A Comparative Analysis of Classifiers for Medical Image Classification

Group Members:
Srijan Kumar 2029202
Sneha Singh 2029203
Jyoti Kumari 2029204

Introduction

Medical image classification is a crucial task in the field of healthcare. Accurate diagnosis and detection of diseases are essential for effective treatment planning. With the recent advancements in deep learning, transfer learning has emerged as a powerful technique for medical image classification. In this study, we compare the performance of various classifiers for medical image classification using transfer learning.

Datasets

To do a comparative analysis of classifiers for medical image classification we use two different datasets.

- Dataset 1 contains of different skin diseases image which comprises of 10 different classes.
- Dataset 2 contains of different skin cancer image which is composed of 9 different classes.

Dataset Summary

Class Label	Class Name	Count
0	Eczema	1677
9	Warts	2103
3	Basal	3323
6	Psoriasis	2055
4	Melanocytic	7970
8	Tinea	1702
2	Atopic	1257
5	Benign	2079
7	Seborrheic	1847
1	Melanoma	3140
Total		27153

Dataset 1 summary

Dataset Summary

Class Label	Class Name	Count
0	pigmented benign keratosis	478
1	melanoma	454
2	vascular lesion	142
3	actinic keratosis	130
4	squamous cell carcinoma	197
5	basal cell carcinoma	392
6	seborrheic keratosis	80
7	dermatofibroma	111
8	nevus	373
Total		2357

Dataset 2 summary

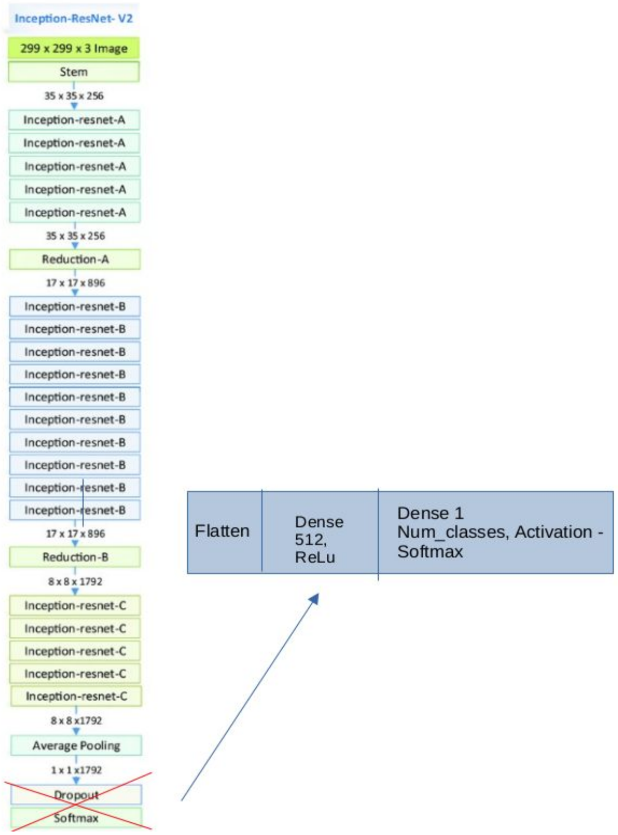
Methodology

Transfer Learning -

Transfer learning involves taking a pre-trained model that has already learned a set of features from a large dataset, and reusing that knowledge to help solve a different problem or to train a new model on a smaller dataset.

