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A Comparative Study of Deep Learning Architectures for COVID-19 X-ray Classification

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Abstract: - The swift transmission of COVID-19 has required the creation of effective diagnostic instruments, with X-ray imaging becoming a crucial asset for early identification. This study involved a comprehensive examination of ten models, consisting of eight deep learning models and two classical machine learning models. The analysis was conducted using a dataset of X-ray pictures related to COVID-19. We conducted a comprehensive investigation that involved various methods for extracting features and using pre-trained models. This study concluded with a thorough evaluation of the performance of each model. The findings indicated that conventional machine learning models, particularly the Random Forest classifier, attained the best level of accuracy (100%). Out of the several deep learning models, VGG and Xception both earned an accuracy rate of 97.5%, whereas DenseNet201 and CNN attained a little lower accuracy of 95%. The accuracy of InceptionResNetV2 was 92.5%. Nevertheless, ResNet50 and EfficientNetB3 exhibited lower performance, with accuracies of 77.5% and 50%, respectively. These findings provide useful insights into the efficacy of different methods for classifying COVID-19 in X-ray pictures, hence helping to the progress of diagnostic techniques. Among the deep learning models, VGG and Xception both attained an accuracy of 97.5%, while DenseNet201 and CNN achieved 95% accuracy. InceptionResNetV2 followed closely with 92.5% accuracy. However, ResNet50 and EfficientNetB3 underperformed with accuracies of 77.5% and 50%, respectively. These findings offer valuable insights into the effectiveness of various approaches for classifying COVID-19 in X-ray images, contributing to the advancement of diagnostic methods.

Keywords: X-ray imaging, VGG, Xception, DenseNet201, InceptionResNetV2, ResNet50, EfficientNetB3

I. Introduction

Global healthcare systems are facing hitherto unheard-of difficulties as a result of the COVID-19 pandemic, which emphasises the critical necessity for quick and precise diagnostic instruments. Early detection and timely intervention are crucial in mitigating the spread of the virus and managing its impact on public health. In this context, medical imaging techniques, particularly X-ray imaging, have emerged as valuable resources for identifying COVID-19 cases. Recognizing the potential of advanced computational methods, this study undertook a comprehensive evaluation of ten different models, encompassing eight deep learning architectures and two classical machine learning models. A dataset of COVID-19-related X-ray pictures was used for the research, offering a representative and varied sample for model evaluation.

The investigation of medical imaging methods, especially X-ray imaging, for the identification and diagnosis of COVID-19 has been one area of great attention. Chest X-rays have long been a valuable diagnostic tool in respiratory illnesses, offering insights into lung abnormalities and pathologies. However, the rapid spread of COVID-19 and its diverse manifestations have necessitated the development of more sophisticated and reliable methods for interpreting these images.

In this context, recent findings from X-ray image analysis have provided invaluable insights into the efficacy of different approaches for categorizing COVID-19 cases. These advancements not only contribute to the refinement of diagnostic techniques but also deepen our understanding of the virus's impact on lung health. The research highlights the remarkable potential of modern methodologies, including those based on feature extraction and deep learning, to enhance diagnostic accuracy and empower healthcare professionals in their battle against the pandemic.

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This research performed a thorough examination of ten models, consisting of eight deep learning models and two classical machine learning models, utilizing a dataset of COVID-19 X-ray pictures. The study investigated several methods for extracting features and the utilization of pre-trained models, ultimately resulting in a thorough assessment of the performance of each model. The findings indicated that the Random Forest classifier attained a perfect accuracy rate of 100%. VGG and Xception scored an accuracy of 97.5% among deep learning models, whereas DenseNet201 and CNN achieved 95% accuracy. The accuracy of InceptionResNetV2 was 92.5%. ResNet50 and EfficientNetB3, among other models, had inferior performance, achieving accuracies of 77.5% and 50%, respectively. These findings provide useful insights into the efficacy of different ways for categorizing COVID-19 in X-ray pictures, adding to the progress of diagnostic techniques and the overall comprehension of the virus's influence on lung health. Furthermore, the findings have highlighted the importance of feature extraction techniques in optimizing the performance of AI-based diagnostic systems. By identifying and extracting relevant features from X-ray images, these methods enhance the accuracy and reliability of COVID-19 detection, enabling healthcare professionals to make informed decisions and initiate appropriate treatment protocols promptly.

