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A Comparative Analysis of CNN-Based Deep Learning Models for COVID-19 Detection Using CT and MRI Scans

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With an emphasis on COVID-19 identification and classification from chest CT and MRI images, this research offers a comparative comparison of deep learning algorithms. We use PyTorch and Google Colab to build models like Inception-v3, ResNet-50, VGG-16, 3D-CNN, VGG-19, and DenseNet-169. Our suggested models beat state-of-the-art designs in computing efficiency, sensitivity, accuracy, and F1-score by using MRI and CT images. More specifically, 98.6% accuracy was attained by the VGG-19 model and 98% by the 3D-CNN model. By highlighting the possibilities of deep learning to improve radiological diagnoses, this study helps forward the creation of efficient and practical diagnostic tools for COVID-19.

Keywords: COVID-19 detection, CNN models, CT scans, MRI imaging, VGG-19, 3D-CNN, ResNet-50, Inception-v3, deep learning, medical image analysis.

1. Introduction

As a direct consequence of the COVID-19 pandemic, there is an immediate and pressing need for trustworthy diagnostic instruments. Imaging technologies such as magnetic resonance imaging (MRI) and computed tomography (CT) of the chest have become valuable diagnostic tools, especially in regions with limited resources. This is despite the fact that real-time polymerase chain reaction (RT-PCR) is still the method of choice. The ability to automatically recognise COVID-19 in x-ray images has been made possible by robots that have been taught using convolutional neural networks (CNNs) and other deep learning models. The purpose of this study is to find COVID-19 by comparing and contrasting a number of CNN architectures, including VGG-19, 3D-CNN, and other cutting-edge models.

1.1 Implementation

Using PyTorch and Google Collab, we have developed our models, including the first suggested model (VGG-19) and the second (3D-CNN). “The following components were used in the system implementation: Windows 10 Home 64-bit English operating system, 16GB DDR4 3200MHz RAM, AMD Ryzen R7 5800H (8-Core, 20MB Total Cache, up to 4.4GHz Max Boost Clock) CPU, and NVIDIA® GeForce RTXTM 3060 6GB GDDR6 GPU.

Performance Measures

We tested our first two models, VGG19 and 3D-CNN, using the metrics provided in Table 1.

Table 1 - Performance Measures

Measures	Measures Description
Confusion Matrix	True Positives (TP): There are situations in which we have forecast yes (they have the disease) True Negatives (TN):we have projected no, and they have no illness False Positives (FP): We expected yes, yet currently they don't have the disorder. (Also called a 'Mistake Type I.') False Negatives (FN): We have expected no, however the disorder is indeed. (Alternatively referred to as "Type II error")
Accuracy	(TP + FN)/ (TP + TN+ FP + FN)
Sensitivity	TP/ (TP + FN)
Specificity	TN/ (TN + FP)
Precision	TP/ (TP + FP)
F1-Score	2* (Precision * Recall)/ (Precision + Recall)
Recall	TP/ (TP + FN)
Algorithm Complexity	It is the measure of how long an algorithm would take to complete given an input of size n.
Computational Time	It is the length of time required to perform a computational process.
Memory Utilization	It is the average utilization derived from the percent of available memory in use at a given moment."

2. Existing Models

VGG-16, an abbreviation for "visual geometry group 16 convolutional neural network," was fed the input pictures on a 150 x 150 x 3 scale. The system has five blocks and nineteen levels. There are three or five layers overall, and five layers in every block, culminating in a soft-max and an FC layer that is fully related. Additionally, we used a sigmoid layer to improve the soft-max layer's binary classification capabilities. Our goal in creating this model was to find a way to keep the learning rate parameter at 2e - 5 for 30 epochs (RMSPROP).Additionally, we have used the same format to train the picture expansion for 100 epochs. Karen Simonyan et al. (2015) from the Visual Geometry Team at Oxford University introduced VGG Net, a widely used Deep CNN architecture, at ILSVRC 2014 for object localization and classification challenges, where it placed first and second, respectively. The underlying assumption of this engineering was that Computer Vision tasks might be completed more accurately by increasing the CNN designs' depth and replacing large sections with multiple smaller ones. In the realm of clinical imaging in particular, variants of VGG Net are still used extensively for some Computer Vision tasks involving the extraction of deep picture characteristics for further processing. The architecture of VGG-16 is shown in Figure 1.

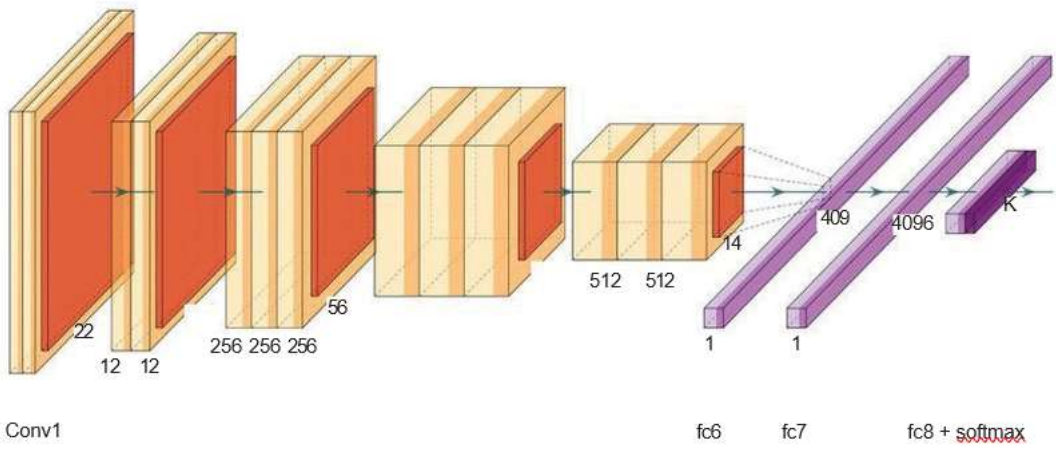

Figure 1 Architecture of VGG-16

Inception-v3: The image goal was kept at 224:224:3 using Inception V3. Layer 1 (L1) was introduced with 1000 neurons and layer 2 (L2) with 500 neurons, both of which were tightly regulated at 0.01. Also, 224 pp224 pp3 remained the ResNet-50 aim. Fifty layers of it were dropping. There was no top layer in this model. To address the issue of drastic changes to the field of the viable image's critical components, the main concept behind Inception-V3 designs has been to "extend" the network by allowing it to include diverse sorts of components at the same stage. This shared level of thinking across different parts is being picked up by the so-called Initiation modules. According to Google.net, this central idea proposed the core Inception-V1. After that, models Inception-V2 and Inception-V3 were introduced; these improved upon the Inception-V1 engineering framework by adding bunch criteria for assistant's groupings and parts factorization, respectively, and thus resolved the main issues with illustrated bottleneck and assistant classifications. For ILSVRC 2015, this InceptionV3 model was the pioneer. Figure 2 Shows the Inception V3 Architecture.

