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EXPLORING PRETRAINED DEEP LEARNING MODELS FOR THE CLASSIFICATION OF ELECTROMAGNETIC RADIATION IMAGES

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Abstract

Artificial intelligence (AI) plays a vital role in both the modern digital world and the medical field. Within healthcare, the diagnostic system is rapidly gaining prominence as it offers clear insights for radiologists and patients alike. However, the automation of medical image processes is challenging for domain experts due to the enormous volume of data generated by traditional systems. Recently, deep learning algorithms have emerged as powerful techniques for investigating medical images, capable of performing various tasks such as identification, classification, prediction, and pattern recognition. Despite ongoing research efforts, medical image classification tasks continue to face various challenges and obstacles that impact the performance and accuracy of classification models. This study focused on the reduce the feature extraction problem in medical image classification by applying fine-tune the hyper parameters. The feature extraction problem requires the development of sophisticated deep models which can capture higher-level abstractions from raw data. In this study, we have taken a significant step by enhancing three pre-trained deep learning models. The proposed methodology focus was on handling a large dataset of multi-class COVID-19 chest X-ray images and explored the three models namely VGG Net, EfficientNet, and InceptionNet. Analysing the outcomes of experiments, each model yielded different results in terms of accuracy and loss rates. The accuracy we achieved for VGG Net was 86%, for EfficientNet it was 93% and for Inception Net was 78% and correspondingly, the loss rates for these models were 0.3, 0.1, and 0.5, respectively. This observation positions the EfficientNet model as a particularly suitable candidate for effectively classifying large-scale medical image datasets with better accuracy and low loss rate.

Keywords:

Medical Images, Deep Learning, Pre-trained models, Classification, Feature Extraction

1. INTRODUCTION

Medical imaging [1] has become an indispensable tool in contemporary medicine, enabling healthcare professionals to visualize and understand the intricate details of the human body. By capturing high-resolution images, medical imaging techniques aid in the detection, characterization, and monitoring of diseases and abnormalities. These images serve as a crucial foundation for accurate diagnosis, treatment planning, and intervention strategies. Over the years [2], medical imaging has witnessed remarkable advancements driven by technological innovations and research breakthroughs. Traditional two-dimensional imaging has evolved into three-dimensional reconstructions, providing clinicians with detailed spatial information. The development of contrast agents has enhanced the visibility of specific organs and tissues, further refining the diagnostic process. Moreover, the integration of functional imaging techniques [3], such as positron emission tomography (PET), Computed Tomography (CT), X-Ray and functional MRI (fMRI), has expanded understanding of physiological processes within the body. However, the rapid growth in medical imaging has resulted in a significant challenge effectively extracting meaningful information from the vast amount of data generated by these techniques. This challenge has spurred the development of sophisticated image analysis techniques [4], particularly in the realm of AI and machine learning. By leveraging these computational methods, healthcare professionals can unlock hidden patterns, detect subtle anomalies, and derive valuable insights from medical images.

Deep learning models [5], particularly convolutional neural networks (CNNs)have shown exceptional performance in various computer vision tasks, including image classification. These models are capable of automatically learning hierarchical representations from raw image data, enabling them to capture intricate features and patterns that are essential for accurate classification. [6] The availability of large-scale labelled medical image datasets and the increase in computational power have further fuelled the success of deep learning-based approaches in medical image classification. Recently, Pre-trained models[7] serve as efficient tools for swiftly deploying deep learning with remarkable precision. Consider a pre-trained deep learning model as a neural network that has undergone initial training on an expansive dataset, laying a strong foundation for its capabilities. Instead of starting the training process from the beginning, these models are pre-trained on an enormous volume of data, typically comprising millions of images or text samples, enabling them to learn and extract high-level representations from the input data. As a consequence, these models can effectively capture general features and patterns that are beneficial for various related tasks. [8] Through the adoption of pre-trained models, researchers and developers can harness the knowledge gleaned from vast datasets and employ it effectively to tackle distinct challenges or assignments. This principle, recognized as transfer learning, is akin to drawing from a deep well of experience to excel in new endeavors.