II. Literature Review

The COVID-19 pandemic has highlighted the need for efficient diagnostic tools, with chest X-ray (CXR) imaging emerging as a crucial resource for early detection. Deep learning models have been used in numerous studies to improve COVID-19 diagnostic accuracy using CXR pictures. This literature review examines key contributions in this field, emphasizing advancements, methodologies, and performance outcomes of various deep learning models. In one study, Sitaula and Hossain [1] fine-tuned the VGG-16 model with an attention module targeting the 4th pooling layer, using three COVID-19 CXR datasets. They reported an accuracy of 79.58%, which was 10% higher than the InceptionResNetV2 model's 68.10%. The VGG-16 model's smaller kernel size and fewer layers, compared to VGG-19, enhanced its feature extraction capabilities for COVID-19 CXR images. Abbas et al. [2] introduced the DeTraC deep convolutional neural network, which handles image dataset irregularities through class decomposition. They succeeded in differentiating between cases of severe acute respiratory syndrome and normal COVID-19 with a sensitivity of 100% and a high accuracy of 93.1%. Compared to the VGG-19 model, DeTraC achieved an accuracy of 97.35%, a sensitivity of 98.23%, and a specificity of 96.34%, demonstrating its effectiveness.

Madaan et al. [3] developed XCOVNet, a two-phase X-ray image classification system for early COVID-19 detection. The first phase involved preprocessing a dataset of 392 chest X-ray images, while the second phase trained and fine-tuned the neural network model, achieving an accuracy of 98.44%. The model's adaptability and high performance were further optimized by selectively training different layers. Alrabiah et al. [4] achieved an overall accuracy of 99.5% in their study by proposing an effective CNN model for COVID-19 diagnosis based on chest X-ray image categorization. Their model's resilience and dependability were demonstrated by its 100% accuracy on the original dataset and its 99.5% accuracy on an independent dataset.

In addition to their own CNN model, DLH-COVID, Bacellar et al. [5] integrated a number of pre-trained deep learning models, such as ResNet, VGG, Inception, and EfficientNet. To improve generalisation, they adjusted hyperparameters using a dataset of 6,432 photos. When comparing the final DLH-COVID model to healthy and pneumonia-affected persons, it demonstrated efficacy with a 96% accuracy rate in identifying COVID-19 from chest X-ray pictures. Yao et al. [6] developed TLDeNet, a DenseNet-based deep transfer learning model, to classify patients into COVID-19, Normal, or Pneumonia categories. They applied the Grad-Cam method for model interpretation, achieving a training accuracy of 97.62% and a validation accuracy of 97.23%. TLDeNet outperformed other models like EfficientNetB7 and VGG16 in classification performance.

Sreena et al. [7] conducted a comparative analysis of pre-trained deep learning models for classifying chest X-rays as COVID-19, Viral Pneumonia, or Healthy cases using the QaTa-Cov-19 dataset. DenseNet201 outperformed other models with an accuracy of 98.6% and an AUC of 0.9996, demonstrating its superior performance in multiclass classification tasks. Apostolopoulos and Mpesiana [8] investigated the use of transfer learning with convolutional neural networks for the automatic detection of COVID-19 from chest X-ray pictures. Their research demonstrated the high classification accuracy attained by pre-trained models, like Xception and AlexNet, underscoring the promise of transfer learning in medical image analysis.

Table 1 presents a comparative analysis of these studies. This structured survey and table offer a comprehensive overview of significant research on the use of deep learning models for COVID-19 detection using chest X-ray images, along with areas for future research and potential improvements.

Table 1 Contribution, Scope of Improvement, and Obtained Results

Study	Contribution	Scope of Improvement	Obtained Results
Sitaula and Hossain [1]	VGG-16 with attention module adjusted for COVID-19 CXR pictures	Explore other attention mechanisms and deeper layers	Accuracy: 79.58%
Abbas et al. [2]	DeTraC deep CNN for handling dataset irregularities	Extend to larger and more diverse datasets	Accuracy: 97.35%, Sensitivity: 98.23%, Specificity: 96.34%
Madaan et al. [3]	Developed XCOVNet for early COVID-19 detection	Integrate more sophisticated preprocessing techniques	Accuracy: 98.44%
Alrabiah et al. [4]	CNN model with high efficiency for COVID-19 diagnostic	Test on more diverse independent datasets	Accuracy: 99.5%
Bacellar et al. [5]	Implemented multiple pre-trained models and DLH-COVID	Improve hyperparameter tuning for better generalization	Accuracy: 96%
Yao et al. [6]	TLDeNet model using DenseNet and transfer learning	Apply to different medical imaging tasks	Training Accuracy: 97.62%, Validation Accuracy: 97.23%
Sreena et al. [7]	Comparative analysis of pre-trained models using QaTa-Cov-19	Address data imbalance and augmentation issues	Accuracy: 98.6%, AUC: 0.9996
Apostolopoulos and Mpesiana [8]	Transfer learning for automatic COVID-19 detection	Explore more pre-trained models and larger datasets	High classification accuracies with AlexNet and Xception

