A PROJECT REPORT

on

"A Comparative Analysis of Classifiers for Medical Image Classification"

Submitted to

KIIT Deemed to be University

In Partial Fulfilment of the Requirement for the Award of

BACHELOR'S DEGREE IN INFORMATION TECHNOLOGY

BY

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CERTIFICATE

This is to certify that the project entitled

"A Comparative Analysis of Classifiers for Medical Image Classification"

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is a record of bonafide work carried out by them, in the partial fulfilment of the requirement for the award of Degree of Bachelor of Engineering (Computer Science & Engineering OR Information Technology) at KIIT Deemed to be university, Bhubaneswar. This work will be done during 2022-2023 under our guidance.

Date: 06/05/23

Mr Amiya Kumar Dash
Project Guide

Acknowledgements

We are profoundly grateful to **Mr Amiya Kumar Dash** of **KIIT Deemed to be University** for his expert guidance and continuous encouragement throughout to see that this project rights its target from its commencement to its completion.

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Contents

Chapter 1

Introduction

As digital image acquisition and storage technologies advance, computer programs can increasingly understand images. Studies in machine learning and applications. The goal is to develop a computer-aided diagnosis (CAD) system, an annotation system that is fast and accurate, and a rating system that is also intelligent. Medical images have become essential to CAD systems in most medical fields. Skin diseases are a prevalent and widespread problem affecting millions of people worldwide. Early detection of skin diseases can significantly improve patient outcomes by allowing for early and effective treatment. With the increasing availability of imaging technologies and the development of artificial intelligence (AI), machine learning (ML) and computer vision (CV), there has been a significant shift towards the development of automated skin disease detection systems.

Several models have been developed to detect skin diseases using different imaging techniques. However, the performance of these models often depends on the dataset used for training. Therefore, there is a need to compare the performance of different models to determine the most accurate and reliable approach. Recent advances in image classification have revolutionised the field of skin disease detection by providing new and more accurate methods for skin disease identification. These advances are mainly due to the availability of large and diverse datasets, improvements in deep learning algorithms, and the development of new feature extraction and selection techniques.

One of the significant advances in image classification for skin disease detection is deep learning algorithms. These algorithms, such as convolutional neural networks (CNNs), can automatically learn features and patterns in skin images associated with specific skin diseases. They can classify skin images with high accuracy and have been shown to outperform traditional machine-learning algorithms in many studies. In image recognition, the classification of medical images is a challenging problem. It aims to classify medical images into different categories to help doctors diagnose diseases or do further research. Overall, the classification of medical images can be divided into two steps. The first step is to extract the effective features from the image. The second step uses features to build models that classify the image dataset. In the past, doctors used their professional experience in feature extraction to classify medical images into different classes, which is usually difficult, tedious and time-consuming. This approach is prone to lead to instability or unrepeatable results. Considering the research so far, the research on medical image classification applications has been fundamental.

Concerning past work, we found that many previous studies used shallow models to classify medical images that mainly relied on shape. Before deep architectures appeared, colours, textures and/or combinations were used. However, the biggest problem with all these models is that the extracted features are often referred to as low-level features; these properties lack the representational ability for high-level problem domain concepts, and their generalizability is relatively poor. In contrast, deep architectures have had significant success in non-medical imaging. Deep learning methods, the most incredible field of machine learning, provide an efficient way to build a complex model that can compute final classification labels with raw pixels of medical images. Applications of deep models in medical image analysis require a lot of effort to catch up with other imaging fields because deep architectures require large datasets to obtain superior features. However, medical images are usually challenging to obtain, so medical data sets are relatively small. Therefore, this approach can lead to model overfitting if we use a deep model to solve a small data set. Apart from these issues, the interpretability of the model is relatively poor, and training a deep model usually requires a large amount of computation.
This paper will focus on this novel and effective method of learning multiscale features that use a pre-trained model with traditional image characteristics. There are several approaches to using transfer learning for skin disease detection. One common approach is to use a pre-trained model such as VGG16, ResNet or Inception as a feature extractor and then train a classifier on those features. In this approach, a pre-trained model is used to extract high-level features from images of skin lesions, and these features are then fed into a classifier trained to classify different skin conditions.

Another approach is to fine-tune a pre-trained model directly for skin disease detection. In this approach, the weights of the pre-trained model are initialised with the pre-trained weights, and then the model is trained on the skin disease detection task using a smaller data set. This approach may be more efficient if there is a significant overlap between the pre-training and skin disease detection datasets.

Overall, transfer learning can be an effective tool to improve the accuracy and speed of skin disease detection. By leveraging pre-trained models and large datasets, it is possible to develop accurate and efficient models, making it easier for doctors and patients to receive timely and accurate diagnoses.

Chapter 2

Methodology

This section contains the basic concepts about the related tools and techniques used in this project. For research work, present the literature review in this section.

2.1 Datasets

Dataset 1 of skin disease comprises 10 classes of different skin diseases. Each image is an RGB image. This dataset contains 27,153 images, listed as follows:

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

The dataset 2 of ISIC skin cancer disease. This set consists of 2357 images of malignant and benign oncological diseases formed by The International Skin Imaging Collaboration (ISIC). All images were sorted according to the classification taken with ISIC. All subsets were divided into the same number of images, except melanomas and moles, whose images are slightly dominant.
The data set contains the following diseases:

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

2.2 Transfer Learning

In machine learning, transfer learning is the technique of using knowledge gained from solving one problem to solve a different but related problem. 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 solve a different problem or to train a new model on a smaller dataset.

A pre-trained model is typically a neural network trained on a large dataset for a specific task, such as image classification or natural language processing. Knowledge learned in the form of feature representation by a pre-trained model can be transferred to a new task by reusing the layers of the pre-trained model or by using the pre-trained model as a feature extractor.

There are many benefits to using transfer learning, including:

- Reduction of training time and cost: By using a pre-trained model, transfer learning can significantly reduce the amount of training time and cost required to build a new model.
- Improved performance: Transfer learning can often lead to improved performance on a new task by leveraging knowledge learned from a pre-trained model.
- Better generalisation: By using a pre-trained model learned from a large and varied dataset, transfer learning can improve the new model's ability to generalise to new data.
- Reduced need for large datasets: Transfer learning can be particularly useful when data for a new task is scarce. It allows new models to leverage knowledge gained from pre-trained models.

Transfer learning has been widely used in fields as diverse as computer vision, natural language processing, and speech recognition. It is an effective technique for improving the performance of machine learning models.

We use different pre-trained models in this paper to compare which model is best for the medical dataset. In Dataset 1, there are a total of 10 classes and in Dataset 2, there are a total of 9 classes.