2. LITERATURE SURVEY

Recently, adoption of deep learning techniques has gained significant prominence in the field of research. Many researchers have delved into the realm of medical image classification using a variety of deep learning models. For instance, Nillmani and colleagues [9] conducted a study where they explored the application of seven distinct pre-trained network models for Pneumonia Classification. These models included VGG16, VGG19, DenseNet201, Xception, InceptionV3, NasnetMobile, and ResNet152, each with five different classes. The researchers employed binary classification, experimenting with various class combinations. Remarkably, they achieved an accuracy of 99.84% using DenseNet, coupled with an impressive AUC (Area Under the Curve) value of 1.0. This demonstrates the potential of deep learning models in achieving exceptional performance in the context of medical image classification tasks.

Shia et al [10] embarked on a journey to harness the capabilities of deep learning in conjunction with the linear Support Vector Machine (SVM) algorithm for feature extraction within a classification task. Their study involved an unlabeled dataset encompassing 2099 images. The performance of their model was assessed through the lens of sensitivity and specificity. Their findings illuminated an impressive accuracy rate of 94.34%, complemented by a specificity score of 93.22%. These outcomes underscore the potential of their approach to yield accurate and reliable classification results.

Alok Tiwari et al. [11] embarked on a journey to leverage the capabilities of pre-trained networks, specifically VGG Net and Inception Net. Their research involved the use of a COVID-19 X-ray image dataset, containing a total of 9206 images across four distinct classes. The study encompassed three different case scenarios, each providing unique insights into the proposed model performance. In Case 1, the proposed model achieved a training accuracy of 91.86% across the four classes. In Case 2, the accuracy was elevated to 97.67% when dealing with three classes. Lastly, in Case 3, the model demonstrated remarkable proficiency, attaining a training accuracy of 99.61%. This comprehensive evaluation was further extended to testing, where the model exhibited an accuracy of 87.32% in Case 1, an impressive 96.89% in Case 2, and an astounding 99.95% accuracy in Case 3. These findings emphasize the robustness and accuracy of their approach in classifying COVID-19 X-ray images across different scenarios.

Das et al. [12] set out on a scientific journey that led them to unveil an ensemble learning strategy that revolved around a method grounded in convolutional neural networks (CNNs). Their study was marked by the integration of multiple advanced models, showcasing the likes of DenseNet201, ResNet50V2, and InceptionV3. Their dataset, though relatively smaller in size, featured 538 cases of Covid-19 positivity and 468 cases of Covid-19 negativity. Through their diligent efforts, they achieved a noteworthy classification accuracy of 91.62%. This accomplishment stands as a testament to their innovative approach and diligent research.

Maghded et al. [13] embarked on a quest to create a pioneering framework empowered by artificial intelligence, aimed at diagnosing Covid-19 through smartphones. Another significant study, conducted by Maghdid and team in 2020, involved a comprehensive collection of data from diverse online resources. Their objective was to craft a Covid-19 detection algorithm of their own. In this endeavor, they employed a straightforward Convolutional Neural Network (CNN) architecture, coupled with a pre-trained AlexNet model. Impressively, this combination led to a commendable accuracy rate of approximately 94.1%. These accomplishments reflect the innovative spirit driving their research in the domain of Covid-19 detection and diagnosis.

Srigiri Krishnapriya and Yepuganti Karuna [14] embarked on a research journey that shed light on brain MRI image classification. They approached the task by leveraging the capabilities of pre-trained deep learning models, specifically VGG19 Net, RestNet50, and Inception V3. Through their dedicated efforts, they achieved remarkable outcomes. The pinnacle of their success came with VGG19, which demonstrated an impressive accuracy of 98.76%, outshining the performance of the other models. It important to note that while their work showcased remarkable achievements, there were certain limitations. For instance, their dataset size was relatively small for the classification task, which could potentially impact the generalizability of the results. Additionally, their approach required significant computational time. Despite these challenges, their findings illuminate the potential of pre-trained models in the field of brain MRI image classification.