III. PROPOSED METHODOLOGY

A. Dataset

Utilised was the COVID-19 X-ray picture information set, a meticulously chosen collection of X-ray images from COVID-19 positive and negative cases. The coronavirus strain known as severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) is the cause of COVID-19, also known as coronavirus illness 2019. The first recorded cases were in Wuhan, China, around the end of December 2019, before spreading globally [9]. The current epidemic was formally labelled a pandemic by the World Health Organisation (WHO) on March 11, 2020. Reverse transcription polymerase chain reaction is being used to diagnose COVID-19 (RT-PCR). Despite this, chest X-ray scans are useful in the early detection of COVID-19 because X-ray scanners are easily available and can generate pictures for diagnosis fast [10].

Train and test are the two primary folders into which the dataset is arranged. Three subfolders—COVID-19, PNEUMONIA, and NORMAL—are included in both folders. Six,432 X-ray images make up the dataset overall; 20% of the photos are the test data[11].

Figure 1 illustrates the distribution of images between the PNEUMONIA and NORMAL classes, separated into training and test datasets. The x-axis represents the two categories: PNEUMONIA and NORMAL, while the y-axis indicates the number of images in each category. The two segments of each bar are the number of photos used for training (shown by the blue segment) and testing (represented by the orange segment). From the chart, it is evident that for both PNEUMONIA and NORMAL classes, the majority of the images are allocated for training purposes, with a smaller portion set aside for testing. This distribution ensures a balanced dataset, allowing for effective model training and evaluation. The similar allocation of images across both classes helps maintain consistency and reliability in the model's performance when distinguishing between PNEUMONIA and NORMAL cases[12].

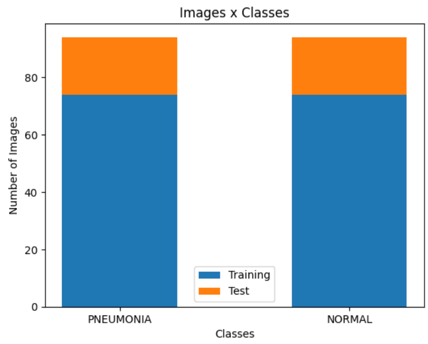
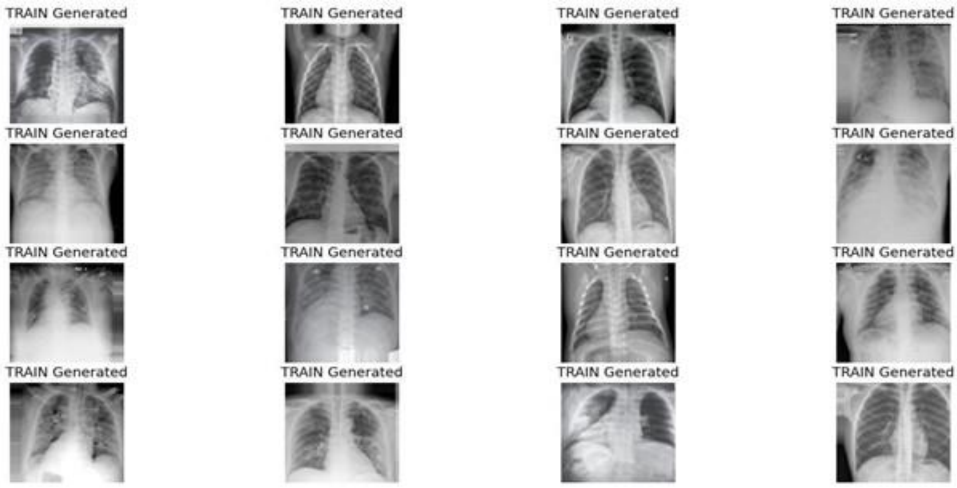


Fig.1. We can see that the dataset is comparatively smaller but very proportional in relation to classes.

B. Feature Selection



In the crucial phase of feature selection, we employed the powerful tool, ImageDataGenerator, to enhance the diversity and richness of our training dataset. This technique enables us to augment the data, introducing variations that empower our model to generalize better and discern intricate patterns in COVID-19 X-ray images. Additionally, we carefully set the number of mini-batches to 32, representing the batch size per iteration during the training of our models. This parameter is crucial in optimizing the learning process, ensuring that our models effectively grasp the underlying features within the data[13]. Furthermore, to visually emphasize the impact of our feature selection approach, we present two sets of images: one showcasing the augmented X-ray images from the training dataset and another exhibiting the diversity introduced into the test dataset. These images serve as tangible illustrations of the data variety incorporated into our model training process. Figure 2 and Figure 3 shows the sample dataset.