Different models used for comparative analysis with transfer learning -

1. VGG 16
2. VGG 19
3. InceptionV3
4. Inception ResNet V2
5. DenseNet 121
6. DenseNet 201

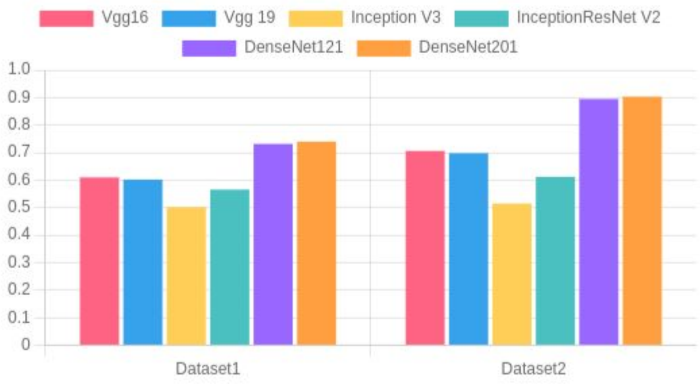


The model architecture of DenseNet 121 using transfer learning

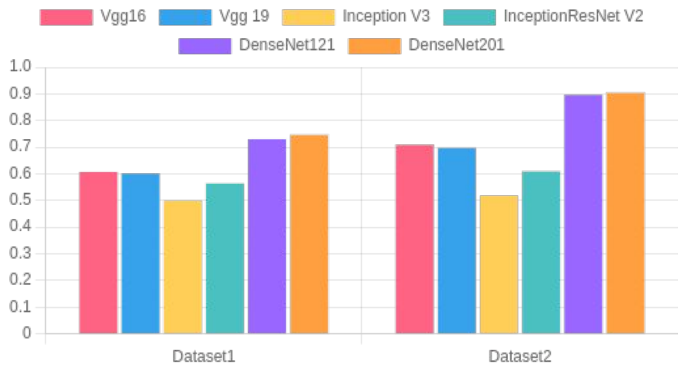
Result Analysis

- ***Accuracy*** measures the percentage of correctly classified images out of all the images in the dataset.

- ***Precision*** measures the percentage of correctly classified positive images out of all the images classified as positive



Accuracy of different algorithm

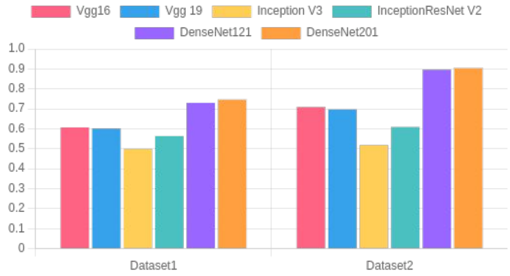


Precision of different algorithm

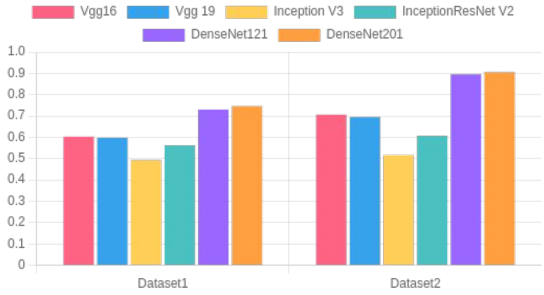
- ***Recall*** measures the percentage of correctly classified positive images out of all the actual positive images in the dataset.

- ***F1 score*** is the harmonic mean of precision and recall and provides a balanced measure of accuracy.

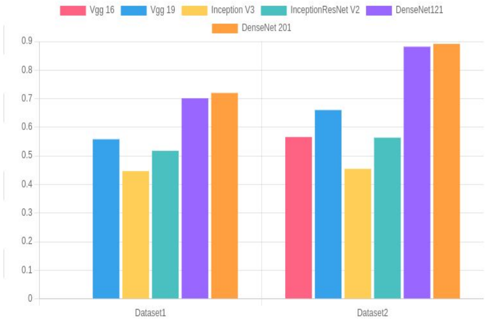
- ***Kappa score*** is a statistical measure of agreement between two raters, which provides a normalized measure of accuracy and accounts for chance agreement.