Vesal et al. [15] delved into the intricate domain of transfer learning, seeking to uncover its effectiveness in classifying breast histology images. Their investigation revolved around a meticulous examination of the classification capabilities of pre-trained networks, focusing on the Inception-V3 and ResNet50 models. Noteworthy outcomes emerged from their experimentation: the Inception-V3 network showcased superior performance, boasting accuracy rates of 97.08% compared to ResNet50 of 96.66%. The authors' commitment to enhancing their results was evident through the integration of augmentation techniques. By employing methods like rotation and flipping, they successfully augmented their pool of training samples. This transformation expanded the original set of 320 training samples to an impressive total of 33,600 training and validation samples. While their study offered valuable insights, it would have been beneficial for the authors to extend their exploration of the augmentation techniques' effectiveness to encompass a broader range of pre-trained models. Such an approach could have provided a more comprehensive understanding of the techniques' applicability and potential impact.

An intriguing study by different researchers [16] delved into the realm of transfer learning, leveraging an AlexNet to enhance the precision of lung nodule classification. Given that AlexNet training transpired on ImageNet, the compatibility of its deep features with lung nodule classification wasn't a certainty. Therefore, the authors employed techniques like fine-tuning and feature selection to refine the transferability process. Notably, the outcomes indicated that this approach could surpass the performance of manually crafted texture descriptors. However, it noteworthy that this approach appears to have applicability primarily within the context of the AlexNet architecture.

3. MATERIALS AND METHODS

We have designed and applied three highly competent pre-trained deep CNNs for the multiclass classification. To carry out this endeavor, we relied on a benchmarking dataset of chest X-ray (CXR) images. This dataset encompassed four distinct classes: COVID, viral pneumonia, lung opacity, and normal images. The dataset origins trace back to the "COVID-19 Radiography Database" on Kaggle [17]. However, it important to note that this dataset presented an imbalance in class distribution, as depicted in Table 1.To ensure a robust evaluation, we randomly divided the dataset in an 80:20 ratio for training and testing purposes. The training subset consisted of 16,930 images, while the testing subset comprised 4,235 images, collectively adding up to a total of 21,165 images. The execution of our proposed experiments took place within the realm of a Python Jupyter notebook. The computational powerhouse at our disposal was an AMD Ryzen 9

6900HX complemented by Radeon Graphics, clocking in at 3.30 GHz, and backed by a capable 16GB of RAM.As visualized in Fig.1, our research journey unfolded along a meticulously planned trajectory, guiding us through the intricacies of the proposed methodology. The Fig.1 provides an depiction of the research workflow, encapsulating our strategy and approach in a single comprehensive visualization.

Table.1. Dataset Details

Class Name	No of Images
COVID	3616
Lung Opacity	6012
Normal	10192
Viral pneumonia	1345

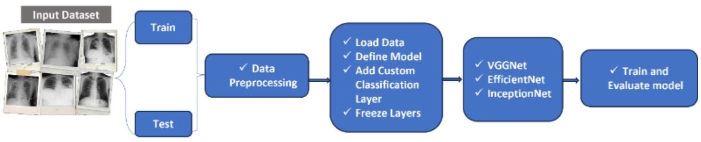


Fig.1. Proposed Methodology

3.1 DATA PREPROCESSING

Data preprocessing takes on a pivotal role in the journey of getting a dataset ready for analysis or model training. Visualized in Fig.2, the steps encompassed in data preprocessing form an integral part of our proposed research methodology. The process unfolds with the initial loading of images from the dataset, followed by a transformation that converts them into grayscale representations. As a next step, the images undergo resizing, uniformly aligning them to a compact 224x224 size to better align with the model expectations. To further enhance the quality of the data and amplify the training and performance of the network models, two pivotal techniques come into play: data augmentation and normalization. These techniques not only elevate the robustness of the data but also empower the models with enhanced learning capabilities. The Data generators serve as effective tools for managing and processing extensive datasets during model training and evaluation, especially when confronted with datasets that exceed memory capacity. Finally, after preprocessing the dataset was loaded into the chosen pre trained network model for training and testing.