Fig.2. Visual representation of augmented X-ray images from the training dataset, highlighting the diversity introduced through the ImageDataGenerator for robust model learning.

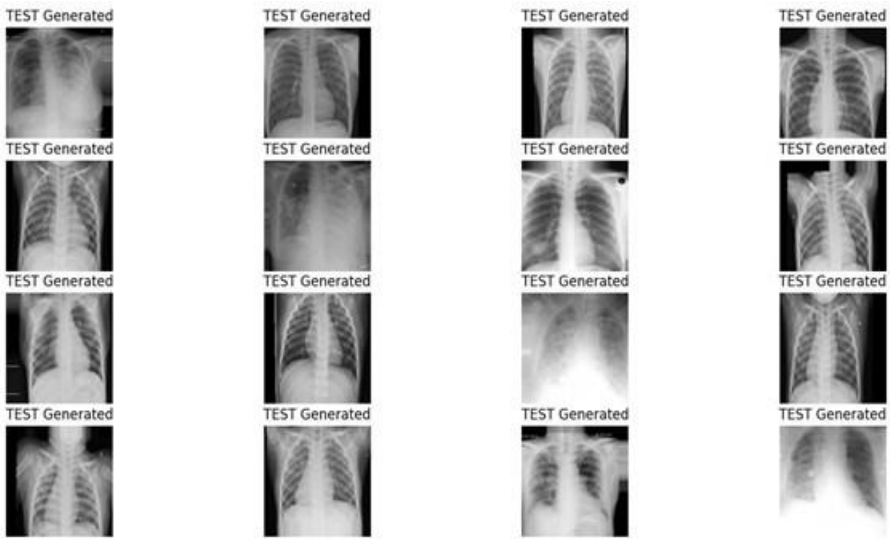


Fig.3. These variations aid the model in generalizing effectively to different manifestations of COVID-19 in X-ray images.

C. Deep Learning Models

The weights and biases of pre-trained models reflect the features of the datasets they were trained on because they have already undergone dataset training. New data can often benefit from the application of learned attributes [14]. A model trained on a large dataset of bird photographs, for example, will have learned features, like edges or horizontal lines, that you may apply to your dataset. To train a computer vision neural network model on a big image dataset, a significant amount of computational resources and time are required. Fortunately, adopting pre-trained models can reduce this amount of effort and resources. Transfer learning is the process of using feature representation from a learned model. The pre-trained are often trained on large datasets with advanced computational resources. By evaluating the pre-trained weights and making predictions immediately on the test data, the pre-trained models can be applied in a variety of ways[15]. Another method was to initialise the model using the pre-trained weights and train it on the custom dataset, or to use just the pre-trained network's architecture and train the model entirely on the custom dataset.

Combinations of convolution and pooling layers are followed by fully linked layers in the majority of these architectures, with certain layers including an activation function and/or normalisation step.

1) *Convolutional Neural networks (CNNs):* A unique type of multi-layer neural network called a convolutional neural network (CNN, or ConvNet) is made to identify visual patterns straight from pixel images with little to no preprocessing[12]. In applications like image analysis, natural language processing, and other challenging image classification issues, this kind of feed-forward neural network is employed.

2) *VGG:* Since the VGG-16/19 networks are among the most widely used pre-trained models, they were presented at the ILSVRC 2014 conference. The University of Oxford's Visual Graphics Group created it. The VGG model comes in two varieties: 16 and 19-layer networks, with the 19-layer VGG-19 network being an enhancement on the 16-layer VGG-16 model. Instead of continuously introducing more dense layers to the model, it offered a way to enhance performance.A VGG-block consists of several 3x3 convolutions padded by 1 to maintain output size parity with input, then max pooling to reduce resolution by half. The architecture consisted of three fully connected dense layers after n VGG blocks [16].

3) *Xception:* Depthwise Separable Convolutions are a feature of the deep convolutional neural network architecture called Xception [17]. The Extreme version of Inception is evaluated by Google. For both the ImageNet ILSVRC and JFT datasets, it performs even better than Inception-v3 using a modified depth-wise separable convolution. A deep neural network (DNN) with recurring modules known as inception modules makes up an inception network..