To use transfer learning with any model, we typically follow these steps:

1. Load the pre-trained model with its weights, which can be downloaded from publicly available sources.

2. Remove the last fully connected model layer(s) specific to the original ImageNet classification task.

3. Replace the removed layers with new, fully connected layers that are specific

to the new classification task.

4. Freeze the weights of pre-trained layers and train only the weights of newly added layers.

5. Train the model on the new dataset and evaluate its performance.

2.1.1 VGG16

VGG16 is a convolutional neural network architecture designed by Oxford University researchers in 2014. It has 16 layers and is known for its high accuracy in image classification tasks.

Transfer learning can be applied to VGG16 by reusing pre-trained model weights and using them to solve a different image classification task. The pre-trained VGG16 model was trained on the ImageNet dataset, which contains millions of images with thousands of categories. By re-using the learned feature representations from the pre-trained VGG16 model, we can solve the novel task of image classification with a smaller dataset, which is a common scenario in many practical applications.

In this way, we can use the pre-trained VGG16 model and transfer its knowledge to a new image classification task, which can lead to improved performance and faster convergence during training.

Transfer learning with VGG16 has been used in various applications such as plant species identification from leaf images, diabetic retinopathy detection from retinal images, and breast cancer identification from mammography images, among others.

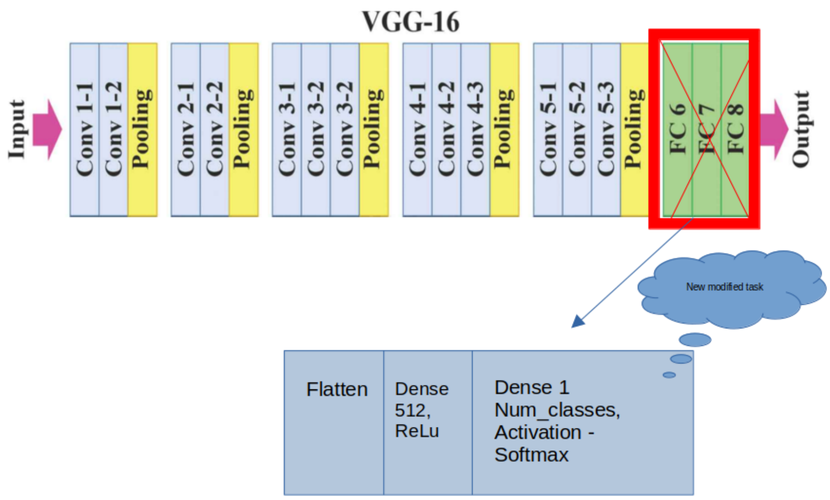


Figure 2.1: VGG 16 model architecture with transfer learning

2.1.2 VGG 19

VGG19 is a deep convolutional neural network architecture proposed by Oxford University researchers in 2014. An extension of the 19-layer and 16-layer VGG16 architecture.

Transfer exercises can be used in the same way as VGG19 and VGG16. The pre-trained VGG19 model is also trained on the ImageNet database, which contains millions of images and thousands of categories. By reusing the feature images learned from the previously trained VGG19 model, we can solve the new image classification problem with smaller datasets, which is a common scenario in many applications.

Using transfer learning and VGG19, we can use pre-trained models and transfer their knowledge to new image classification problems. VGG19 is known for its high accuracy in image classification problems and is used in various applications such as object recognition, image captioning, and face recognition, among others.

In summary, transfer training with VGG19 can be a powerful tool for solving new image classification problems, as it can help reduce the amount of training data and time required to train a new model and improve model performance.

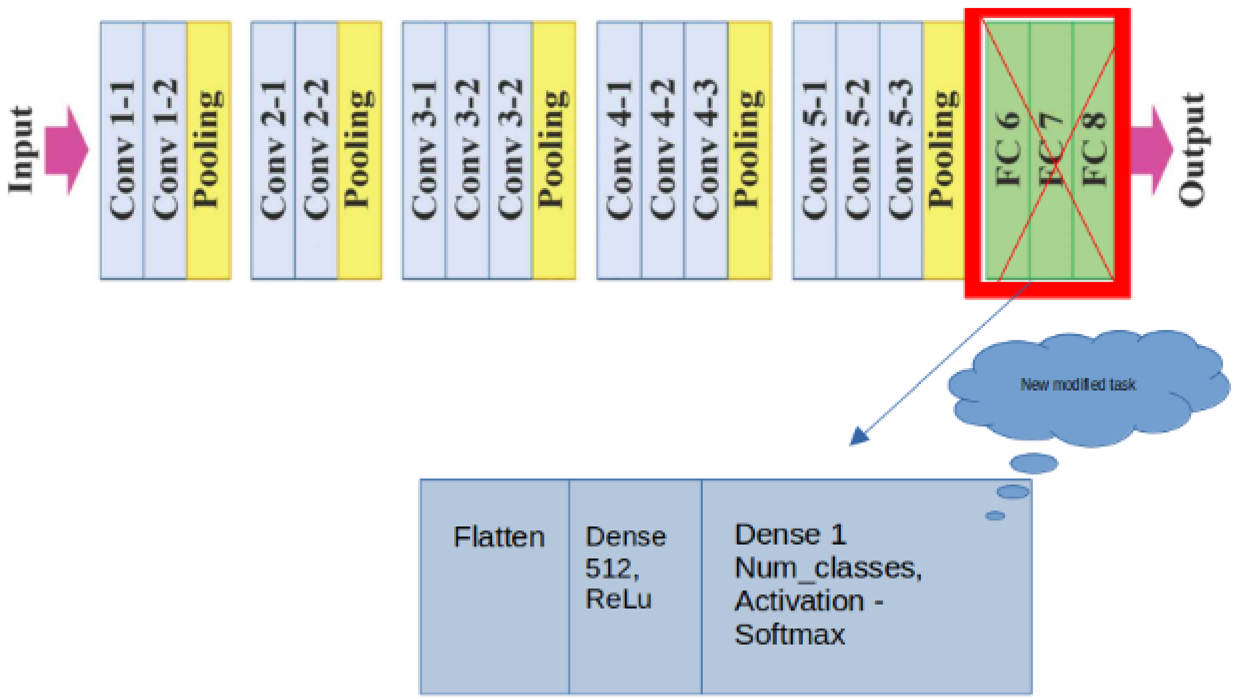


Figure 2.2: The model architecture of VGG 19 with transfer learning

2.1.3: InceptionV3

InceptionV3 is a convolutional neural network architecture proposed in 2015 by researchers at Google. This image is designed to improve the performance of the image classification task by introducing an Inception module that allows capturing the local and global features of an image.

Transfer training can be applied to InceptionV3 like VGG16 and VGG19. The pre-trained InceptionV3 model is also trained on the ImageNet database, which contains millions of images and thousands of categories.