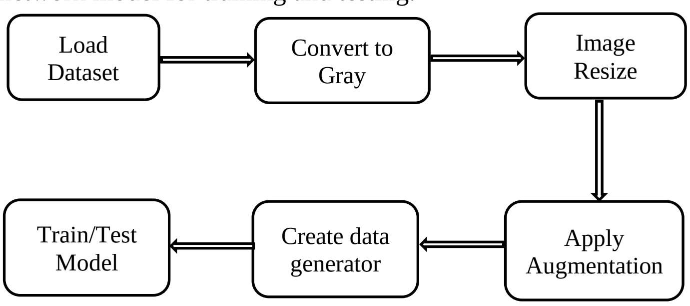


Fig.2. Data preprocessing steps

3.2 DEFINE MODEL

Define a model is used to refers the specifying the architecture, structure, and parameters of a computational model that is designed to learn patterns and make predictions from data. This involves determining the layers, connections, and operations within the model, as well as configuring hyperparameters and settings that control how the model learns. It is often done using programming frameworks or libraries that provide building blocks for creating neural networks. Once the model is defined, it can be trained using data to learn the underlying patterns and relationships. The trained model can then be used to make predictions on new, unseen data, allowing it to generalize its learned knowledge to make informed decisions or classifications. In the scope of our proposed study, this meticulous process of defining models is accompanied by the strategic selection of common hyperparameters to ensure consistency and fairness across the evaluation of different pre-trained models. These parameters were used to same value for three models such image size is 224x224, batch size is 32, number of classes is 4, epoch is 50 and class mode is categorical – all working harmoniously to create a level playing field for the model evaluations.

3.2.1 Custom Classification Layer:

Adding a custom classification layer to a pre-trained network is a fundamental technique in transfer learning. This process involves extending a pre-existing deep neural network with a new classification layer tailored to specific classification task.It is used to leverage the deep features learned by the pre-trained model while tailoring the model for medical image classification problem.

3.2.2 Freeze Layer:

Freezing a layer in a neural network refers to preventing its weights and biases from being updated or modified during the training process. When freeze a layer, its parameters remain fixed, and only the parameters of non-frozen layers are updated through the process of backpropagation and gradient descent.By freezing certain layers, we retain the learned features from the original task while fine-tuning the remaining layers to suit the new task.

3.2.3 VGG Net Model:

VGGNet, introduced by a group of researchers from the University of Oxford back in 2014, stands out as a highly favoured pre-trained deep learning model in the realm of image classification tasks [18] and the visualization of VGGNet example architecture is shown in Fig.3. Despite its straightforward structure, VGGNet managed to shine brightly in the domain of image recognition, even securing a remarkable second place in the prestigious 2014 ImageNet Large Scale Visual Recognition Challenge (ILSVRC). [19] One of the standout features of VGGNet is remarkable depth—it boasts a network composed of a total of 19 layers. This architecture is built around a series of compact 3x3 convolutional filters stacked on each other, offering the advantage of increased depth while keeping the parameter count quite manageable. [20] To effectively manage dimensions, VGGNet employs max-pooling layers and leverages fully connected layers for making predictions. VGGNet journey began with initial training on the vast ImageNet dataset, encompassing countless labeled images spanning a multitude of classes. Through this training, VGGNet acquired the remarkable ability to discern high-level features and intricate patterns within images, turning it into a potent feature extractor. In the system we have developed and enhanced the VGG Net model which is breaking it down into five blocks, each comprising multiple convolutional and max pooling layers. Let delve into the specifics: In Block 1, we have embedded two convolutional layers, each working with a 224x224 image size. This is followed by a MaxPooling2D layer. Block 2 is equipped with two convolutional layers handling 112x112 images, accompanied by a MaxPooling2D layer. Moving on to Block 3, it contains three convolutional layers dealing with 56x56 images and MaxPooling2D layer. Block 4 hosts three convolutional layers catering to 28x28 images, followed byMaxPooling2D layer. In Block 5, used three convolutional layers tasked with 14x14 images and MaxPooling2D layer, and two dense layers tucked in as well. To sum up the technical details, in this study, we have put the VGG Net to work with a total of 14,979,396 parameters for both training and testing phases.