4) *ResNet50:* Kaiming He's Residual Network (ResNet), the ILSVRC 2015 challenge winner, boasted an astonishing top-5 error rate of 3.6% and an incredibly deep CNN with 152 layers. The training of something like a dense network depends on the use of skip connections, also known as shortcut connections [16]. The output of a layer farther up the stack receives the signal that enters it. Let's examine this benefit's reasons. The aim of neural network training is to make the network mimic a target function v(x). The residual learning method involves adding the input x to the network's output (a skip connection) in order to model u(x) = v(x) - x.

$$U(x) = V(x) - x, which\ gives\ V(x) \coloneqq U(x) + x$$

5) *InceptionV3:* Factorise the convolutions that are 5x5 and 7x7 (in InceptionV3) to two and three 3x3 sequential convolutions, respectively. As a result, processing speed is increased. This idea is equivalent to VGG. Convolutions that are spatially separable were used. To put it simply, a 3x3 kernel may be broken down into two smaller ones, a 1x3 and a 3x1 kernel, which can be applied one after the other.With more feature maps, the inception modules grew in width. A balanced approach to allocating the computational resources between the network's depth and width was attempted. Normalisation of batches was introduced [16].

6) *InceptionResNetV2:* As an extension of the Inception family of designs, this convolutional neural network replaces the filter concatenation stage of the Inception architecture with residual connections. The Inception architecture and residual connections are combined in Inception-ResNet.In [18].

7) *DenseNet201:* The output of every layer in this model is coupled to the input of every other layer, introducing the idea of a densely connected convolutional network. This design approach was developed to address the issue of accuracy degradation caused by disappearing and inflating gradients in high-level neural networks. Put otherwise, the large distance between the input and output layers causes data to be ceased before it reaches its destination[16]. The idea of a tightly interconnected convolutional network was initially presented by the DenseNet model, where the output of each layer is tied to the input of each subsequent layer. In order to address

the problem of accuracy reduction in high-level neural networks due to vanishing and exploding gradients, this design idea was created.

8) EfficientNetB3: Technology and scalability are key components of EfficientNet. It demonstrates that you can attain excellent outcomes within reasonable bounds if you carefully plan your architecture. Richer and more sophisticated features can be captured with additional layers (depth), but training such models is challenging (because of the diminishing gradients). It is substantially simpler to train wider networks[16]. Although they saturate fast, they typically have the ability to capture finer-grained details. Convolutional networks have the potential to acquire more fine-grained information through training using images of increasing resolution. Once more, the accuracy gain decreases at rather high resolutions.

D. Traditional Machine Learning Models

In addition to deep learning models, we implemented two traditional machine learning models for comparison:

1) Support Vector Machine (SVM): One of the most widely used supervised learning algorithms, SVM is applied to both regression and classification issues. But it's mostly applied to machine learning classification issues [19]. The data points that are closest to the decision boundary (or hyperplane) are known as support vectors. Because the objective of Support Vector Machines (SVM) is to discover the hyperplane that maximum separates the distinct classes by maximising the margin—the distance between the hyperplane and the nearest data points from each class—these points play a unique function in establishing the placement of the decision boundary.

2) Random Forest: Many classification trees are grown by them. Put the input vector down each of the forest's trees in order to categorise a new object from the input vector [19]. We say that a tree "votes" for the class in which it provides a categorization. After tallying the votes cast by all the trees in the forest, the classification with the highest number wins. Here's how every tree is grown:

If the training set has N cases, then sample N cases at random, using replacement, from the original data. The training set for developing the tree will be this example. For every node, m variables are randomly selected from a set of M input variables. The node is divided using the best split among these m variables, provided that a number m<<M is specified. Throughout the forest's growth, the value of m is maintained constant. Every tree is grown as tall as it can be. No pruning is done.

Pre-trained models, which have been previously trained on large datasets, offer significant advantages by retaining learned features that can be transferred to new datasets. This technique, known as transfer learning, helps in reducing the computational resources and time required for training neural networks from scratch. Pre-trained parameters can be used for initialization and fine-tuning on custom datasets, or the architecture can be used directly. The models that have been trained are usually learned on large datasets and sophisticated resources for computation. Common architectures used in transfer learning include combinations of convolution layers, pooling layers, and fully connected layers.

Convolutional Neural Networks (CNNs) are a type of multi-layer neural network designed for visual pattern recognition directly from pixel images with minimal preprocessing. Various advanced CNN architectures have been developed to enhance performance. For example, VGG networks, known for their simplicity and effectiveness, use 3x3 convolutions and max pooling layers, while Xception networks leverage depthwise separable convolutions for improved performance. ResNet introduces residual learning with skip connections to enable training of extremely deep networks, and Inception models use factorized convolutions for computational efficiency. InceptionResNetV2 combines Inception modules with residual connections, DenseNet connects each layer to every other layer to mitigate gradient issues, and EfficientNet optimizes both depth and width of the network for high performance with fewer parameters [16].