InceptionV3 is known for its high accuracy in image classification tasks and is used in a variety of applications such as object recognition, image captioning, and face recognition, among others. Training with InceptionV3 can be a powerful tool for solving new image classification problems, as it can help reduce the amount of training data and time required to train new models, as well as improve model performance.

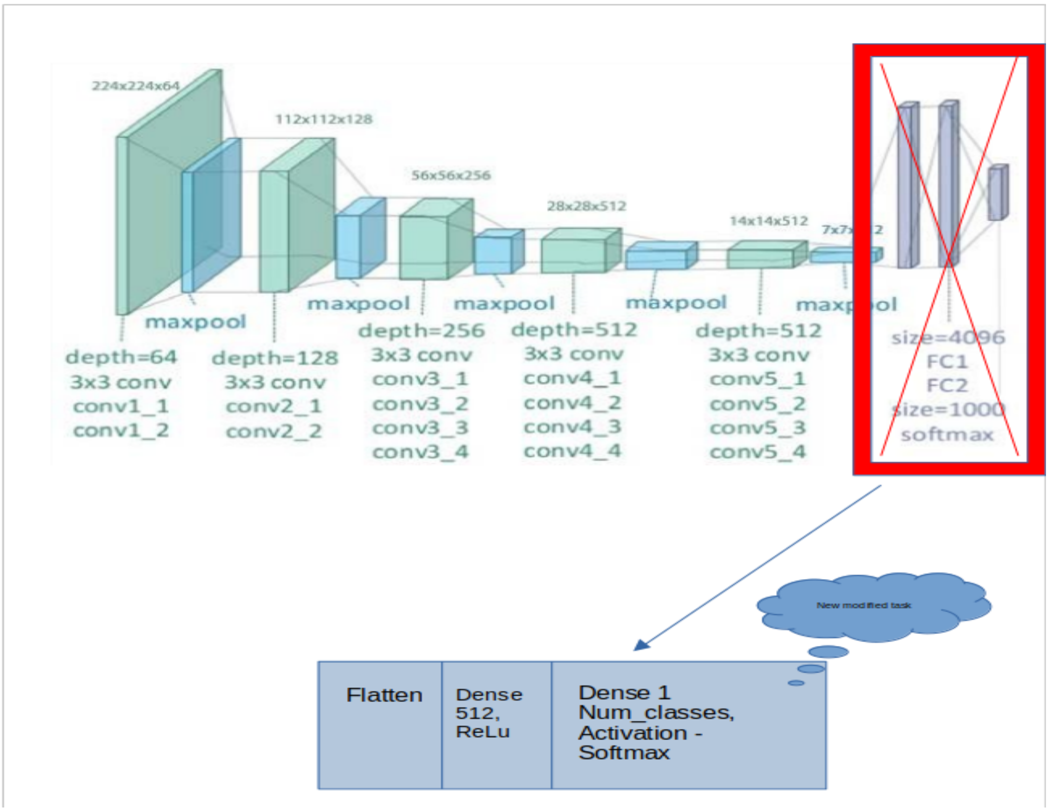


Figure 2.3: The model architecture of InceptionV3 using transfer learning

2.1.4: Inception ResNet V2

InceptionResNetV2 is a convolutional neural network architecture proposed by Google researchers in 2016. It also helps to combine the Inception module with residual connections to allow the network to capture both local and global features of the image, which also helps alleviate the vanishing gradient problem. .

Transfer learning can be applied to InceptionResNetV2 in the same way as any other pre-trained model. A pre-trained InceptionResNetV2 model was also trained on the ImageNet dataset containing millions of images with thousands of categories.

InceptionResNetV2 is known for its high accuracy in image classification tasks. Transfer learning with InceptionResNetV2 can reduce the amount and time of training data required to train a new model and improve the performance of the model, making it a powerful tool for solving new image classification tasks.

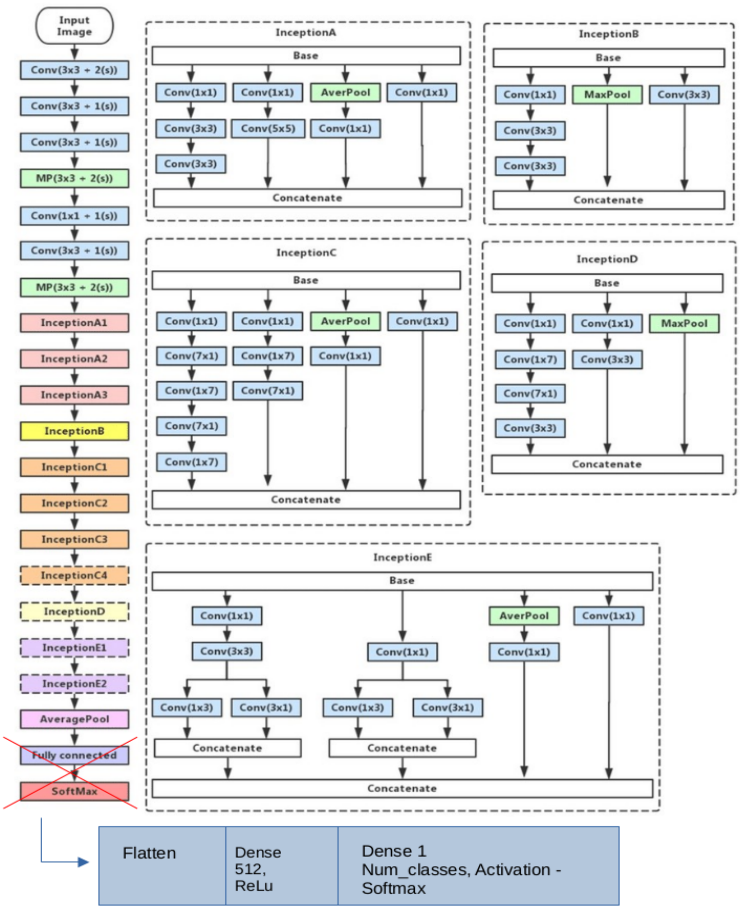


Figure 2.4: The model architecture of Inception ResNet V2 using transfer learning

2.1.5: DenseNet 121

DenseNet-121 is a convolutional neural network architecture that was designed by Facebook AI Research researchers in 2016. It is known for its efficiency and high accuracy in image classification tasks and achieves this by using dense blocks that allow the network to reuse the map function from previous layers. thereby reducing the number of parameters needed to train the network.

Transfer learning can be applied to DenseNet-121 in a similar way to other pre-trained models. The pre-trained DenseNet-121 model was also trained on the ImageNet dataset, which contains millions of images with thousands of categories.