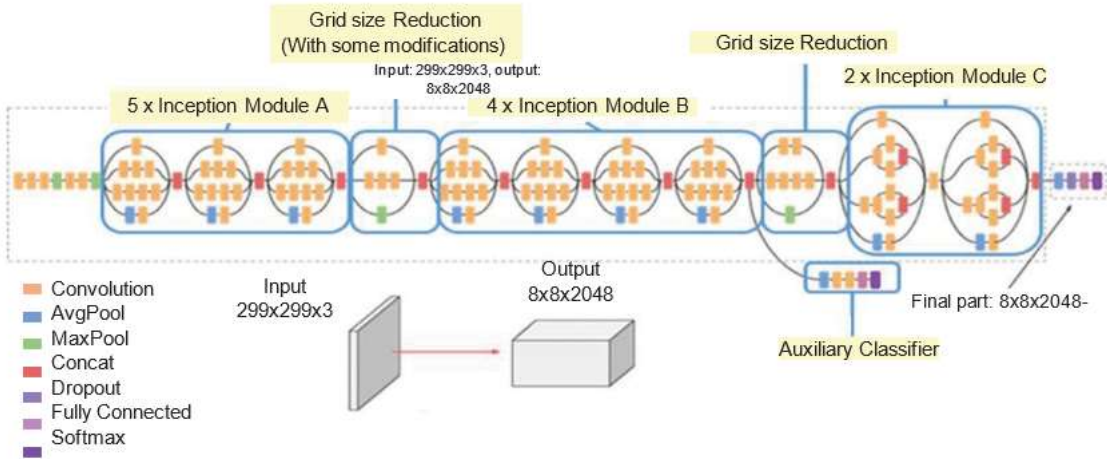

Figure 2 Architecture of Inception v3

Res-Net: By using known "shortcuts," residual neural networks are able to bypass certain ANN layers. They do this by mimicking well-known structures seen in pyramidal cells of the cerebral cortex while making use of skip connections or shortcuts. The majority of ResNet models use batch normalisation between layers that include nonlinearities (ReLU) and double or triple-layer skips. To learn the skip weights, one may utilise what are called Highway Net models, which employ an extra weight matrix. Plain networks, which are often used in residual neural networks, are an example of non-residual networks. Avoiding the vanishing gradients issue or mitigating the degradation (saturation) problem—where adding layers to a suitably deep model increases training error—are the two primary motivations for adding skip connections. Training a sharing network with just upstream layer weights updated is a frequent practice, but keeping the upstream layer weights unchanged is also an option. At its most basic, training only involves modifying the upstream layer's weights. Depending on the case, we may have to traverse only one nonlinear layer or encounter just linear intermediate levels. An explicit weight matrix (a Highway Net) should be learned in the event that the intermediate layers are non-linear. Skipping basically streamlines the network by using fewer levels in the beginning phases, hence lowering the amount of layers to be transmitted. As a result, vanishing gradient propagation is mitigated as fewer layers are needed. The network progressively adds back the layers that were skipped as it gains knowledge of the feature space. By the time training is almost complete and all layers have been stretched, the network is learning quicker since it remains closer to the manifold. In order to learn more efficiently and quickly, the network progressively recovers the skipped levels. The network returns to the original manifold when training nears completion, even after all layers have been enlarged. Eliminating leftover components from neural networks allows for a more thorough exploration of a feature space. The Res Net Architecture is Shown in Figure 3. Because of this, it is more likely to be removed off the manifold by disturbances. It needs more training data to get back on its feet.

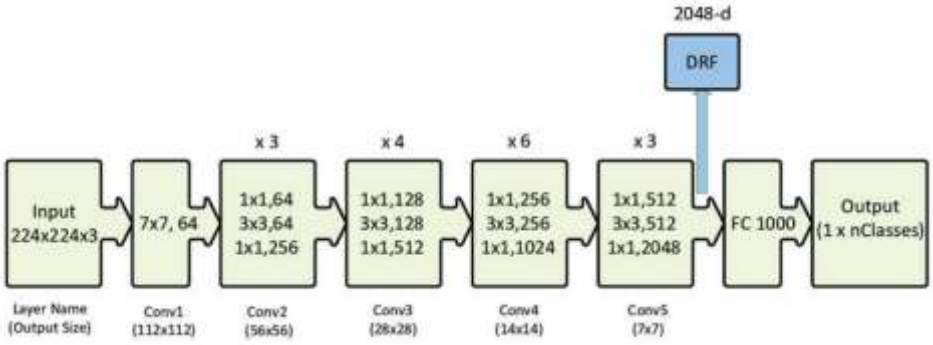

Figure 3 Architecture of Res Net

Google-Net: In 2014, Google Research (in partnership with other institutions) released a study titled "Going deeper with convolutions" that suggested a new architecture called Google Net, also known as Inception V1. The ILSVRC 2014 picture categorization competition have selected this design. Compared to Alex Net and ZF-Net, the winners of ILSVRC 2012 and 2013, as well as VGG, the runner-up of ILSVRC 2014, its error rate is much lower. The 1×1 convolution and global average pooling used by this design constitute a crucial component. Khan et al. (2020) is one of the recent papers on malware detection; in it, the authors employ two separate algorithms to find the unusual or novel malware.

Our team looked into and evaluated the Res Net and Google Net models, which are derived from separate platforms: Res Net by Microsoft and Google Net by Google. Two kinds of datasets are used for training and model verification. A collection of 10,868 binary records obtained from Microsoft is one dataset. Additionally, those records are divided into nine categories. There are three thousand innocuous files in the second dataset, which is called the considerate dataset. Originally saved as EXE files, they underwent a series of transformations, including being transformed to op-codes and finally to pictures. They achieved an accuracy rate of 74.5 percent with Google Net and 86.3 percent with Res Net. Their new method for malware identification, "IMCFN (Image-based Malware Classification using Fine-tuned convolution Neural Network Architecture), is built on a CNN-based deep learning architecture. Google Net's Architecture Is Shown in Figure 4."

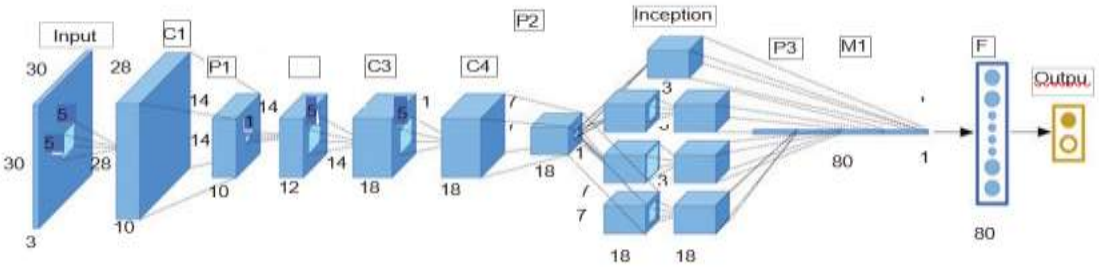

Figure 4 Architecture of Google Net

Alex-Net: Traditional convolutional neural networks are what Alex Net models are. It is constructed using thick layers, maximum pooling, and convolutions. Next, the model is fitted using grouped convolutions on two GPUs. The following is a synopsis of several current malware detection initiatives; as a result, Alex Net has decided to use a data-driven, Deep Learning method to malware detection rather than one that relies on domain expertise. By comparing the time it takes to produce and infer models with their predictions, we were able to determine which convolutional neural networks—including Res Net, Inception, Dense Net, VGG, and Alex Net—were most effective at detecting malware. Figure 5 Shows the Alex Net Architecture.