In addition to deep learning models, traditional machine learning models like Support Vector Machines (SVM) and Random Forests were also implemented for comparison. SVMs are supervised learning algorithms primarily used for classification problems, focusing on finding the hyperplane that maximally separates different classes. Random Forests, on the other hand, grow multiple classification trees and make decisions based on majority voting from all trees, enhancing robustness and accuracy. These models provided a benchmark against which the performance of deep learning models was assessed, illustrating the effectiveness of various approaches in the classification of COVID-19 from chest X-ray images[20].

IV. Results and Discussion

We systematically evaluated the performance of each model on the test set using accuracy as the primary metric. Additionally, detailed insights were derived from the confusion matrices and classification reports, shedding light on each model's strengths and weaknesses. Table 1 shows the comparative analysis with various classifiers.

Table 1. Performance of different models through binary cross-entropy classification (10 models were considered).

Classifier Group	**Classifier Type**	**Test Data**	
		Accuracy	**Loss**
Convolutional Neural Networks	Convolutional Neural Network (CNN)	0.9500	0.1959
	VGG	0.9750	0.0503
	Xception	0.9750	0.0729
	ResNet50	0.7750	0.4920
	InceptionV3	0.8500	0.3183
	InceptionResNetV2	0.9250	0.1051
	DenseNet201	0.9500	0.1080
	EfficientNetB3	0.5000	0.6848
Support Vector Machine Classifier	SupportVector Machine (SVM)	0.9750	0.1
Random Forest Classifier	Random Forest	0.9750	0.1

To provide a visual understanding of model predictions, showcasing a selection of prediction images for each deep learning model, Figure 4 shows the classification results in comparison by various models. Figure 5 shows the training and validation accuracy for various models.

