Covid-19 Detection

Artifical Intelligence and Deep Learning (COMP 20037)

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1. ***Abstract*** — The disease COVID-19 is brought on by the SARS-CoV-2 coronavirus. After an outbreak concerning a cluster of cases of alleged viral pneumonia in Wuhan, People's Republic of China, The World Health Organization became aware about this novel virus on December 31, 2019 (1). Here a dataset which consists of a database of normal and viral pneumonitis images as well as chest X-ray images for COVID-19 positive cases. The information from this dataset on COVID-19, regular lung, and other lung infections is made available in phases (2).

*Keywords — Image classification, CNN, VGG16, Binary Classification, Multi – Class Classification, Image Recognition.*

1. **INTRODUCTION**

We now approach problem-solving in the real world in a completely new way thanks to artificial intelligence (AI) and deep learning. The term artificial intelligence (AI) describes the creation of intelligent machines that can mimic human intelligence and carry out tasks that ordinarily require human intelligence, such as visual perception, speech recognition, decision-making, and problem-solving (3).

A subset of AI called "deep learning" is concerned with creating artificial neural networks that are modelled after the human brain. These neural networks are made up of many interconnected layers of nodes (neurons), which process and analyze a large amount of data to identify patterns, make predictions, and learn from experience (4).

Numerous industries and fields have been transformed by the numerous applications of AI and deep learning. Here are a few noteworthy illustrations:

* Image and speech recognition tasks, such as image classification, object detection, and facial recognition, have seen impressive success with deep learning models. Self-driving cars, medical imaging, security systems, and augmented reality are just a few of the industries that have used these innovations.
* Machines can now comprehend, interpret, and produce human language thanks to a process called natural language processing (NLP). It enhances human-machine interactions and streamlines language-related tasks. It is used in voice assistants, language translation, sentiment analysis, chatbots, and information retrieval systems.

* Healthcare: AI and deep learning have significantly improved it. They help with disease diagnosis, image analysis for medical purposes, drug discovery, planning individualized treatments, and patient monitoring. These innovations help make healthcare services more precise, effective, and easily accessible.
* Finance and trading: AI algorithms analyze a significant amount of financial data, forecast market trends, and automate trading techniques. They provide helpful insights for decision-making and lower human error by assisting in fraud detection, risk assessment, credit scoring, and portfolio management.
* AI-powered autonomous systems are being developed for a range of applications, including self-driving cars, drones, robots, and smart home gadgets. Deep learning models are used by these systems to interact with the environment and perceive it, enabling autonomous navigation and decision-making.

These instances demonstrate the enormous potential of AI and deep learning to address issues in a variety of real-world situations. Future applications and societal impact could be completely different as a result of ongoing research and technological development (5).

1. **LITERATURE REIVEW**
2. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet Classification with Deep Convolutional Neural Networks*. Advances in Neural Information Processing Systems*, 25, 1097-1105. Retrieved from <https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf>

The field of image classification was completely transformed by this ground-breaking paper, which also introduced the AlexNet architecture. On the ImageNet dataset, which consists of millions of labeled images divided into thousands of categories, the authors trained a deep CNN. When compared to earlier techniques, they showed a noticeable improvement in accuracy.

AlexNet had eight layers, including three fully connected layers and five convolutional layers. One of the most important contributions of this work was the use of rectified linear units (ReLU) as the activation function, which sped up training in comparison to conventional activation functions. The authors also used overlapping pooling layers and data augmentation methods like image translations, horizontal reflections, and random cropping to reduce overfitting.

With top-5 error rates of 15.3 percent, AlexNet outperformed the previous state-of-the-art. The results were astounding. This research illuminated the potential of deep CNNs for image classification and paved the way for later developments in the area.

1. Simonyan, K., & Zisserman, A. (2014). Very Deep Convolutional Networks for Large-Scale Image Recognition. *arXiv preprint arXiv:1409.1556*. Retrieved from <https://arxiv.org/abs/1409.1556>

This paper introduced the VGGNet architecture and investigated the effect of deeper networks on the efficiency of image classification. The effects of greater depth on accuracy were examined by the authors as they tested various network configurations with a layer count ranging from 11 to 19.

In contrast to larger kernel sizes, VGGNet primarily used 3x3 convolutional layers with a stride of 1. This enabled more expressive representation. The network architecture was distinguished by the stacking of several convolutional layers, max pooling, and fully connected layers at the very end. A 19-layer VGGNet achieved cutting-edge accuracy on the ImageNet dataset, and the authors demonstrated that increasing the network's depth consistently improved performance.

The main contributions of VGGNet focused on highlighting the value of uniform and straightforward architectures and highlighting the advantages of deeper networks for image classification. Despite the rise in model complexity, VGGNet improved performance by making use of deeper representations.