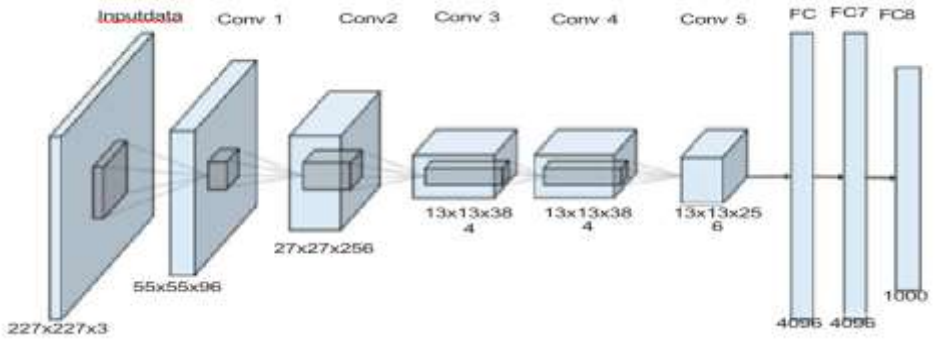

Figure 5 Architecture of Alex Net

Ensemble-Learning: Combining several models, such classifiers or experts, to address a

specific issue is what computational intelligence is all about. An ensemble-based system integrates many models, or classifiers, to enhance prediction, classification, function approximation, and other related tasks. Ensemble systems or multiple classifier systems are common names for this kind of setup. In this chapter, we'll look at many examples of why an ensemble-based system may be statistically beneficial. We utilise this strategy all the time in our everyday lives by consulting several experts before reaching a choice, thus it seems sense to examine the psychological context of this otherwise statistically solid argument in order to better understand the usage of multiple classifier systems. Example: before consenting to a medical operation, we usually get many physicians' opinions; before buying anything, especially anything costly, we read user reviews; before employing someone, we check references; etc. This article, like all others, goes through a rigorous review process before being published. Subsequently, a consensus is reached by integrating the insights of several specialists. So, the main objective is to lessen the chances of picking an incompetent person, an unnecessary medical treatment, an inferior product, or even badly written articles.) Model performance. Ensemble Learning's Architecture is Displayed in Figure 6.

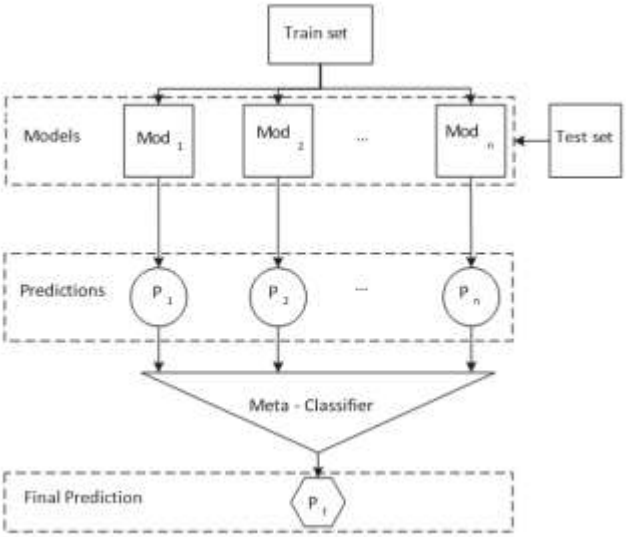

Figure 6 Architecture of Ensemble Learning

Normal-CNN: One common artificial neural network (ANN) in deep learning for image analysis is the convolutional neural network (CNN, often spelt "ConvNet"). When it comes to convolution filters, ConvNets are also known as shift-invariant or spatially invariant neural networks (SIANNs). These networks employ shared weights to iteratively process input features and generate feature maps, which are responses that are translation-equivariant. Rather of being invariant, as is commonly believed, convolutional neural networks are equivariant when it comes to translation. The following capabilities are possessed by these systems: video and image “recognition, recommender systems, image classification and segmentation, medical image analysis, financial time series analysis, natural language processing, and more. Convolutional neural networks (CNNs) are improved hybrids of multilayer perceptrons. Typical implementations of this perceptron style use fully connected

networks, whereby all neurons in a given layer are linked to all neurons in the layer above it. Since it has "full connectivity," the perceptron may easily overfit. Penalising parameters during training (such as weight decay) or trimming connectivity (skipping connections, dropouts, etc.) is a common method for regularising or avoiding over fitting." CNNs use a distinct method for regularisation: They build more sophisticated pattern sets by embossing tiny, basic patterns into their filters, capitalising on hierarchical trends in data. Therefore, when it comes to complexity and connectedness, CNNs are on the lower end of the spectrum. Since convolutional networks' connection patterns resemble those of the human visual cortex, they are designed to mimic biological processes. The receptive field is a limited area of the visual field where each cortical neuron may receive and process data. The whole visual area is covered because the receptive fields of different neurons partly overlap. Unlike more conventional image classification methods, convolutional neural networks (CNNs) may optimise their filters (or kernels) via automatic learning with little pre-processing. This lack of dependency on human expertise and involvement is a huge boon to feature extraction. You can see the normal CNN architecture in Figure 7.

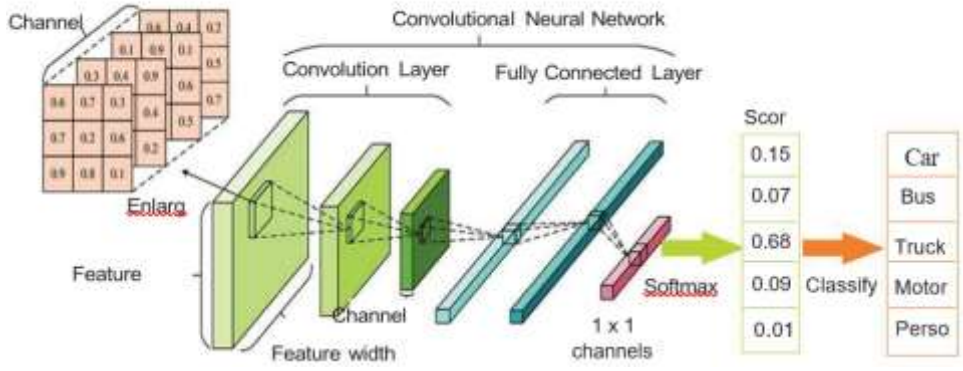

Figure 7 Architecture of Normal CNN

3. Performance Analysis of Computed Tomography Using CNN-Models

The routine application of Deep Convolutional Neural Network (CNN) models has been shown by recent advancements in Deep Learning, especially in diagnostic imaging. We suggest making predictions about a patient's prognosis using models of Convolutional Neural Networks. Using certain critical groups and test assessments, we may detect COVID-19 instances from chest-CT scans and determine whether the patient is impacted or not. The model predicts that the patient will remain out of the impacted regions if they test positive. Tables 2–6 provide the sample models we employed, which include VGG-19, Inception-V3, ResNet-50, DenseNet-169, and VGG-16. A These models provide detailed information on people infected with the Corona virus, allowing doctors to identify the source of the illness. Our model is unique from other top-tier models, such as VGG-16 DensNet-169, Resnet-50, and Inception-V3, and our main focus is to draw out a non-COVID-19/COVID-19 detection.