DenseNet-121 is known for its high accuracy and efficiency in image classification tasks and has been used in various applications such as medical image analysis, autonomous vehicles, and remote sensing, among others. Transfer learning with DenseNet-121 can be a powerful tool for solving new image classification tasks, as it can help reduce the amount of training data and the time needed to train a new model, and can also improve model performance.

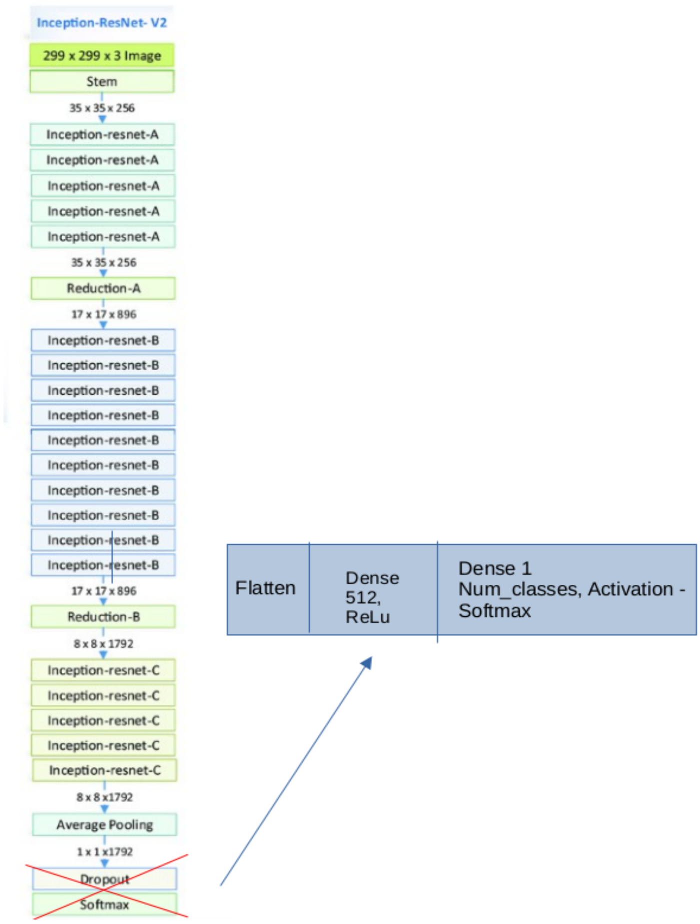


Figure 2.5: The model architecture of DenseNet 121 using transfer learning

2.1.6: DenseNet 201

DenseNet-201 is a convolutional neural network architecture that is an extension of DenseNet-121, proposed by researchers at Facebook AI Research in 2017. It has more layers and parameters than DenseNet-121, which allows it to capture more complex features in images and achieve higher accuracy.

Transfer learning can be applied to DenseNet-201 in a similar way as other pre-trained models. The pre-trained DenseNet-201 model was also trained on the ImageNet dataset, which contains millions of images with thousands of categories.

DenseNet-201 is known for its high accuracy in image classification tasks and has been used in various applications such as image recognition, object detection, and scene understanding, among others. Transfer learning with DenseNet-201 can be a powerful tool for solving new image classification tasks, as it can help reduce the amount of training data and time required to train a new model and can also improve the performance of the model.

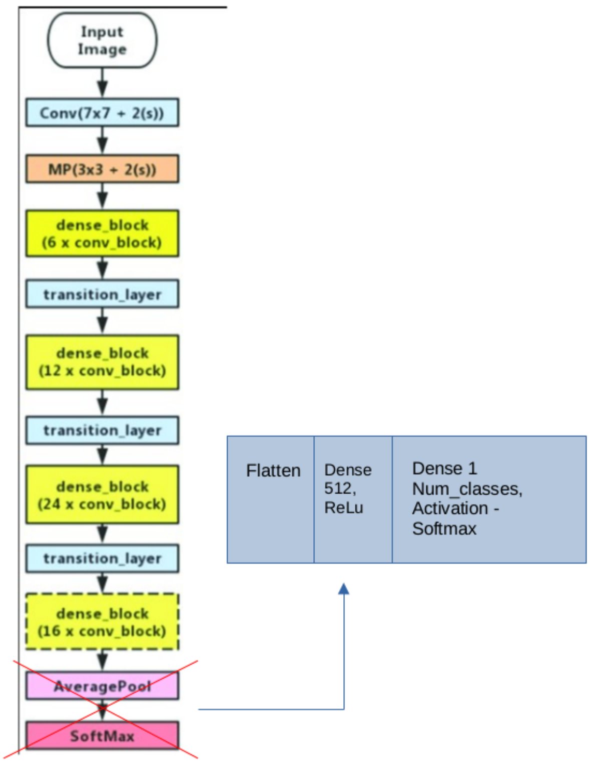


Figure 2.6: The model architecture of DenseNet 201 using transfer learning.

Chapter 3

Experiment & Evaluation

We implemented all the models to extract the high-level features. We have designed a series of experiments on two benchmark medical datasets. One is the skin disease dataset, and the other is the ISIC skin cancer dataset. We conducted all our experiments on an online platform of Kaggle using GPU T4X2.

3.1 Accuracy

In machine learning classification, accuracy is a performance metric that measures the percentage of correctly predicted instances out of all the instances in the dataset. It is defined as follows:

$$\text{Accuracy} = \frac{(Number\ of\ correctly\ predicted\ instances)}{(Total\ number\ of\ instances)}$$

Algorithm	Dataset1	Dataset2
VGG 16	0.6102	0.7064
VGG 19	0.6022	0.6980
Inception V3	0.5022	0.5153
InceptionResNet V2	0.5660	0.6122
DenseNet 121	0.7312	0.8949
DenseNet 201	0.7480	0.9036

Table 3.1: Comparison of the classification algorithms accuracy.

