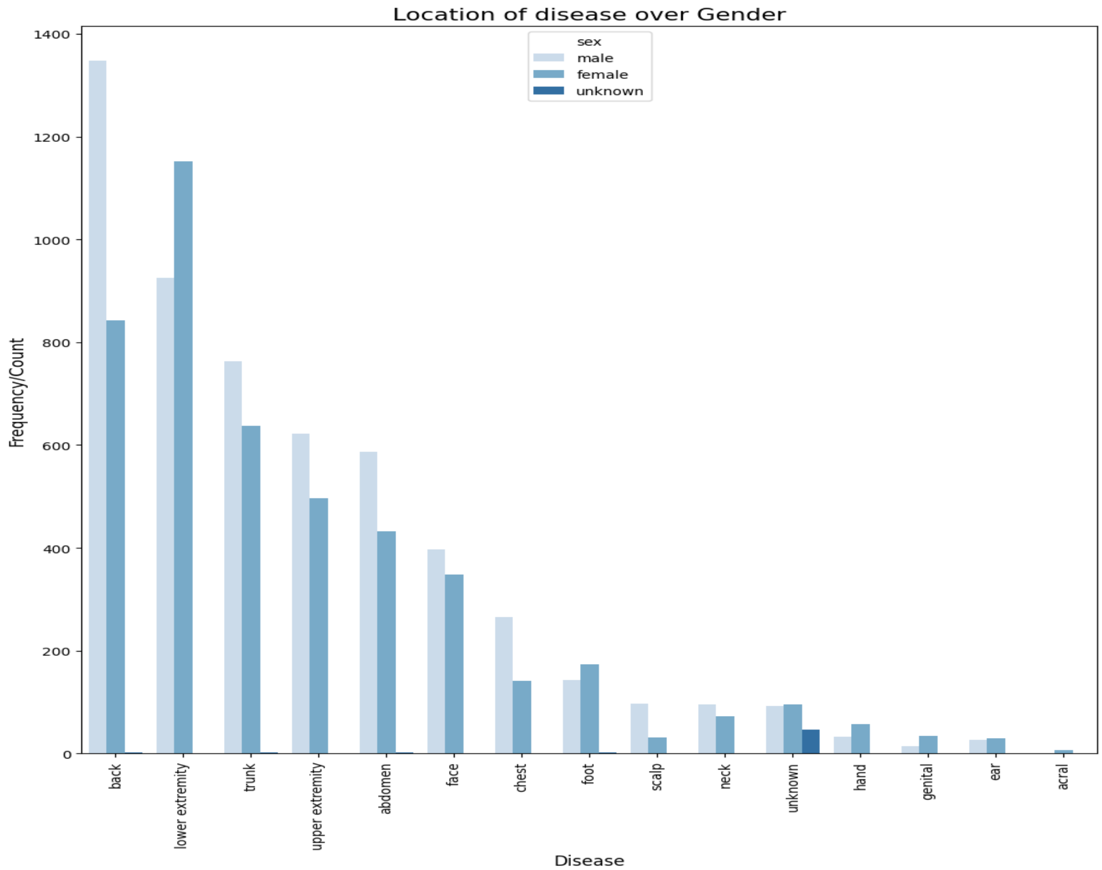
1. Frequency distribution plot of data is obtained as follows stating nv as major disease class among all.



2. Hist plot of the column “Age ” is obtained as follows , showing the age group of 40 to 70 are mostly prone to skin diseases.



3. A distribution plot is obtained among male and female , locating the area of infection. From plot we can say back, lower extremity, trunk and lower extremity are major areas on body where people get infected with skin diseases.



4. The dataset is oversampled using "RandomOversampler" to balance the class distribution in the dataset.
5. **Normalization:**
   Z- score normalization/ zero mean one standard deviation normalization method is applied along the input variable to make sure that all instances will be between 0 and 1.
6. **Splitting:**
   The input and output variable are split into training and testing sets where 80% data is allocated for training with random state of 42. Now the data is ready to feed into a CNN model.