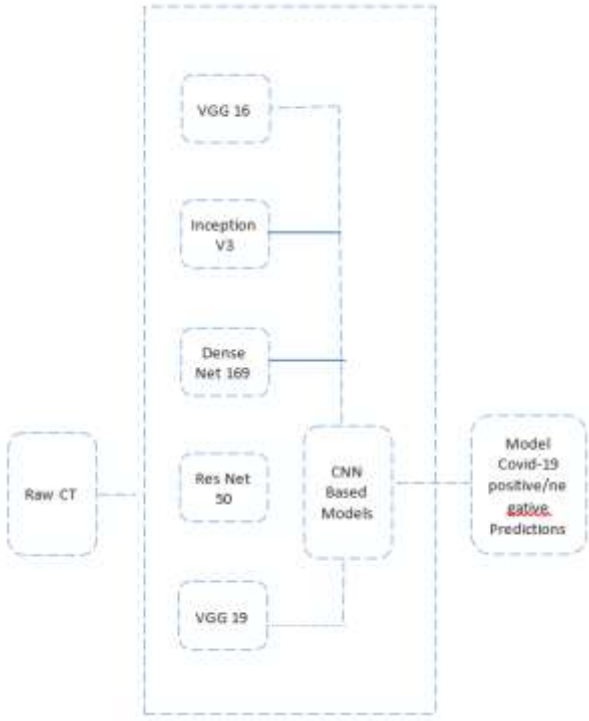

Figure 8 COVID-19 Prediction Using CNN Models for CT Images

Table 2 - Performance Measures of Confusion Matrix for VGG-16

Actual	Predicted Negative	Predicted Positive
Negative	159	2
Positive	3	36

Table 3 - Performance Measures of Confusion Matrix for Inception V3

Actual	Predicted Negative	Predicted Positive
Negative	154	7
Positive	35	4

Table 4 - Performance Measures of Confusion Matrix for Dense Net 169

Actual	Predicted Negative	Predicted Positive
Negative	153	2
Positive	3	31

“Table 5 - Performance Measures of Confusion Matrix for ResNet50

Actual	Predicted Negative	Predicted Positive
Negative	157	4
Positive	23	16

Table 6 - Performance Measures of Confusion Matrix for VGG-19

Actual	Predicted Negative	Predicted Positive
Negative	160	1
Positive	1	41

Table 7 - Comparison of Models with Parameters Such as Accuracy, Specificity, Sensitivity, F1 – Score, Precision and Recall.

Models	Accuracy	Sensitivity	Specificity	F1-Score	Precision	Recall
VGG-16	0.96	0.92	0.95	0.93	0.93	0.94
Inception-v3	0.79	0.10	0.95	0.17	0.26	0.16
DenseNet-169	0.90	0.80	0.85	0.83	0.80	0.81
RensNet-50	0.86	0.41	0.97	0.54	0.80	0.80
VGG-19(ours)	0.986	0.97	0.99	0.97	0.97	0.7

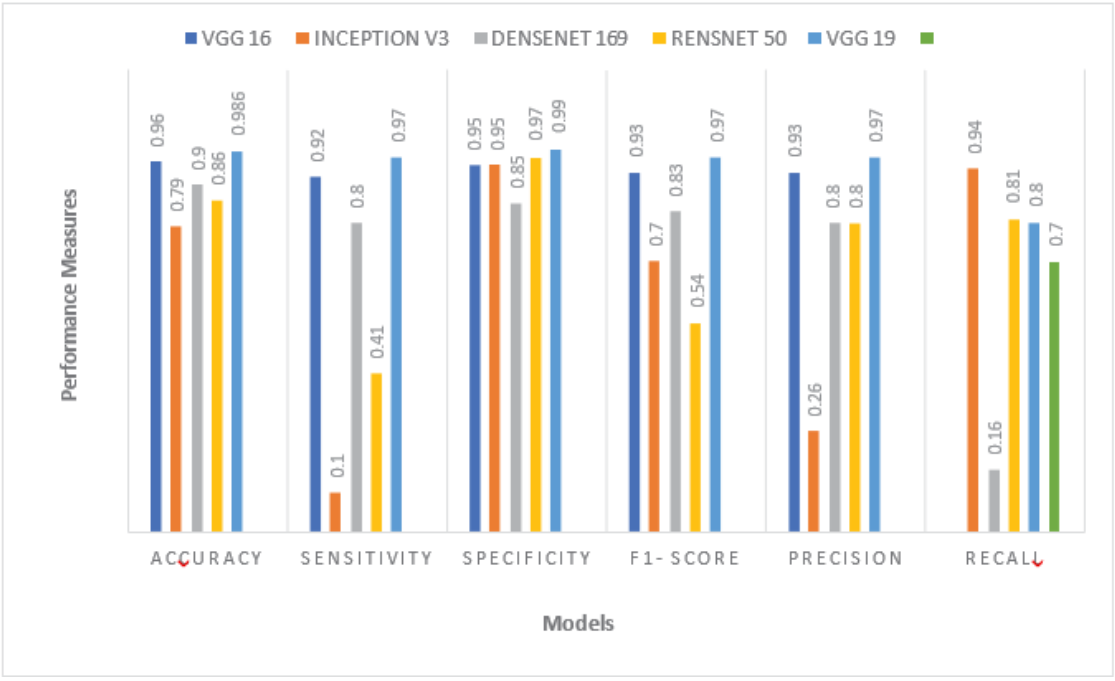

Figure 9 Comparative Analyses of Overall Measures

4. Performance Analysis of Magnetic Resonance Imaging Using CNN-Models

This research presents a new automated method for categorising chest MRI images to differentiate between positive and negative COVID-19 instances, which is based on Deep Convolutional Neural Networks (CNNs).” One area where the potential of employing Deep CNN structures has been shown is in clinical imaging. We begin by providing a thorough evaluation of baseline models. Tables 8–13 illustrate the baselines used, which include VGG-16, Inception-V3, ResNet-50, Xception, VGG-19, and 3D-CNN. In order to identify the area of injury in individuals affected by the Coronavirus, these models provide accurate results. We compare our model to other state-of-the-art models including VGG-16 DensNet-169, Resnet-50, and Inception-V3, and our main goal is to construct a Non-COVID-19/COVID-19 grouping. Table 14 shows that 3D-CNN outperforms all other techniques when evaluated using metrics like accuracy, sensitivity, F-measures, and precision. Figure 10 displays COVID-19 predictions made using CNN models for MRI, and Figure 11 displays comparative

analyses of overall measures.