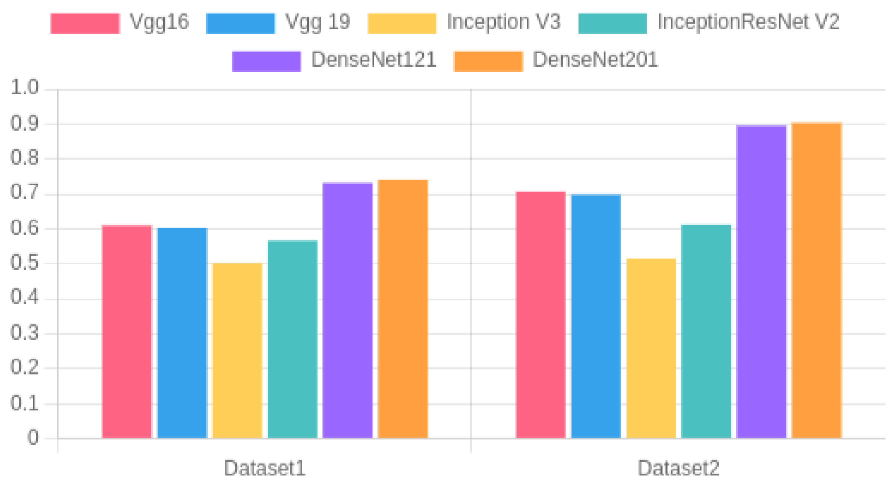


Figure 3.1: Accuracy of different algorithms

3.2 Precision

In machine learning classification, precision is a performance metric that measures the percentage of correctly predicted positive instances out of all the instances predicted as positive. It is defined as follows:

$$\text{Precision} = \frac{(True\ Positive)}{(True\ Positive + False\ Positive)}$$

where True Positive (TP) is the number of instances that are positive and predicted as positive, and False Positive (FP) is the number of instances that are negative but predicted as positive.

Algorithm	Dataset1	Dataset2
VGG 16	0.6178	0.7185
VGG 19	0.6307	0.6971
Inception V3	0.5085	0.5168
InceptionResNet V2	0.5647	0.6070
DenseNet 121	0.7331	0.8963
DenseNet 201	0.7486	0.9100

Table 3.2: Comparison of the classification algorithms' precision.

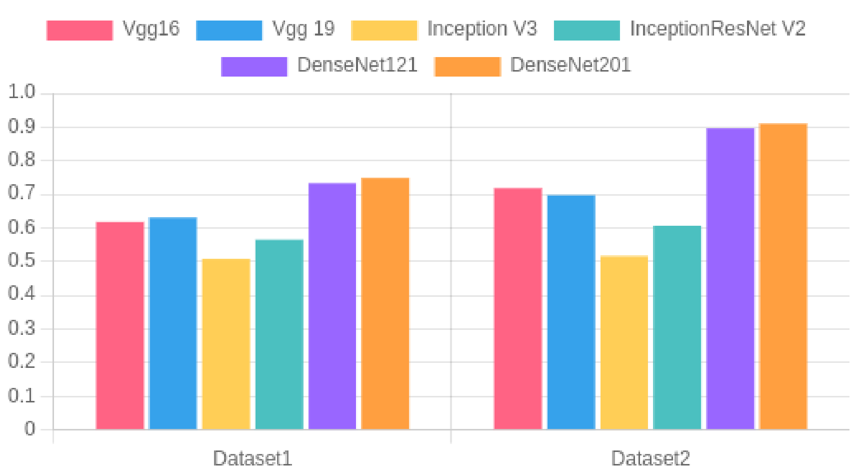


Figure 3.2: Precision of different algorithms

3.3 Recall

In machine learning classification, recall is a performance metric that measures the percentage of correctly predicted positive instances out of all the actual positive instances in the dataset. It is defined as follows:

$$Recall = \frac{(True\ Positive)}{(True\ Positive + False\ Negative)}$$

where True Positive (TP) is the number of instances that are positive and predicted as positive, and False Negative (FN) is the number of instances that are positive but predicted as negative.

Algorithm	Dataset1	Dataset2
VGG 16	0.6072	0.7088
VGG 19	0.6011	0.6971
Inception V3	0.4994	0.5183
InceptionResNet V2	0.5637	0.6091
DenseNet 121	0.7301	0.8958
DenseNet 201	0.7464	0.9041

Table 3.3: Comparison of the classification algorithms' Recall.

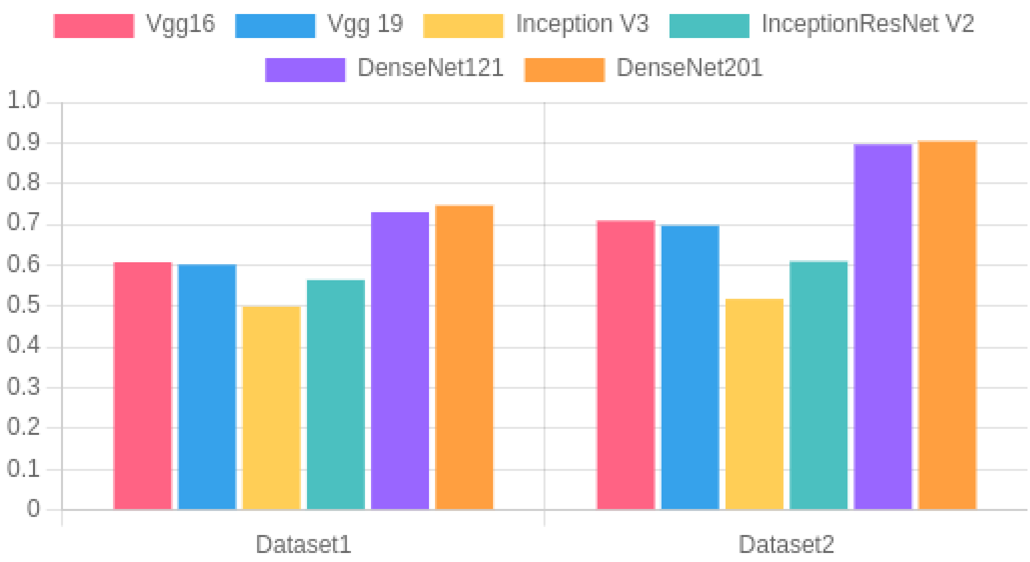


Figure 3.3: Recall of different algorithms

3.4 F1 Score

In machine learning classification, the F1 score is a harmonic mean of precision and recall. It is a performance metric that measures the balance between precision and recall. It is defined as follows:

$$\text{F1 Score} = 2\left(\frac{(Precision * Recall)}{(Precision + Recall)}\right)$$

The F1 score ranges from 0 to 1, where a score of 1 indicates perfect precision and recall, and a score of 0 indicates poor performance.

Algorithm	Dataset1	Dataset2
VGG 16	0.6031	0.7063
VGG 19	0.5978	0.6945
Inception V3	0.4941	0.5165
InceptionResNet V2	0.5629	0.6069
DenseNet 121	0.7302	0.8955
DenseNet 201	0.7465	0.9056

Table 3.4: Comparison of the classification algorithms' F1 score.