MODEL BUILDING:

1. **Architecture:**
   The model architecture consists of a custom built convolutional neural network (CNN) designed for multi-class classification of skin cancer lesions. Input images were resized to 28x28x3 pixels. The network comprised a sequence of convolutional blocks with 3x3 filters and increasing number of channels (32, 64, 128), interspersed with 2x2 max pooling for down sampling. Batch normalization and dropout layers were added for regularization. This was followed by flattening and 3 fully connected layers with 256, 64 and 7 units respectively. The final layer used softmax activation to output probabilities over 7 lesion classes. The convolutional blocks used a novel residual-style architecture called blockred. Each blockred module contained 3 parallel convolutional branches.

inspired by Inception, VGG and ResNet models. In the output layer we have softmax as activation function as our target is multi class classification.

2. **Model Training:**

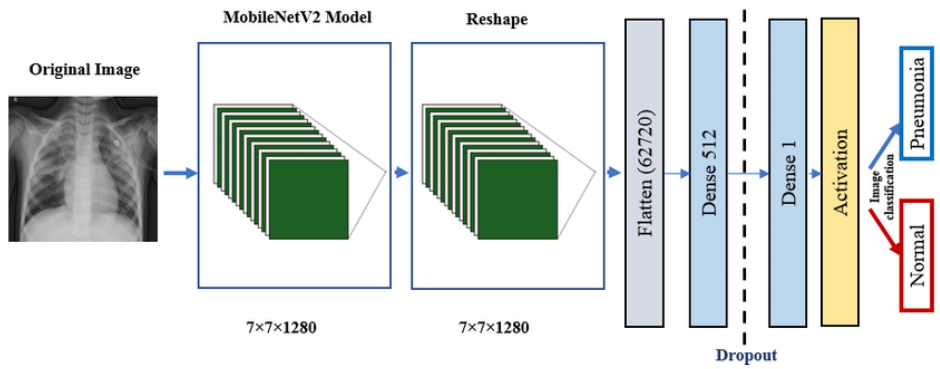
The model was trained for 30 epochs using categorical cross-entropy loss optimized with the Adam algorithm (learning rate=0.001, $\beta 1$=0.9, $\beta 2$=0.999). The training set of 9000 images was augmented on-the-fly with rotations, zooms and flips. A validation set of 1000 images was used to monitor convergence of the model. Training will be stopped if validation accuracy won't improve for 3 consecutive epochs. Performance was monitored using accuracy, AUC, precision, recall and other classification metrics. The final model weights were saved at the epoch when it obtains maximum validation accuracy.

TRANSFER LEARNING:

Pretrained ImageNet models like ResNet, EfficientNet and VGG19 were used for transfer learning. Their fully connected layers were removed. The remaining convolutional layers were kept frozen to retain the learned features. New classifier layers were added on top - global pooling, batch normalization, dropout, dense and softmax layers. Hence the model will be fine tuned by just training the newly added layers.

RESNET152V2:

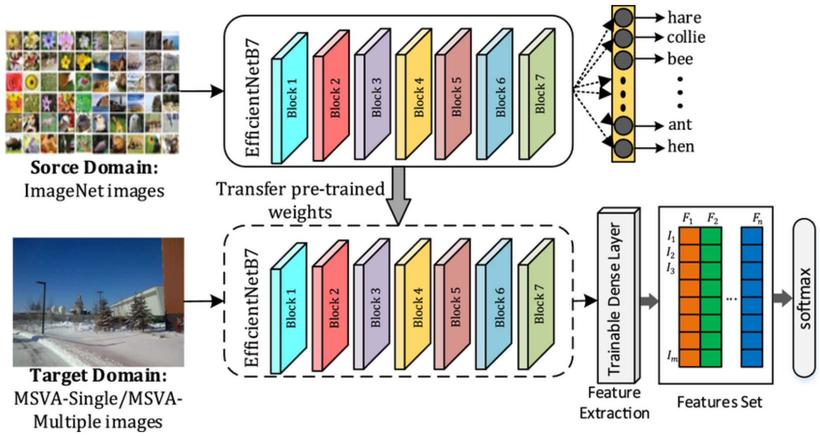
ResNet-152V2 is an extended version of ResNet, using 152 layers to create a deeper architecture. It leverages residual units with skip connections, overcoming vanishing gradients. This approach led to a winning 152-layer model in a challenge, demonstrating effective training and improved accuracy while maintaining low false-positive rates.