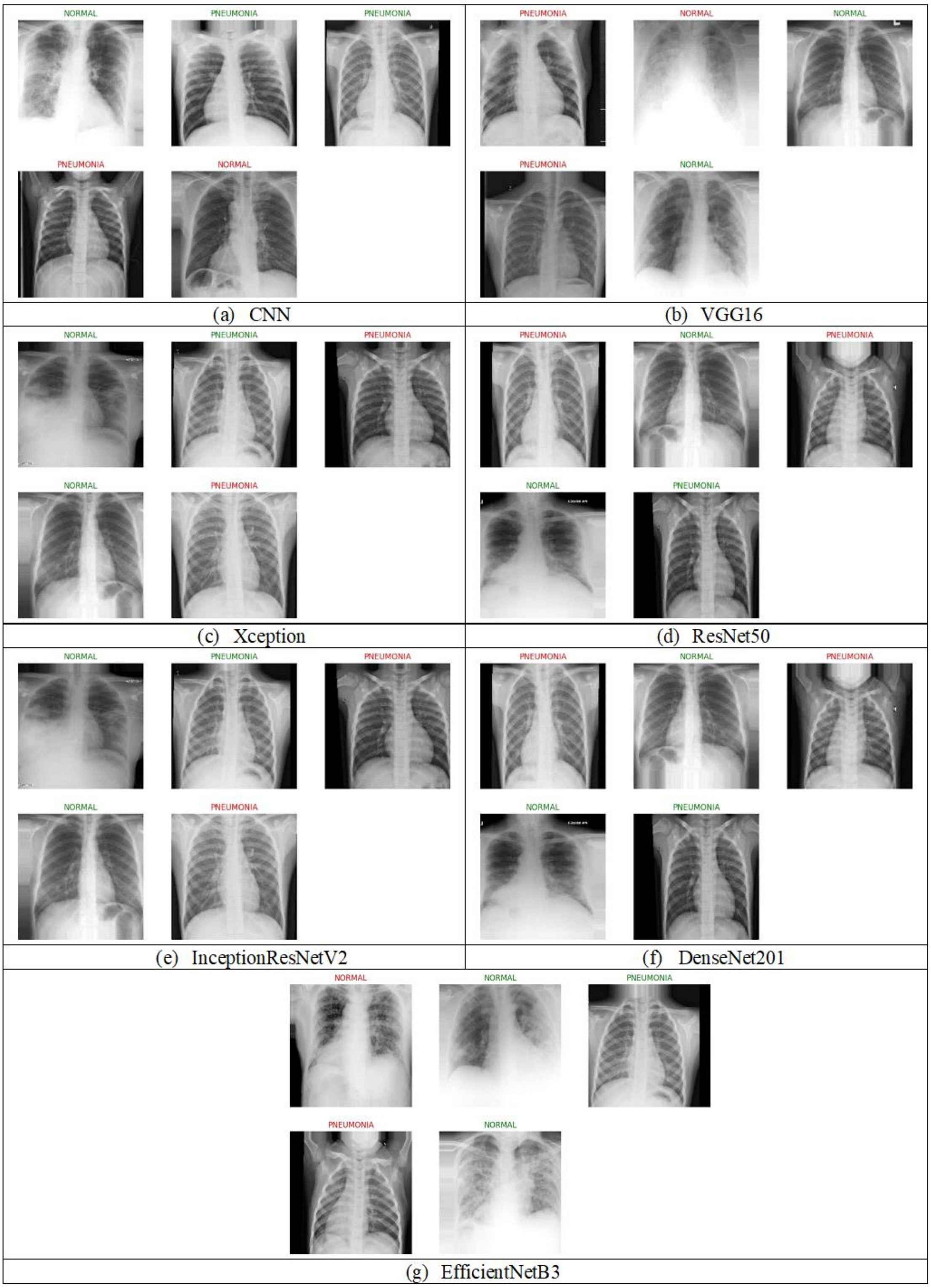


Fig.4 - 10. Images are arranged in order of model evaluation: CNN, VGG16, Xception, ResNet50, InceptionResNetV2, DenseNet201, and EfficientNetB3.