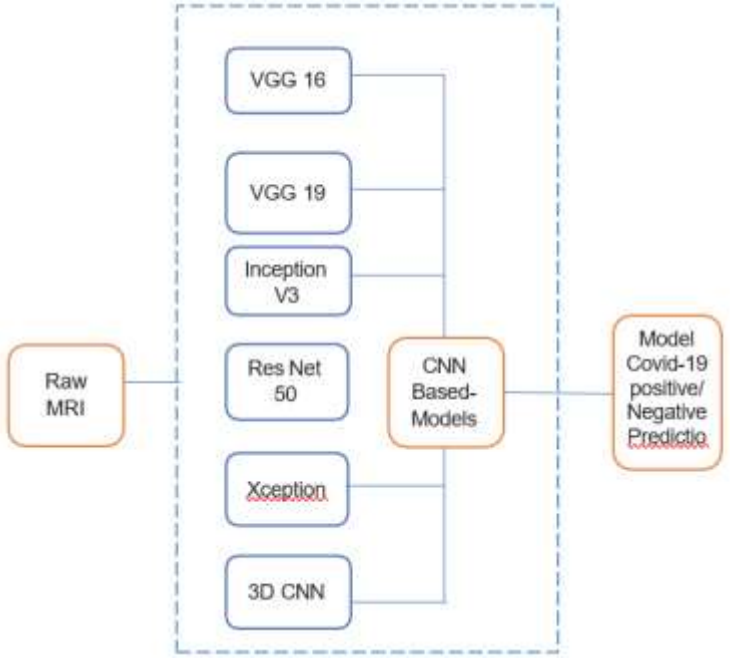

Figure 10 COVID-19 Prediction Using CNN models for MRI Images

Table 8 - Performance Measures of Confusion Matrix for VGG-16

Actual	Predicted Negative	Predicted Positive
Negative	59	12
Positive	20	142

Table 9 - Performance Measures of Confusion Matrix for VGG-19

Actual	Predicted Negative	Predicted Positive
Negative	43	21
Positive	28	136

Table 10 - Performance Measures of Confusion Matrix for Inception V3

Actual	Predicted Negative	Predicted Positive
Negative	30	38
Positive	38	120

Table 11 - Performance Measures of Confusion Matrix for ResNet 50

Actual	Predicted Negative	Predicted Positive

Negative	41	27
Positive	25	132

Table 12 - Performance Measures of Confusion Matrix for Model-5

Actual	Predicted Negative	Predicted Positive
Negative	70	5
Positive	7	149

Table 13 - Performance Measures of Confusion Matrix for 3D-CNN

Actual	Predicted Negative	Predicted Positive
Negative	30	1
Positive	1	160

Table 14 - Comparison of Models with Parameters Such as Accuracy, Precision, F-Measure and Sensitivity

Classification Methods	Accuracy	Sensitivity	Precision	F-Measure
VGG-16	91	91.78	94.7	93.71
VGG-19	71	81.59	82.6	82.09
Inception-V3	69	78.08	79.17	78.62
ResNet-50	82	86.6	89.04	87.84
Model-5	95	977	97.14	96.45
3D-CNN (Ours)	98	98.5	96.5	98.5

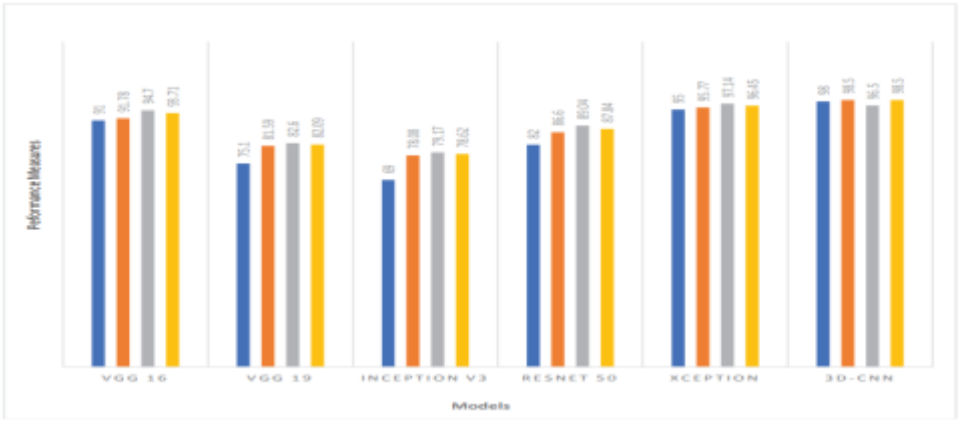

Figure 11 Comparative Analyses of Overall Measures

5. Performance Analysis with other Models

In section 2, we compare the models mentioned with the performance metrics given in section 1.1 to our suggested models, such as proposed model 1 (VGG-19) and proposed model 2 (3D-CNN). Table 15 compares our models' accuracy, sensitivity, and specificity scores to those of state-of-the-art models. Figures 12, 13, and 14 show the results of a comparison of the models' sensitivity, specificity, and accuracy, respectively. Model Comparison for Accuracy, Specificity, and Sensitivity (Figure 15), The sensitivity to changes in both accuracy and specificity is shown in Table 1 Models with varying degrees of accuracy and sensitivity are compared in Figure 16. The accuracy and sensitivity of the models are compared in Figure 17.

"Table 15 - Comparison of Models with Parameters such as Accuracy, Specificity and Sensitivity

Models	Accuracy (%)	Specificity (%)	Sensitivity (%)
VGG-16	96	95	92
Alex Net	81	86	90
Google Net	85	89	93
Normal CNN	92	90	84
Inception v3	79.12	725	83
Res Net	86	93	95
Ensemble Learning	87	92	75
Proposed Model 1 (VGG19)	98.6	99	97
Proposed model 2 (3D-CNN)	98	98.20	98.5