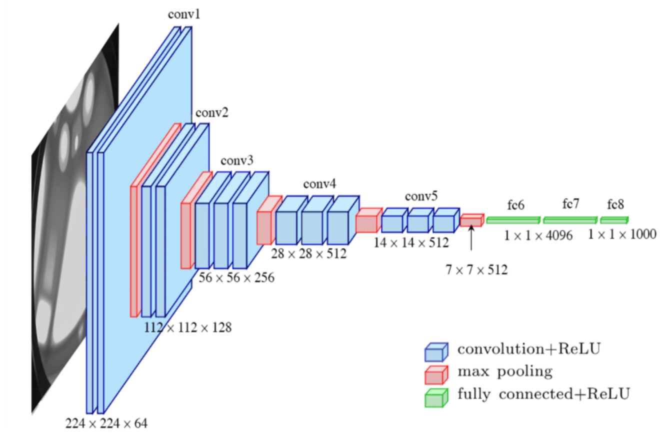


Fig.3. Example of VGG Model Architecture [21]

3.2.4 EfficientNet Model:

EfficientNet [22], introduced by Google AI team in 2019, is a highly efficient and potent pre-trained deep learning model designed specifically for image recognition tasks and visualization example of EfficientNet architecture representing in figure4 [23]. The model aims to find an optimal trade-off between model size, computational efficiency, and performance. [24,25] Its architecture is crafted to achieve state-of-the-art accuracy in image classification while demanding fewer computational resources compared to other models. The core concept driving EfficientNet efficiency is compound scaling. These techniques significantly reduce the number of parameters and operations, resulting in a more computationally efficient model without sacrificing accuracy. Additionally, the model employs a variant of the Swish activation function, which has been found to enhance performance compared to traditional activation functions like ReLU.[26] The architecture that emerges makes use of mobile inverted bottleneck convolution (MBConv), which shares similarities with MobileNetV2 and MnasNet. In this study, we are enhanced the EfficientNet model which contains seven blocks, applying batch normalization and ZeroPadding for each block. The EfficientNet Model Architecture layer details are explained in below: block 1: Rescaling and Normalization layer, Stem Convolution layer, Block Layers, Depth wise convolutions, batch normalization and activation functions and Squeeze-and-Excitation (SE) layer.

block 2: two Rescaling and Normalization layer, two Stem Convolution layer, two Block Layers, two Depth wise convolutions, two batch normalization and activation functions and two Squeeze-and-Excitation (SE) layer.

block 3: two Rescaling and Normalization layer, two Stem Convolution layer, two Block Layers, two Depth wise convolutions, two batch normalization and activation functions, two Squeeze-and-Excitation (SE) layer and one dropout layer.

block 4: three Rescaling and Normalization layer, three Stem Convolution layer, three Block Layers, three Depth wise convolutions, three batch normalization and activation functions, 3 Squeeze-and-Excitation (SE) layer and one dropout layer.

block 5: 3 Rescaling and Normalization layer, 3 Stem Convolution layer, 3 Block Layers, 3 Depth wise convolutions, 3 batch normalization and activation functions,3 Squeeze-and-Excitation (SE) layer and one dropout layer.

block 6: four Rescaling and Normalization layer, four Stem Convolution layer, four Block Layers, four Depth wise convolutions, four batch normalization and activation functions, 4 Squeeze-and-Excitation (SE) layer and one dropout layer.

block 7: Rescaling and Normalization layer, Stem Convolution layer, Block Layers, Depth wise convolutions, batch normalization and activation functions, Squeeze-and-Excitation (SE) layer and finally used the two dense layer.