EFFICIENTNETB7:

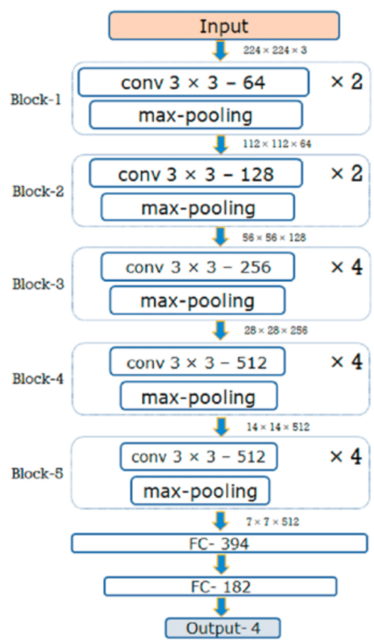
EfficientNet-B7 is an advanced iteration of the EfficientNet architecture. It's designed to strike a balance between depth, width, and resolution, achieving optimal performance. Unlike the assumption that "deeper is always better," EfficientNet-B7 demonstrates that increasing depth can lead to diminishing returns. By scaling up width and resolution while controlling depth, it achieves efficiency. EfficientNet-

B7 introduces novel compound scaling laws, which efficiently balance these dimensions. This approach yields powerful models without excessive complexity.



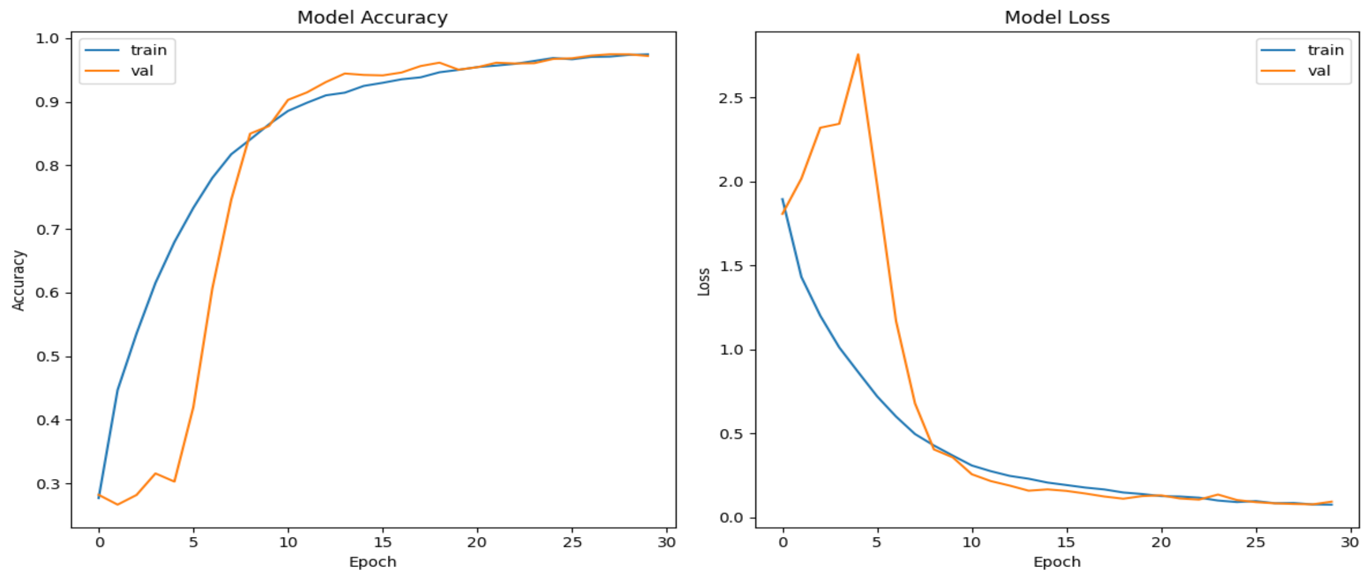
VGG19:

VGG19 is a variant of the VGG model which in short consists of 19 layers (1 convolution layers, 3 Fully connected layer, 5 MaxPool layers and 1 SoftMax layer). The increased depth and small filters allow it to learn very complex features with fewer parameters. Rather than having a few large convolutional layers, multiple stacked smaller conv layers allow more non-linearities and learn more complex patterns.



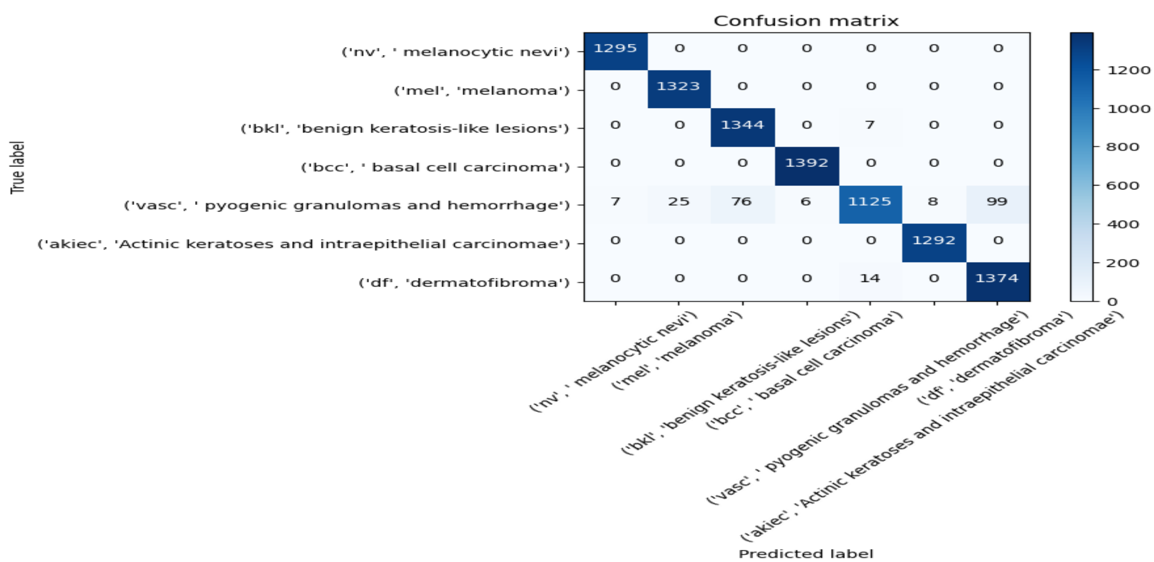
RESULTS AND DISCUSSIOS:

Following are the results, plots and evaluations of metrics used for evaluation such as accuracy, confusion matrix, classification report.



Above plot shows the variation of accuracy and loss over every epoch. Over a period of time accuracy increases gradually while decreasing the cross entropy loss.