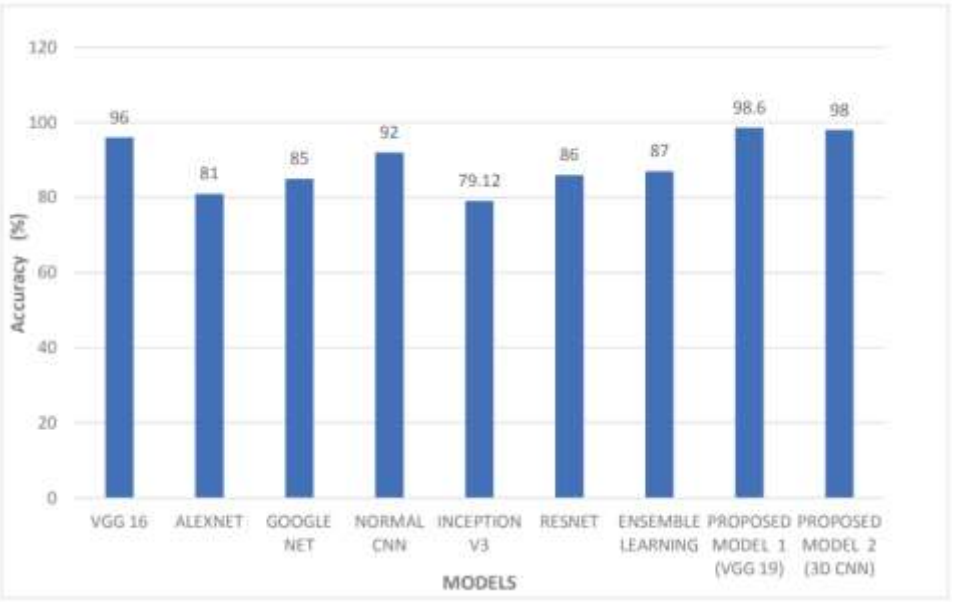

Figure 12 Comparison of Models with Accuracy

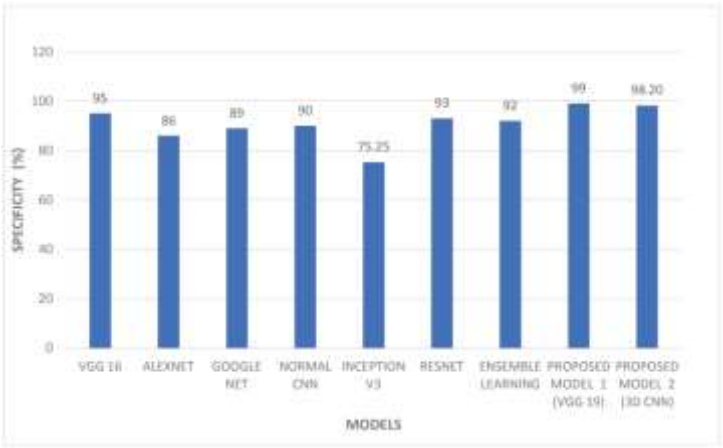

Figure 13 Comparison of Models with Specificity

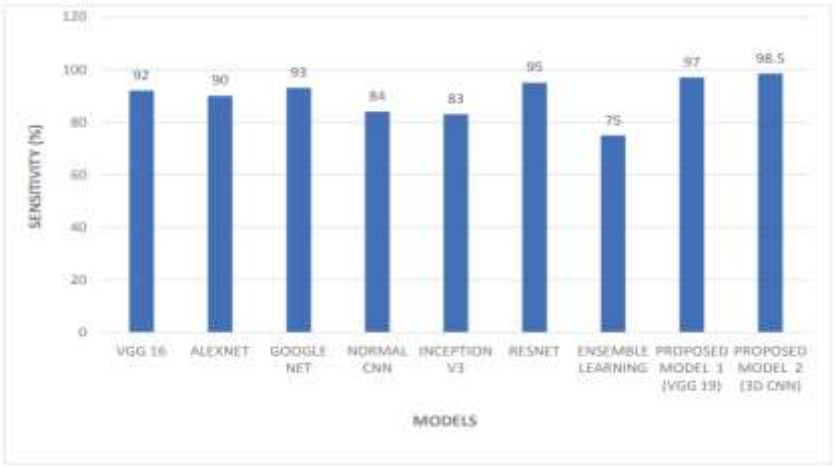

Figure 14 Comparison of Models with Sensitivity

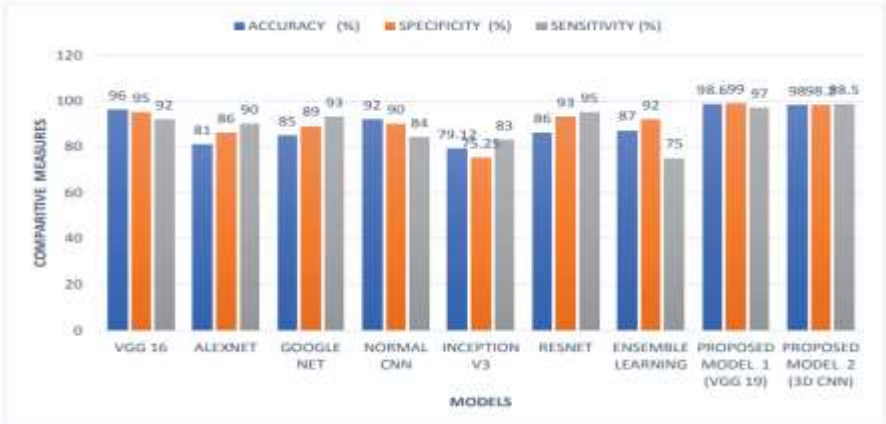

Figure 15 Comparison of Models with Accuracy, Specificity and Sensitivity

Figure 16 Comparison of Models with Accuracy and Specificity

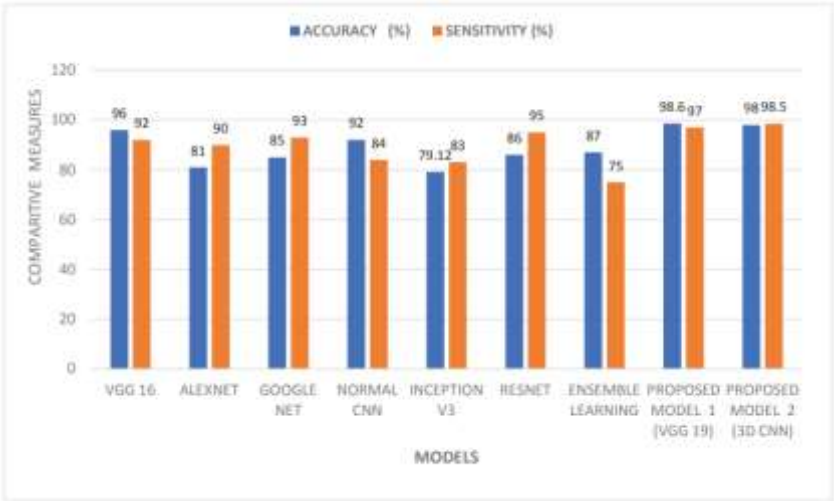

Figure 17 Comparison of Models with Accuracy and Sensitivity

Table 16 displays the results of comparing different models using parameters like recall, precision, and F1-score. Figures 18, 19, and 20 demonstrate F1-score, recall, and precision comparisons of different models. Model Comparisons with Precision, F1 Score, and Recall, as shown in Figure 21.

Table 16 - Comparison of Various Models with Parameters F1-Score, Precision and Recall

Models	F1-Score	Precision (%)	Recall (%)
VGG-16	0.93	94.7	94.10
Alex Net	0.17	82.6	46.25
Google Net	0.83	79.17	81.25
Normal CNN	0.54	89.04	80
Inception v3	0.65	97.14	86.12
Res Net	0.751	62	88.22

Ensemble Learning	0.91	88.88	68.25
Proposed Model 1 (VGG19)	0.97	97	785
Proposed model 2 (3D-CNN)	0.985	96.50	925