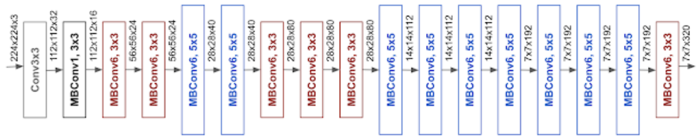


Fig.4. Example of EfficientNet model Architecture [27]

3.2.5 InceptionNet Model:

The Inception model, also known as GoogLeNet, was introduced by Google Deep Learning team in 2014. The architecture of this model is quite complex and can be seen in the [28]. The term “Inception” draws inspiration from the movie “Inception,” where layers of reality unfold, mirroring the depth and intricacy of this model. The main aim of Inception was to tackle the challenges posed by deep neural networks, including computational demands and the vanishing gradient problem, all while achieving impressive accuracy in image classification tasks [29]. The Inception model lies in its use of various filter sizes (1x1, 3x3, 5x5) within a single layer. This ingenious approach allows the network to effectively capture both local and global features.

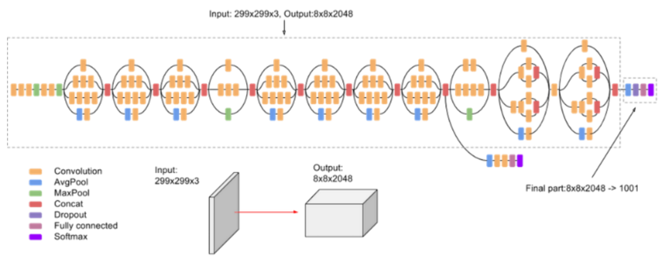


Fig.5. Example of InceptionNet model Architecture [29]

The model incorporates these filters into modules that blend the outcomes of diverse filter operations. This fusion enables the model to grasp a wide array of features concurrently. In this study, we have taken the InceptionNet model and elevated it by implementing various combinations of convolutional and pooling layers. The architecture crafted involves 89 convolutional layers, 93 batch normalization layers, 93 average pooling activation layers, and two dense layers. Through these layers, the model forms a sophisticated framework for understanding complex patterns in data. Notably, this model is composed of a total of 22,853,924 parameters, reflecting its capacity to learn intricate relationships in the data it encounters.

4. RESULT AND DISCUSSION

In our proposed research, we adopted the enhanced 3 proficient pre-trained Deep Learning Network models, meticulously chosen to tackle the intricate task of medical image classification. The culmination of this effort was the evaluation of these models, a process that entailed the use of performance metrics to measure their prowess. Performance metrics, in essence, are the quantitative yardsticks that we employ to meticulously measure the effectiveness of a classifier. They stand as numerical representations of a model capabilities, offering us a comprehensive view of how well it is accomplishing its designated task.

One of the indicators we delved into is accuracy. This pivotal metric captures the essence of the model performance by assessing how well it aligns its predictions with the actual outcomes. The formula that encapsulates this measure is as follows:

Accuracy=(No of Correctly classified images)/(Total images) (1)

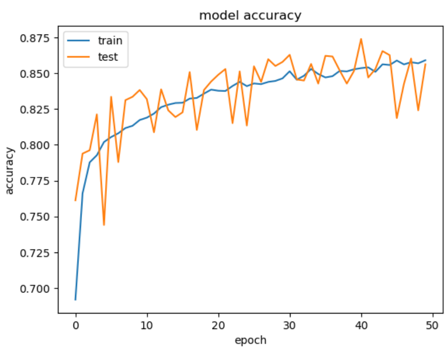
This experimental study was produced the confusion matrix which is a systematic arrangement employed to evaluate the efficacy of a classification model.