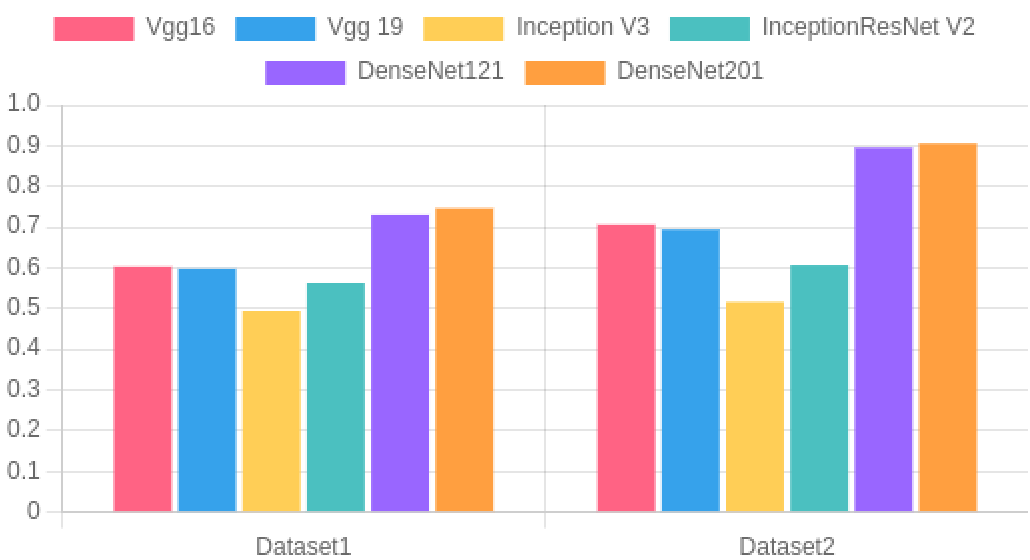


Figure 3.4: F1 score of different algorithms

3.5 Kappa Score

In machine learning classification, the kappa score (also known as Cohen's kappa coefficient) is a performance metric that measures the agreement between the predicted and actual classes, taking into account the possibility of agreement occurring by chance. It is defined as follows:

$$Kappa\ Score = \frac{(Observed\ Accuracy - Expected\ Accuracy)}{(1 - Expected\ Accuracy)}$$

where Observed Accuracy is the actual accuracy of the classifier on the dataset, and Expected Accuracy is the expected accuracy of the classifier if the predictions were made by chance.

The kappa score ranges from -1 to 1, where a score of 1 indicates perfect agreement between the predicted and actual classes, a score of 0 indicates agreement that is no better than chance, and a score of -1 indicates perfect disagreement between the predicted and actual classes.

Algorithm	Dataset1	Dataset2
VGG 16	0.566	0.6698
VGG 19	0.5581	0.6602
Inception V3	0.4468	0.4547
InceptionResNet V2	0.5177	0.5637
DenseNet 121	0.7014	0.8817
DenseNet 201	0.7200	0.8915

Table 3.5: Comparison of the classification algorithms' Kappa score.

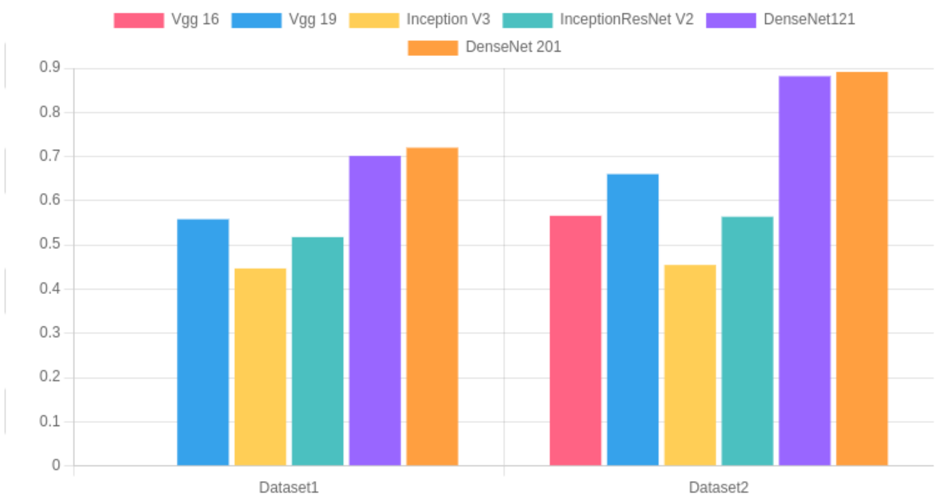


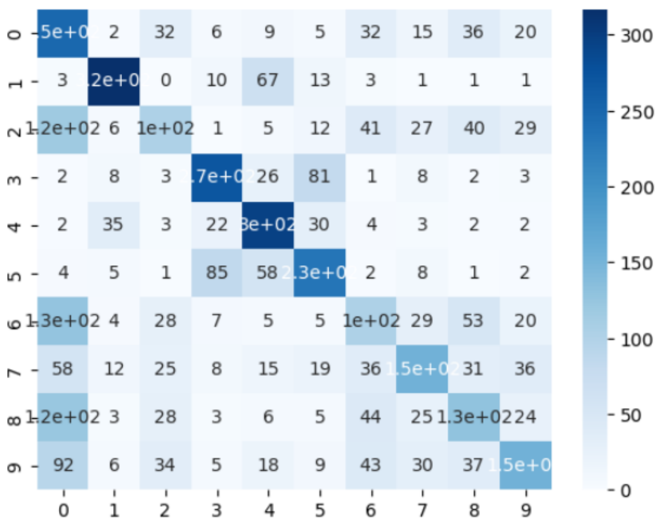
Figure 3.5: Kappa score of different algorithms

3.6 Confusion Matrix

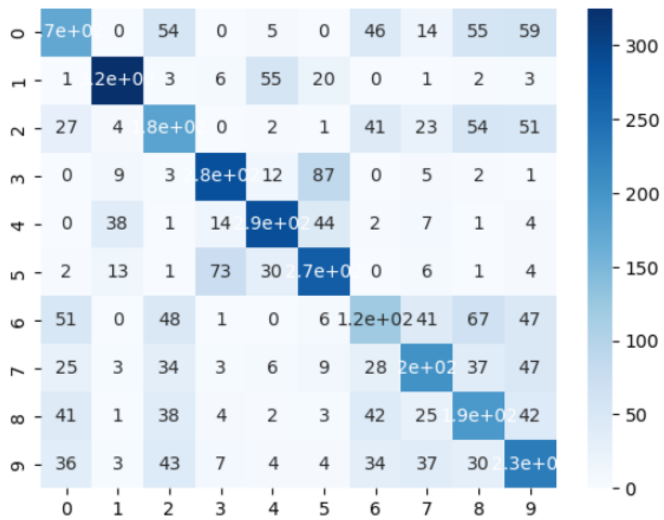
In machine learning classification, a confusion matrix is a table that summarizes the performance of a classification algorithm on a data set by showing the number of true positives, true negatives, false positives, and false negatives. It is a useful tool to understand the classification performance of a model.