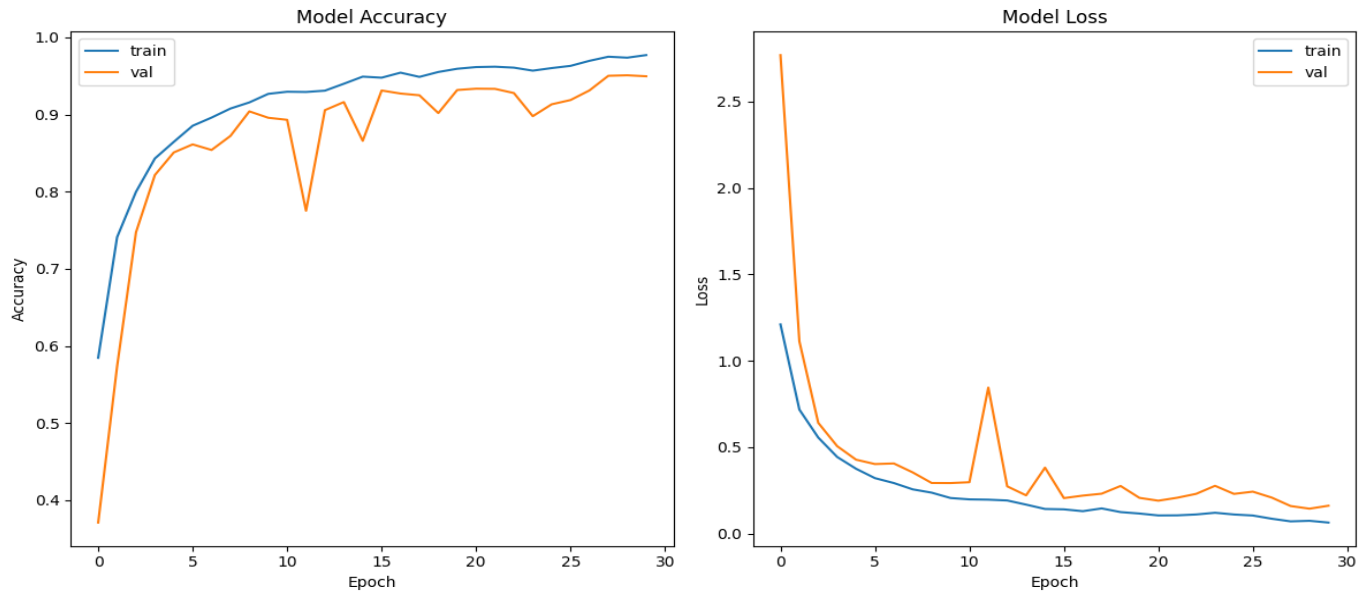
<u>Confusion matrix and classification report on custom cnn model:</u>



	precision	recall	f1-score	support
0.0	0.99	1.00	1.00	1295
1.0	0.98	1.00	0.99	1323
2.0	0.95	0.99	0.97	1351
3.0	1.00	1.00	1.00	1392
4.0	0.98	0.84	0.90	1346
5.0	0.99	1.00	1.00	1292
6.0	0.93	0.99	0.96	1388
accuracy			0.97	9387
macro avg	0.98	0.97	0.97	9387
weighted avg	0.97	0.97	0.97	9387

Classification Report

Results after fine tuning the model :