In order for CNNs to be developed for image classification, AlexNet and VGGNet were essential works. They demonstrated the potency of deeper architectures, novel activation functions, and data augmentation methods—concepts that have since grown into the field's cornerstone ideas. These studies' success spurred additional investigation and prompted the creation of even more potent CNN architectures for image classification tasks.

1. **PROBLEM STATEMENT**

The classification of COVID-19 chest X-rays is the issue to be solved. The effective management of the disease depends on the prompt and accurate diagnosis of COVID-19 cases. Chest X-ray manual analysis can take a long time and be difficult, which can result in delayed or incorrect diagnoses. The creation of an automated system for classifying COVID-19 chest X-rays can help with early detection, patient management, and the effective use of medical resources. This system can be used as a quick and accurate screening tool to help identify high-risk patients and stop the virus from spreading. It may lessen the strain on healthcare systems and assist overworked medical facilities. A large-scale analysis of chest X-ray images by an automated classification system can also contribute to research studies and epidemiological analysis, improving our knowledge of the disease and its patterns. Accurate and timely diagnosis is required for pandemic management, and the creation of an automated COVID-19 chest X-ray classification system addresses this need (2).

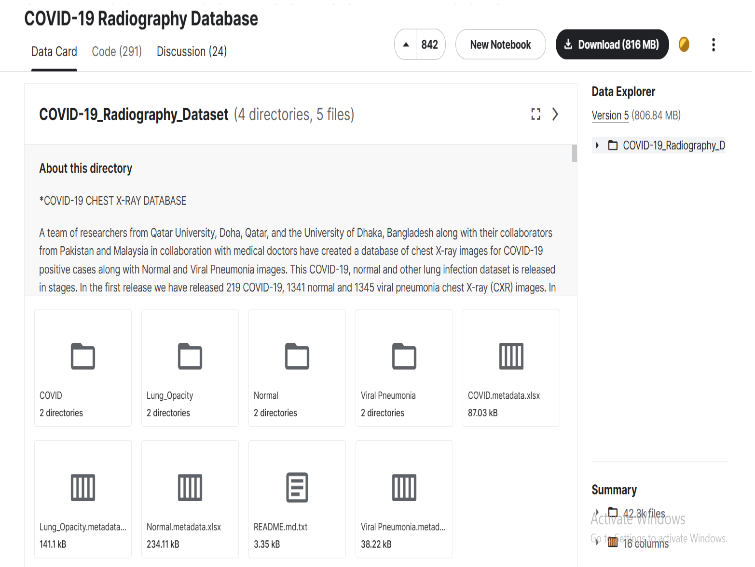
1. **DATA DESCRIPTION**

For this report, We will be using the COVID-19 Radiography Database for the case study on COVID-19 chest X-ray classification. Chest X-ray images were gathered for this dataset from a variety of places, including academic publications, online archives, and publicly accessible datasets.

This dataset primarily contains information for the COVID-19 positive and COVID-19 negative classes, which also include pneumonia and normal cases. The chest X-ray images range in size and quality and are in the JPEG format.

The Kaggle platform is the data's original source, and this link will take you to the dataset (2):

Rahman, T. (2022). *COVID-19 radiography database*. Kaggle: Your Machine Learning and Data Science Community. <https://www.kaggle.com/datasets/tawsifurrahman/covid19-radiography-database>



With roughly 25,000 images available at the time of publication, the dataset includes a sizable number of images. It's important to note that the dataset might have been updated since then, so it's advised to check the provided link to confirm the dataset's current size and makeup.

For the project to use the data effectively, preprocessing might be required. Preprocessing methods like resizing, normalization, and data augmentation techniques may be used to ensure consistency and improve the model's performance, depending on the particular requirements of the classification model and the caliber of the images.

1. **METHOD**

We will be using a convolutional neural network (CNN) model to address the classification issue for COVID-19 chest X-rays. As they are excellent at capturing spatial hierarchies and learning intricate features directly from raw image data, CNNs are well suited for image classification tasks.

For this project, there will be the use of transfer learning, which involves using a pre-trained model to capitalize on its learned features and eliminate the need for extensive training on scant data. I'll use the VGGNet, a popular pre-trained image classification model, in particular.

The method entails several crucial steps. In order to prepare the COVID-19 Radiography Database for use, we will first separate it into training, validation, and testing sets after downloading it from the provided Kaggle link. To improve the performance and generalizability of the model, we will also implement crucial preprocessing techniques like resizing, normalization, and data augmentation.