Recall score of different algorithms

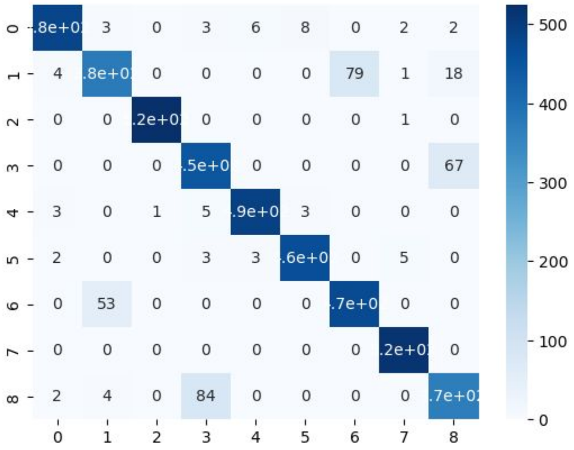


F1 score of different algorithms

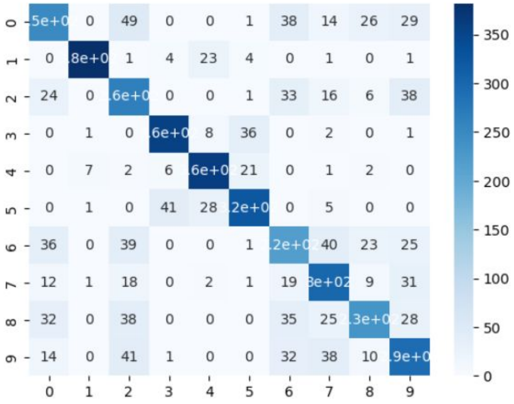


Kappa score of different algorithms

- ***Confusion Matrix*** is a table that summarizes the performance of a classification algorithm on a dataset by showing the number of true positives, true negatives, false positives, and false negatives.



Confusion matrix of dataset 2 using DenseNet 201

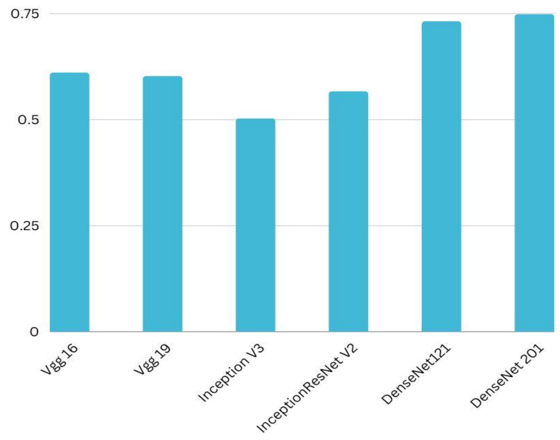


Confusion matrix of dataset 1 using DenseNet 201

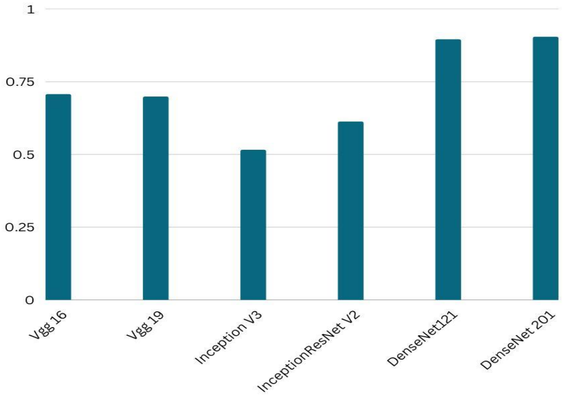
Conclusion

The results of this study provides a valuable insights into the effectiveness of different classifiers for medical image classification, and helps in choosing the appropriate classifier for similar applications in the future.

- Our results showed that all six models performed well for medical image classification, with DenseNet 201 achieving the highest accuracy of all models, followed closely by InceptionV3 and DenseNet121.



Accuracy bar graph of Dataset 1



Accuracy bar graph of Dataset 2

Future Scopes

Finally, the development of automated pipelines that integrate transfer learning with pre-trained models for medical image classification could significantly reduce the amount of time and resources required for training new models. Such pipelines could help to accelerate medical research and improve patient outcomes in clinical settings.

- Future research could explore the use of transfer learning for other medical imaging modalities, such as magnetic resonance imaging (MRI), computed tomography (CT), and ultrasound.
- Applying transfer learning to these modalities could potentially improve the accuracy and efficiency of medical image analysis for a wide range of clinical applications.

Reference

[1] Roger Singh Chugh, 2Vardaan Bhatia, 3Karan Khanna, 4Vandana Bhatia “A Comparative Analysis of Classifiers for Image Classification”
.
[2] ZhiFei Lai and HuiFang Deng “Medical Image Classification Based on Deep Features Extracted by Deep Model and Statistic Feature Fusion with Multilayer Perceptron ”

[3] Research on image classification model based on deep convolution neural network Mingyuan Xin1 and Yong Wang2*

THANK YOU