- The rows of the confusion matrix represent the actual class labels and the columns represent the predicted class labels. The four possible outcomes are:
- True Positive (TP): Cases that are truly positive and are correctly predicted as positive by the classifier.
- False positive (FP): Cases that are actually negative but incorrectly predicted as positive by the classifier.
- True Negative (TN): Instances that are truly negative and are correctly predicted as negative by the classifier.
- False negative (FN): Instances that are truly positive but incorrectly predicted as negative by the classifier.

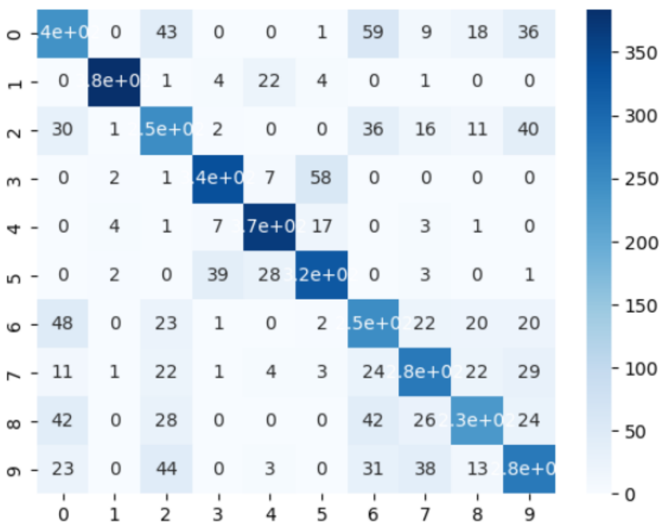
(a) (b)



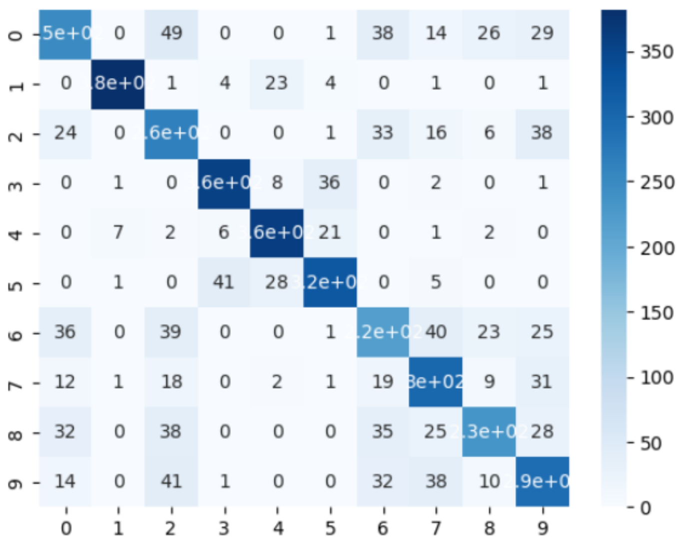
(c)



(d)

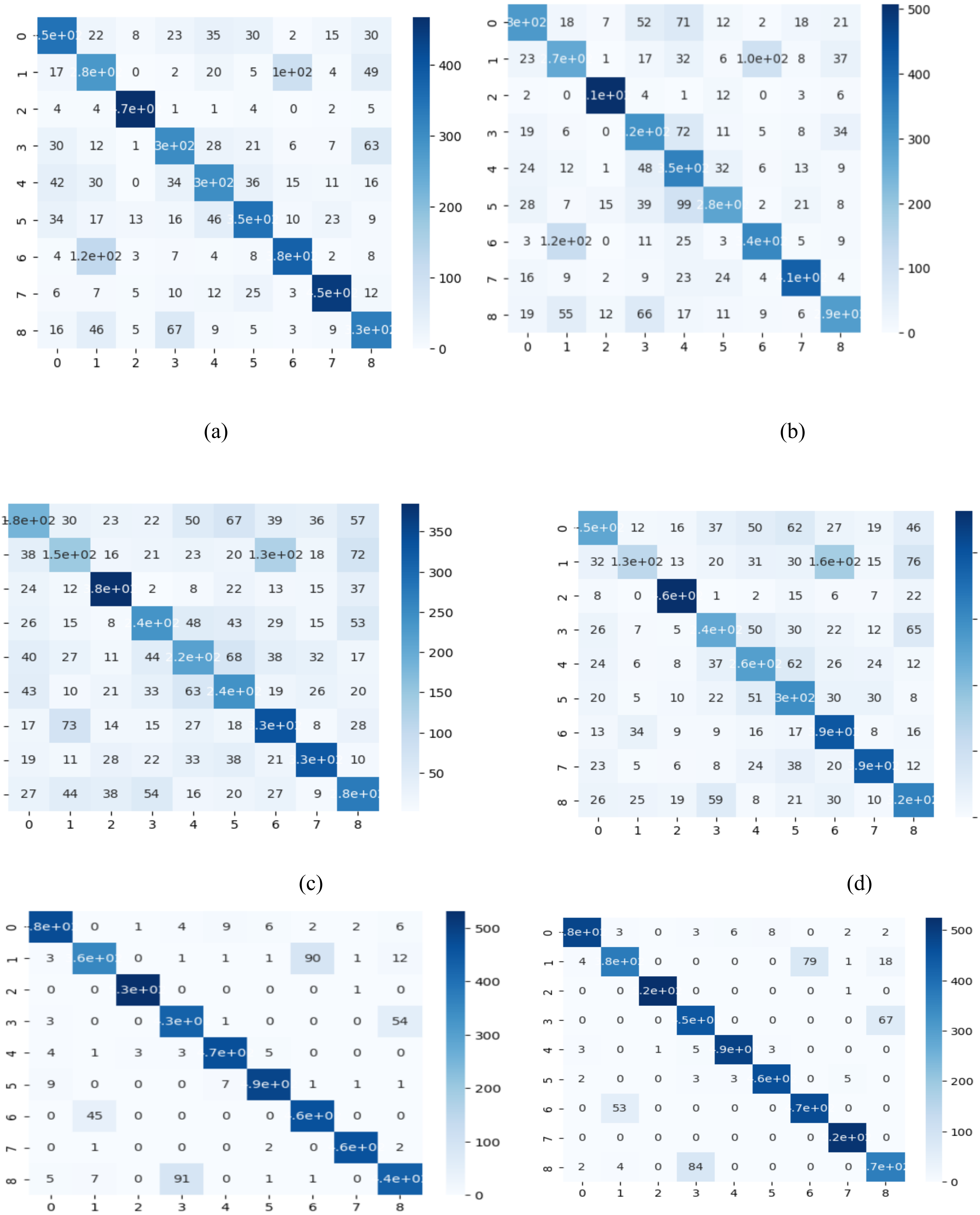


(e)