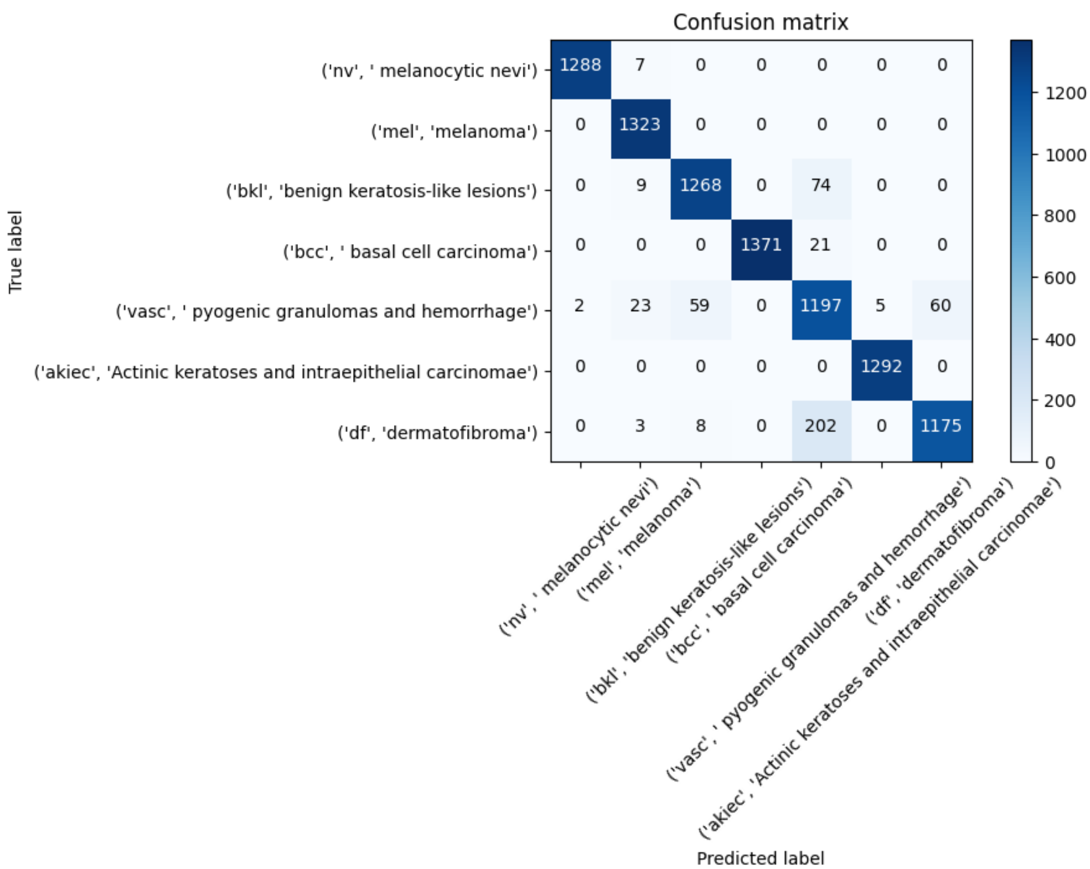


The results obtained after transfer learning are better when compared to earlier stage. Accuracy obtained is 97%. In this type of problem, we should not only focus on true positives and true negatives we must focus on false positives and false negatives in the confusion matrix.

Confusion matrix and classification report after fine tuning:

	precision	recall	f1-score	support
0.0	1.00	0.99	1.00	1295
1.0	0.97	1.00	0.98	1323
2.0	0.95	0.94	0.94	1351
3.0	1.00	0.98	0.99	1392
4.0	0.80	0.89	0.84	1346
5.0	1.00	1.00	1.00	1292
6.0	0.95	0.85	0.90	1388
accuracy			0.95	9387
macro avg	0.95	0.95	0.95	9387
weighted avg	0.95	0.95	0.95	9387

Classification Report after transfer learning



CONCLUSIONS AND FUTURE WORK:

This project demonstrates how deep convolutional neural networks and transfer learning may be used effectively for multi-class skin lesion categorization. On the HAM10000 dataset, a custom 17-layer CNN model was created and trained from scratch, attaining 95% accuracy. Using transfer learning, more performance enhancements were gained. ResNet, EfficientNet, and VGG19 pre-trained ImageNet models were fine-tuned by adding new classifier layers and retraining only those layers. This transfer learning method increased accuracy to 97%. As the dataset is small and we need to handle the more diverse real-life situations, there is need for large diverse dataset. There is a need to explore more sophisticated transfer learning algorithms for better performance. Overall, the study demonstrates the capability of AI in improving early detection and treatment of skin cancer. Automated lesion analysis system can help the less expertise dermatologists handling the patients.

REFERENCES:

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