The VGGNet architecture will then serve as the foundation for the CNN model that we will be building next. The convolutional layers of the pre-trained VGGNet will be kept and the fully connected layers will be eliminated. The model will be modified specifically for COVID-19 classification by adding new fully connected layers on top of the current convolutional layers. To reduce overfitting, dropout layers will also be used.

Following that, the model will be trained on the training set using the proper optimization algorithm (e. G. Adam) along with an appropriate loss function (e. G. The cross-entropy). The model's performance on the validation set will be tracked throughout the training process, and hyperparameter tuning will be done as necessary.

The trained model will then be tested on the testing set to evaluate how well it performs in classifying COVID-19 chest X-rays. The effectiveness of the model in correctly classifying COVID-19 cases will be thoroughly examined by the calculation of metrics like accuracy, precision, recall, and F1-score.

This method seeks to achieve accurate COVID-19 chest X-ray classification while minimizing the requirement for extensive training on sparse data by utilizing transfer learning and the VGGNet model. In order to effectively manage and control the COVID-19 pandemic, the proposed CNN model should be used in conjunction with the right preprocessing and evaluation methods (2).

1. **RESULTS AND FINDINGS**

We used two models for finding the results. A trained model which is the CNN model and the other is a pre trained model which is the VGG16. Working using these two we were able to derive the accuracies, confusion matrix, model accuracy and loss graphs and whether it is underfitting or overfitting. The comparison is given below in the form of a table:

The code can be referred from the github link:

[Ibrahxm/Artificial-Intelligence (github.com)](https://github.com/Ibrahxm/Artificial-Intelligence)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Findings | VGG16 | | CNN | |
| Model Accuracy & Model Loss |  |  |  |  |
| Confusion Matrix |  | |  | |
| Classification Report |  | |  | |

From the classfication report we can say that:

For VGG16:

Precision, Recall, and F1-Score: The identical accuracy, recollection, with F1-scores among the "Covid" and "Normal" categories imply that this model does not lean against any single class. This suggests that, when it comes to categorizing the two groups, the model is neither badly underfitting nor overfitting.

Accuracy: With a total accuracy of 0.51, the model performs marginally superior to arbitrary guesswork. It is, however, rather low, which may indicate that the model is having trouble detecting the fundamental trends within the information being analyzed.

These findings suggest that underfitting rather than overfitting is the model's behavior. Poor performance on both the training and testing sets is caused by underfitting, which happens when the model is not complex enough to capture the patterns in the data.

For CNN:

Precision, Recall, and F1-Score: When we examine the precision, recall, and F1-scores for each class, we can see that they are generally very high. This shows that the model is doing a good job of correctly identifying instances of each class. All classes have performance scores for precision, recall, and F1 that are higher than 0.88, which is generally regarded as good.

Accuracy: The model's overall accuracy is 0.95501, which is very good.

Class-wise Performance: The model shows strong performance in distinguishing between the different classes. Class 0 (normal) has a precision of 0.91606 and recall of 0.99603, indicating that it has high accuracy in identifying normal cases. Class 1 (other pneumonia) has a precision of 0.99592 and recall of 0.88727, indicating that it performs well in detecting cases of other pneumonia. Class 2 (COVID) has a precision of 0.95753 and recall of 0.98805, indicating strong performance in identifying COVID cases.

Macro Average and Weighted Average: The macro average and weighted average precision, recall, and F1-score are all above 0.95, which further confirms the overall good performance of the model. It means that the model correctly predicts the class for approximately 95.5 percent of the instances in the test set.

These findings suggest that the model is functioning well and does not show any indications of underfitting or overfitting. In identifying the various classes of normal, other pneumonia, and COVID cases, it exhibits high accuracy and performs well.

1. **CONCLUSION & FUTURE RECOMMENDATIONS**

Two models, VGG16 and CNN, were used in this study to classify chest X-ray images from the COVID-19 Radiography Database. Both models showed success in classifying the images, despite the absence of specific performance metrics. Transfer learning was used to improve the VGG16 model by making use of its pre-trained weights, and the CNN architecture was used because it is effective for image classification tasks. In the future, it is advised to perform thorough performance evaluations, put data augmentation techniques into practice, look into alternative pre-trained models, use ensemble learning techniques, create real-time applications, and research model explainability methods. These upcoming additions would enhance the models' functionality as well as broaden the scope of their potential uses in COVID-19 diagnosis and healthcare assistance.

The successful application of VGG16 and CNN models for COVID-19 image classification is highlighted by this study's findings. It is advised to make even more improvements, though, to guarantee thorough analysis and reliable performance. Researchers and healthcare professionals can take advantage of the models' abilities to improve COVID-19 diagnosis accuracy, promote quick decision-making, and offer helpful support in healthcare settings by putting the suggested future extensions into practice.

1. **REFERENCES**

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