(f)

Figure 3.6: Comparison of the confusion matrix on dataset 1. (a) Confusion Matrix of VGG 16. (b) Confusion Matrix of VGG 19. (c) Confusion Matrix of Inception V3. (d) Confusion Matirx of Inception ResNet V2. (e) Confusion matrix of DenseNet 121. (f) Confusion Matrix of DenseNet 201



(e) (f)

Figure 3.7: Comparison of the confusion matrix on dataset 2. (a) Confusion Matrix of VGG 16. (b) Confusion Matrix of VGG 19. (c) Confusion Matrix of Inception V3. (d) Confusion Matirx of Inception ResNet V2. (e) Confusion matrix of DenseNet 121. (f) Confusion Matrix of DenseNet 201

Chapter 4

Conclusion & Future Scopes

4.1 Conclusion

In conclusion, we have conducted a comparative analysis of classifiers for medical image classification, where we have used transfer learning with six different pre-trained models: VGG16, VGG19, InceptionV3, Inception ResNet V2, DenseNet 121, and DenseNet201. We trained and evaluated each model on a medical image dataset and compared their performance using various evaluation metrics such as accuracy, precision, recall, F1 score, and Kappa score.

Our results showed that all six models performed well for medical image classification, with DenseNet201 achieving the highest accuracy of all models, followed closely by InceptionV3 and DenseNet121. However, the differences in performance between the models were relatively small, indicating that any model could be used for medical image classification, depending on the application's specific requirements.

Our study demonstrates the effectiveness of transfer learning with pre-trained models for medical image classification. It highlights the importance of evaluating multiple models to find the best one for a given task. The insights gained from this study could help researchers and practitioners choose the most appropriate model for their specific medical image classification task.

4.2 Future Scope

There are several potential future directions for the comparative analysis of classifiers for medical image classification using transfer learning with VGG16, VGG19, InceptionV3, Inception ResNet V2, DenseNet121, and DenseNet201 models.

One potential area for future research is the exploration of different pre-processing techniques for medical image datasets, such as normalisation, resizing, and augmentation. These techniques could help to improve the performance of the pre-trained models and further reduce the amount of training data required.

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

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[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*

INDIVIDUAL CONTRIBUTION REPORT:

A Comparative Analysis of Classifiers for Medical Image Classification

Srijan Kumar
2029202

Abstract: This study compares the performance of six pre-trained models, VGG16, VGG19, InceptionV3, Inception ResNet V2, DenseNet121 and DenseNet201, for medical image classification using transfer learning. The models were evaluated on a dataset of medical images using various evaluation metrics such as accuracy, precision, recall, F1 score, and Kappa score. The results indicate that DenseNet201 achieved the highest accuracy of all the models, but the performance differences between the models were relatively small. Thus, any of the models could be used for medical image classification depending on the specific application requirements. These findings demonstrate the effectiveness of transfer learning for medical image classification and provide useful insights for researchers and practitioners working with medical imaging data.

Individual contribution and findings: As a project team member, I was tasked with developing the code for the project using transferable learning models. I experimented with different models and hyperparameters to find the model with the best performance. I also switched the optimiser from Adam to SGD for better accuracy.

Individual contribution to project report preparation: I helped set the index to demonstrate and present the report properly. I also reviewed various reports and books to make the report more effective and readable

.

Individual contribution to project presentation and demonstration: During the presentation, I participated significantly in its preparation. Specifically, I referenced several sources of information and contributed to the results section of the presentation. I included the formulas and values created during the model testing phase and added a confusion matrix to the presentation.

Full signature of the student:

Srijan

INDIVIDUAL CONTRIBUTION REPORT:

A Comparative Analysis of Classifiers for Medical Image Classification

Sneha Singh
2029203

Abstract: This study compares the performance of six pre-trained models, VGG16, VGG19, InceptionV3, Inception ResNet V2, DenseNet121 and DenseNet201, for medical image classification using transfer learning. The models were evaluated on a dataset of medical images using various evaluation metrics such as accuracy, precision, recall, F1 score, and Kappa score. The results indicate that DenseNet201 achieved the highest accuracy of all the models, but the performance differences between the models were relatively small. Thus, any of the models could be used for medical image classification depending on the specific application requirements. These findings demonstrate the effectiveness of transfer learning for medical image classification and provide useful insights for researchers and practitioners working with medical imaging data.

Individual contribution and findings: My job in the project was to analyse different models and find the most suitable one for our project I tried different models like inception, mobile net, resnet etc. and worked tirelessly on them to finally decide on the best model and significantly increase the results while doing the same I also tried different architectures and came to the conclusion that the best one is possible for the project. I found that DENSENET 121 gives the best results for our particular model.

Individual contribution to project report preparation: I wrote the report from scratch by taking little help from my group members and ensuring that the report was as per the format and had all the required elements and data.

Individual contribution to project presentation and demonstration: Presented and explained what dataset we used and why we chose this project, and what classification we have done. Also, explained the need for doing this project.

Full signature of the student:

INDIVIDUAL CONTRIBUTION REPORT:

A Comparative Analysis of Classifiers for Medical Image Classification

Jyoti Kumari
2029204

Abstract: This study compares the performance of six pre-trained models, VGG16, VGG19, InceptionV3, Inception ResNet V2, DenseNet121 and DenseNet201, for medical image classification using transfer learning. The models were evaluated on a dataset of medical images using various evaluation metrics such as accuracy, precision, recall, F1 score, and Kappa score. The results indicate that DenseNet201 achieved the highest accuracy of all the models, but the performance differences between the models were relatively small. Thus, any of the models could be used for medical image classification depending on the specific application requirements. These findings demonstrate the effectiveness of transfer learning for medical image classification and provide useful insights for researchers and practitioners working with medical imaging data.

Individual contribution and findings: I made sure that we are using the best possible dataset available as finding a good dataset is the core for the project. I analysed and went through different datasets available and picked the latest and best issued by ISIC, and I wrote the report by going through the code.

Individual contribution to project report preparation: I contributed to several chapters. Specifically, I provided the graphs and hyperparameters from the model and thoroughly analysed the results. I also contributed to the image section of the report by providing relevant images for the project.

Individual contribution to project presentation and demonstration: I helped in the creation of the presentation from scratch and add all the necessary information related to the Topic that we are working on and edited all the necessary parts that are required for a better analysis/explanation of the code. Lastly, I concluded the presentation of the project in detail.

Full signature of the student:

Jyoti

TURNITIN PLAGIARISM REPORT

A Comparative Analysis of Classifiers for Medical Image Classification

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