Precision=(True positive)/(True Positive+False Positive) (2)

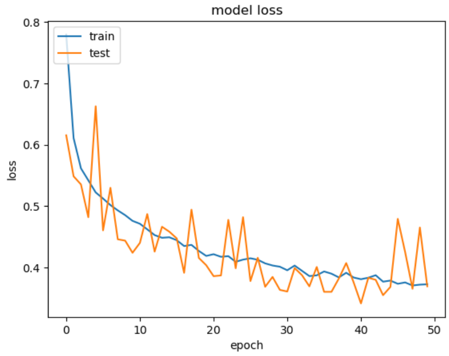
Recall=(True positive)/(True Positive+False Nagative) (3)

$$F-Score=\frac{1}{\frac{1}{\text{Recall}}+\frac{1}{\text{Precision}}} \quad (4)$$

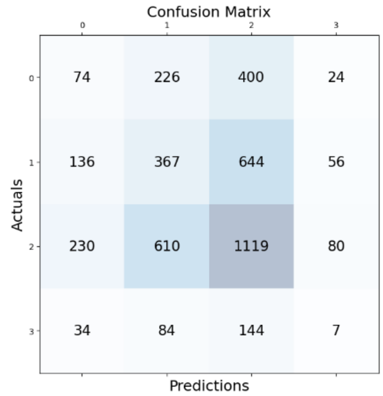
where, True Positive denoted the count of instances accurately predicted as positive by the model, False Positive refer the count of instances predicted as positive by the model, yet they truly belong to the negative class, also referred to as a Type I error. False Negative denoted the count of instances predicted as negative by the model, yet they truly belong to the positive class.



(a) Model accuracy



(b) Model Loss

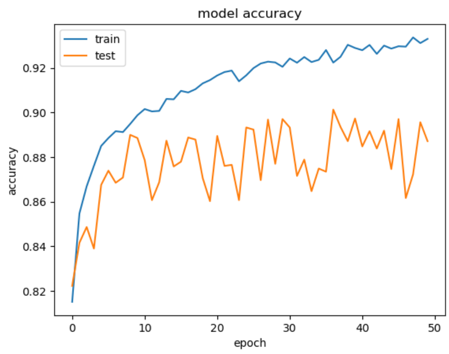


(c) Confusion matrix

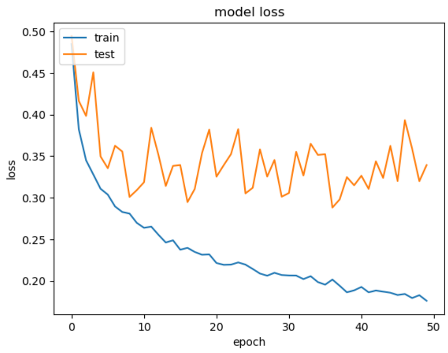
Fig.6. VGG Net Model Performance

In this study, we explored the performance of various pre-trained deep Convolutional Neural Networks for classifying medical images across multiple categories. The proposed methodology allowed us to compare the capabilities of VGG Net, Efficient Net, and Inception Net using the performance metrics discussed earlier.

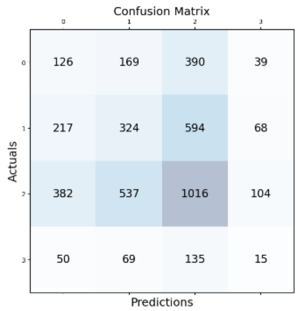
After careful evaluation, it became evident that among these networks, the Efficient Net displayed the highest efficiency and accuracy. The experimental results revealed that VGG Net achieved an accuracy of 86%, Efficient Net reached an impressive 93%, and Inception Net achieved a score of 78%. Moreover, their respective loss rates were recorded at 0.3, 0.1, and 0.5. EfficientNet outperformed both VGG Net and Inception Net, achieving a remarkable accuracy of 93%.