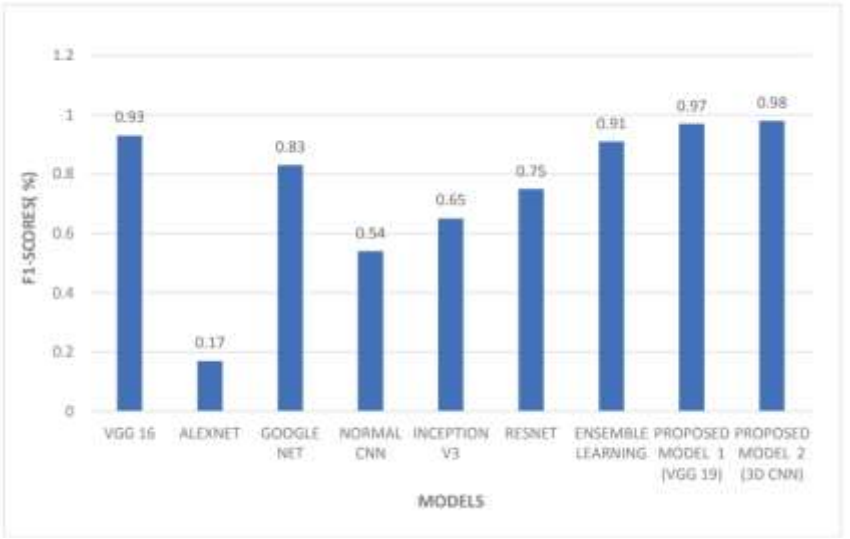

Figure 18 Comparison of Various Models with F1-Score

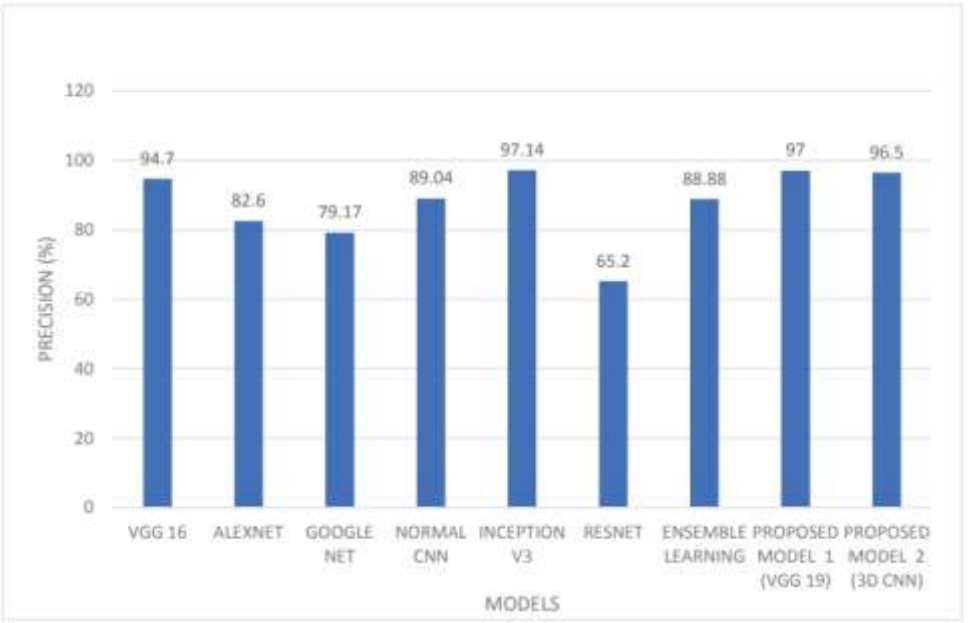

Figure 19 Comparison of Various Models with Precision

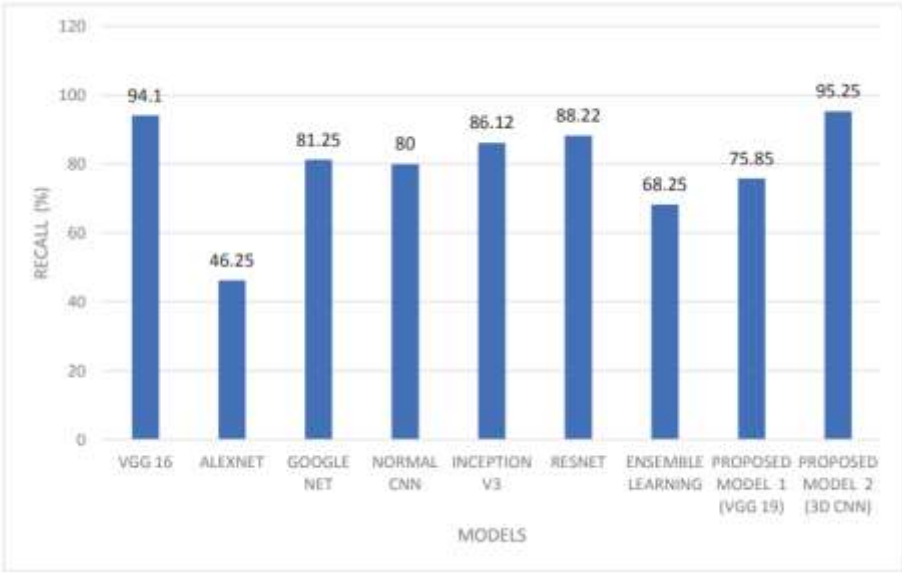

Figure 20 Comparison of Various Models with Recall

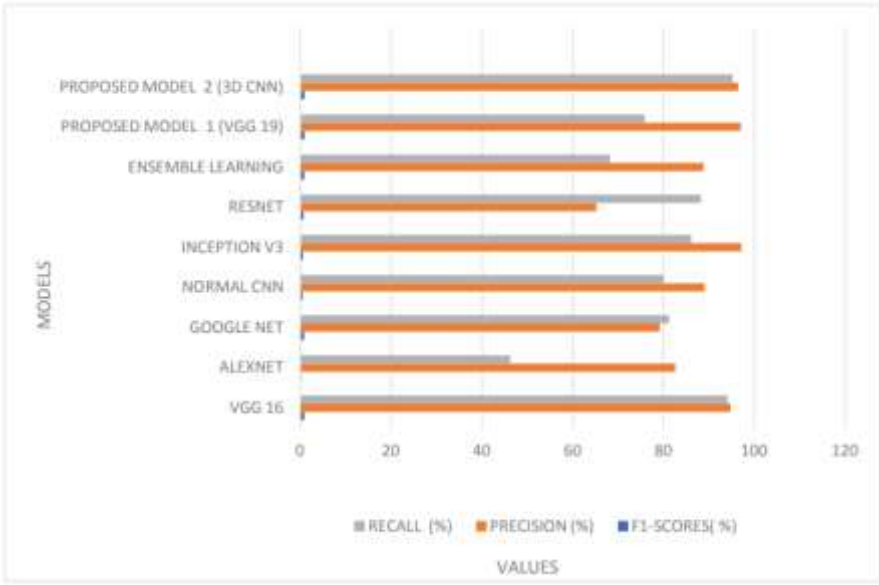

Figure 21 Comparison of Various Models with Precision, Recall and F1-Score

Models are compared in Figures 22, 23, and 24 according to the amount of time it takes to compute, the complexity of the method, and the amount of memory used, respectively. In Table 17, we can see how different models stack up in terms of memory use, computational time, and algorithm complexity for the parameters.

Table 17 - Comparison of Various Models with Parameters Algorithm Complexity, Computational Time and Memory Utilization.