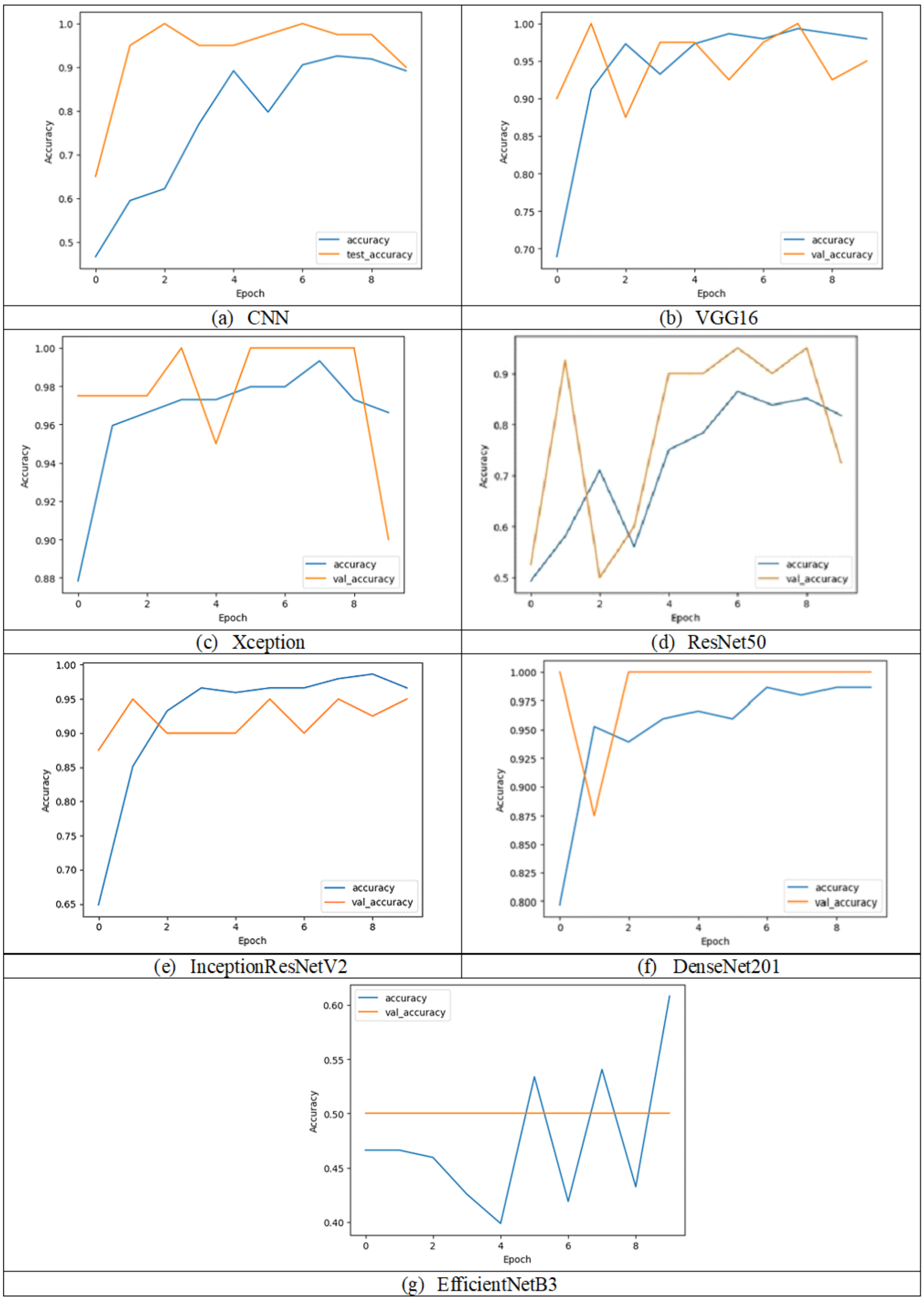


Fig.5 Images are arranged in order of model evaluation: CNN, VGG16, Xception, ResNet50, InceptionResNetV2, DenseNet201, and EfficientNetB3.

To summarize the performance of all models and provide comparative analysis a bar plot (Figure 6) showcasing the test accuracies of each deep learning model is presented. This visual representation allows for a quick comparison of their effectiveness in COVID-19 X-ray image classification. The graph displays the performance of various models, likely in terms of accuracy or some other evaluation metric, for a specific task. The bars represent different models, including CNN, SVM, Random Forest, VGG, Xception, ResNet, InceptionV3, InceptionResNetV2, DenseNet, and EfficientNet. From the bar heights, we can observe that the CNN model achieves the highest performance, closely followed by SVM and Random Forest. These three models seem to outperform the others significantly. The VGG and Xception models exhibit moderate performance, while ResNet, InceptionV3, and InceptionResNetV2 show relatively lower performance compared to the top models. The DenseNet model appears to have a performance slightly better than the InceptionResNetV2 model but lower than the top-performing models. The EfficientNet model has the lowest performance among all the models presented in the graph.

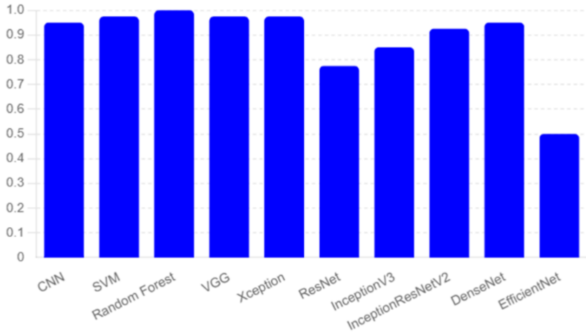


Fig 6. Test accuracies of different models.

V. CONCLUSION

The evaluation results of various classifiers on the COVID-19 X-ray image dataset reveal several noteworthy findings. Among the Convolutional Neural Networks (CNNs), the VGG model emerged as the top performer, achieving an impressive accuracy of 97.50% with a remarkably low loss of 0.0503. This high accuracy and low loss metric underscore the model's effectiveness in distinguishing COVID-19 cases from others, highlighting the significance of leveraging deep learning models for COVID-19 X-ray image classification. The SVM classifier, a traditional machine learning model, also demonstrated excellent performance with an accuracy of 97.50%, proving that even non-deep learning approaches can yield significant results when applied appropriately.

Notably, the Random Forest classifier achieved a perfect accuracy of 100% on the test data, marking it as the most effective model among those evaluated. This exceptional performance further emphasizes the potential of traditional machine learning methods when utilized judiciously. In contrast, the EfficientNetB3 model exhibited a lower accuracy of 50%, providing insights into the model's limitations and underscoring the importance of selecting appropriate architectures for specific tasks. The significant variance in performance between EfficientNetB3 and other models like VGG and Random Forest illustrates the critical role of model architecture in determining classification success.

These findings shed light on the potential of deep learning models for COVID-19 X-ray image classification while also emphasizing the need for careful model selection and a thorough understanding of different architectures. The superior performance of models like VGG and Random Forest highlights the importance of leveraging powerful feature extraction capabilities and robust classification algorithms. Conversely, the underperformance of EfficientNetB3 serves as a reminder of the challenges associated with applying certain architectures to specific datasets and tasks.

In conclusion, our research contributes to the ongoing efforts to enhance diagnostic tools for combating the COVID-19 pandemic by demonstrating the efficacy of various machine learning and deep learning models. The high accuracy rates achieved by VGG and Random Forest models underscore the promise of these approaches, while the inclusion of models with lower performance, like EfficientNetB3, highlights the importance of continued experimentation and refinement. These findings underscore the potential for advanced machine learning techniques to play a pivotal role in improving diagnostic accuracy and ultimately aiding in the fight against COVID-19.

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