(a) Model accuracy

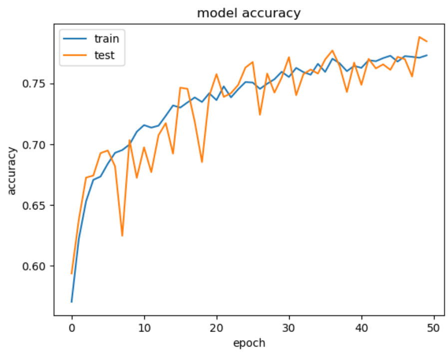


(b) Model loss

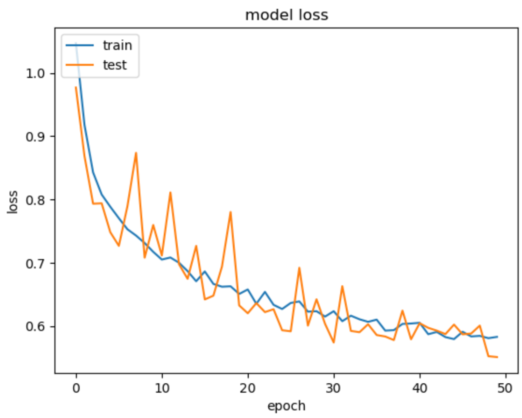


(c) Confusion matrix

Fig.7– EfficientNet Model Performance

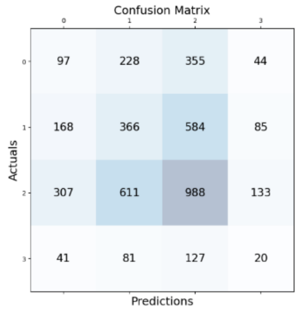


(a) Model accuracy



(b) Model loss

To provide a visual representation of these findings, Fig.6 illustrates the performance of the VGG Net model. Sub-figures (a), (b), and (c) display the model accuracy, loss, and confusion matrix, respectively. Similarly, Fig.7 showcases the performance of the Efficient Net model, while Fig.8 provides insights into the Inception Net model performance. Each of these figures portrays accuracy, loss, and confusion matrix results. The Fig.9 offers a comprehensive comparison of the accuracy achieved by each model - VGG Net, Efficient Net, and Inception Net.



(c) Confusion matrix

Fig.8. Inception Network Model Performance

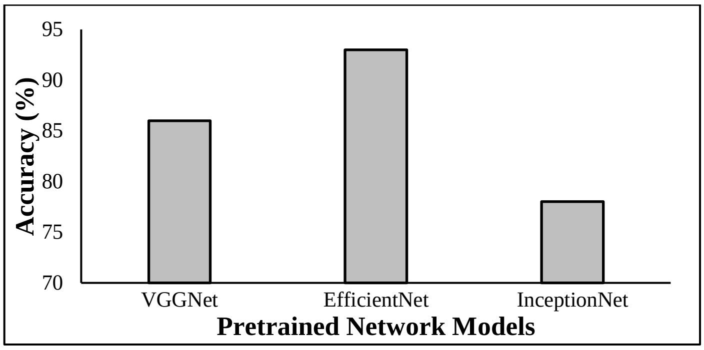


Fig.9. Comparison of each Model Accuracy

5. CONCLUSION

The proposed system placed 3 different enhanced pre-trained deep convolutional neural network models to the test. These models were assessed using a substantial dataset composed of 4 classes of Covid-19 X-Ray medical images. The outcomes of our experiments were intriguing. We employed 3 models – VGG Net, EfficientNet, and InceptionNet for observing classification accuracy results. Specifically, VGG Net achieved an accuracy of 86%, EfficientNet excelled at 93%, and InceptionNet displayed a commendable 78%. The corresponding loss rates were recorded as 0.3, 0.1, and 0.5 respectively. When it came to choosing the optimal model for medical image classification on a larger scale, EfficientNet emerged as the top contender. Its exceptional performance, efficient architecture, and scalability made it stand out. By harnessing the power of compound scaling and integrating efficient building blocks, EfficientNet proved capable of accurately and robustly classifying medical images while making optimal use of available computational resources. Its adaptability to various medical imaging contexts and resource constraints underscores its significance within the realm of medical image analysis and healthcare.

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