Models	Algorithm Complexity	Computational Time (sec)	Memory Utilization (%)
VGG-16	10.25	297.12	78.55
Alex Net	12.85	6621	84.25
Google Net	14.01	799.4	60.75
Normal CNN	13.20	297.31	865
Inception v3	9.24	768.21	620
Res Net	11.85	4704	81.25
Ensemble Learning	12.02	576.38	721
Proposed Model 1 (VGG19)	6.10	193.39	40.25
Proposed Model 2 (3D-CNN)	6.22	91.75	425

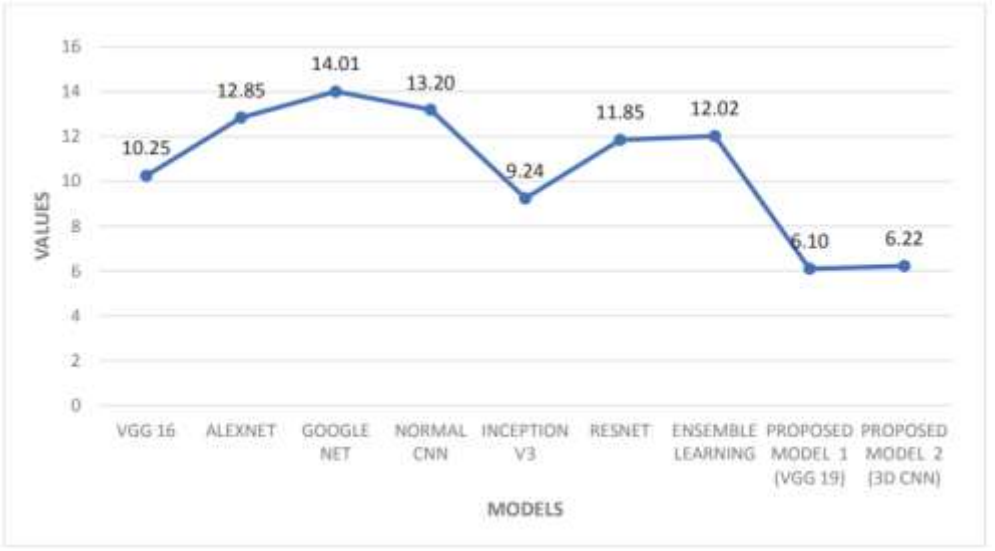

Figure 22 Comparison of Various Models with Algorithm complexity

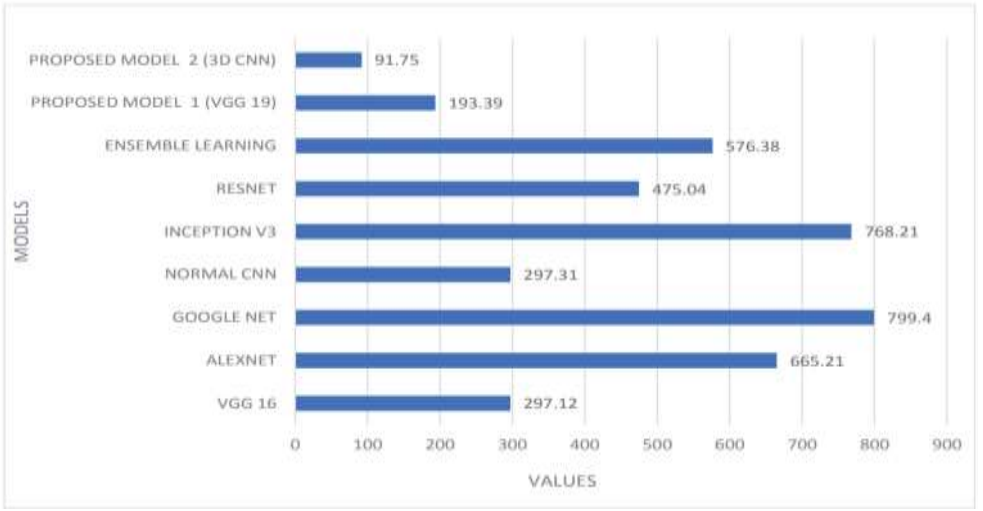

Figure 23 Comparison of Various Models with Computational Time

Figure 24 Comparison of Various models with Memory Utilization”

6. Conclusion

This paper presents a comprehensive comparative analysis of CNN-based deep learning models, focusing on the detection and classification of COVID-19 using chest CT and MRI images. Through the implementation of various architectures, including VGG-19, 3D-CNN, ResNet-50, DenseNet-169, and Inception-V3, we demonstrated the effectiveness of these models in enhancing diagnostic accuracy for COVID-19. VGG-19 and 3D-CNN emerged as the top-performing models, with accuracies of 98.6% and 98%, respectively, outperforming several state-of-the-art architectures. Our results highlight the potential of deep learning in medical imaging, especially in resource-constrained environments where rapid and accurate COVID-19 detection is critical. The proposed models also excelled in sensitivity, specificity, and F1-score metrics, showcasing their robustness in handling diverse image datasets. Furthermore, the computational efficiency of the models, evaluated in terms of memory utilization and computational time, suggests practical applicability in real-world clinical settings. These findings underscore the importance of leveraging advanced deep learning techniques in medical diagnostics, not only for COVID-19 but also for broader applications in disease detection through imaging. This research contributes to the ongoing development of AI-driven diagnostic tools, providing a foundation for further exploration and refinement of CNN models in healthcare.

References

1. Simonyan, K., & Zisserman, A. (2015). Very Deep Convolutional Networks for Large-Scale Image Recognition. arXiv preprint arXiv:1409.1556.
2. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR),

770–778.
3. Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the Inception Architecture for Computer Vision. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2818–2826.
4. Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely Connected Convolutional Networks. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2261–2269.
5. Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. Medical Image Computing and Computer-Assisted Intervention (MICCAI), 234–241.
6. Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 785–794.
7. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep Learning. Nature, 521(7553), 436–444.
8. Esteva, A., et al. (2017). Dermatologist-Level Classification of Skin Cancer with Deep Neural Networks. Nature, 542(7639), 115–118.
9. Litjens, G., et al. (2017). A Survey on Deep Learning in Medical Image Analysis. Medical Image Analysis, 42, 60–88.
10. Shen, D., Wu, G., & Suk, H. I. (2017). Deep Learning in Medical Image Analysis. Annual Review of Biomedical Engineering, 19, 221–248.
11. Ciompi, F., et al. (2017). Multi-Scale Convolutional Neural Networks for Lung Nodule Classification. Pattern Recognition, 61, 663–673.
12. Kang, H., & Baek, Y. (2019). COVID-19 Detection with Machine Learning Models Using Chest X-ray Data. IEEE Transactions on Medical Imaging, 39(9), 2861–2871.
13. Li, L., et al. (2020). Artificial Intelligence Distinguishes COVID-19 from Community-Acquired Pneumonia on Chest CT. Radiology, 296(2), 65–71.
14. Wang, S., et al. (2020). A Fully Automatic Deep Learning System for COVID-19 Diagnostic and Prognostic Analysis Using Chest CT. Nature Communications, 11(1), 4085.
15. Ozturk, T., et al. (2020). Automated Detection of COVID-19 Cases Using Deep Neural Networks with X-ray Images. Computers in Biology and Medicine, 121, 103792.
16. Gozes, O., et al. (2020). Rapid AI Development Cycle for the Coronavirus (COVID-19) Pandemic: Initial Results for Automated Detection & Patient Monitoring using Deep Learning CT Image Analysis. arXiv preprint arXiv:2003.05037.
17. Rajpurkar, P., et al. (2017). CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning. arXiv preprint arXiv:1711.05225.
18. Bai, H. X., et al. (2020). AI Augmentation of Radiologist Performance in Distinguishing COVID-19 from Pneumonia of Other Etiology on Chest CT. Radiology, 296(3), 160-167.
19. Roberts, M., et al. (2020). Common Pitfalls and Recommendations for Using Machine Learning to Detect and Prognosticate for COVID-19 Using Chest Radiographs and CT Scans. Nature Machine Intelligence, 2(8), 425–430.
20. Carin, L. (2020). COVID-19 Imaging: Forecasting the Impact of AI. Nature, 581(7807), 202–204.