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Data Science FINAL PROJECT REPORT

Project Title:

DETECTION OF COVID-19 FROM CHEST X-RAY IMAGES USING DEEP LEARNING & CNN

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DECLARATION STATEMENT

This report is submitted in partial fulfilment of the requirement for the degree of Master of Science in Data Science at the University of Hertfordshire.

I have read the guidance to students on academic integrity, misconduct and plagiarism information at Assessment Offences and Academic Misconduct and understand the University process of dealing with suspected cases of academic misconduct and the possible penalties, which could include failing the project module or course.

I certify that the work submitted is my own and that any material derived or quoted from published or unpublished work of other persons has been duly acknowledged. (Ref. UPR AS/C/6.1, section 7 and UPR AS/C/5, section 3.6). I have not used chatGPT, or any other generative AI tool, to write the report or code (other than where declared or referenced).

I did not use human participants or undertake a survey in my MSc Project.

I hereby give permission for the report to be made available on module websites provided the source is acknowledged.

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Abstract:

COVID-19 has made a name for itself as one of the worst virus outbreaks in history, with most of the world experiencing an outbreak of the virus. Even though numerous nations have already created various vaccines against this fatal virus, COVID-19 is still ravaging people worldwide on a regular basis, necessitating the development of more precise and quick tests everywhere. The main reasons for sign and symptom for Chest x-rays are more readily available and cost-effective than chest CT (computed tomography) scans for diagnosing viruses that cause lung infections like this one.

One of the most helpful areas of ML, Deep_Learning, can be helpful for quickly screening these x-ray images. Using the PA (posteroanterior) perspective of several individuals, both healthy and infected with COVID-19, I captured hundreds of chest x-ray pictures, adjusted them for clarity, and added data augmentation to them. After that, I tested and trained three separate CNN (convolutional neural network) models on these photos for COVID-19 and compared each model's accuracy separately. The three models are Google Net, ResNet50, and VGG19.

I used 282 chest x-ray pictures from the Kaggle repository for training and testing these models; 222 the photos were used to train and the remaining 60 for testing. According to the comparison's findings, VGG19 provided the best accuracy (i.e., 94.99%) among these three models. This work solely aims to verify several approaches for COVID-19 diagnosis; it makes no claims regarding medical accuracy or advocating replacing conventional testing methods with these alternative ways.

Keywords: machine learning, COVID19, Deep_Learning, and chestX-ray image

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Introduction:

Since COVID-19 was discovered in Wuhan, China in December 2019, nearly 3 million people have died from it. In 192 countries as of April 2021. COVID-19 is the worst virus to emerge in the twenty-first century, even though the death toll is far lower than that of other pandemics such as the Spanish Flu, Black Death, and Plague of Justinian. By April 2021, there are currently 13 vaccinations approved for use in the public worldwide; however, since many countries are dealing with the second wave of COVID-19, there is an even greater need than there was for the first wave of testing findings to be obtained quickly and accurately.

Viral RNA (ribonucleic acid) fragment tests are the usual diagnostic procedures, and while they can detect the virus itself, they are restricted in their ability to assess the duration of infectivity, especially with the number of deaths rising daily. CT scans are not advised for routine screening, although they will be helpful to quickly identifying covid_19 patients with a high number of symptoms. Furthermore, in certain regions of the world, the expense of RNA testing is so exorbitant that only those with severe symptoms think about getting checked out.

Several x-ray pictures of healthy people and COVID-19 sufferers were made public in repositories such as Kaggle and GitHub in March 2020 in reaction to the worldwide threat. As of right now, patients are just receiving necessary treatments for the afflicted organs because there is no specific COVID-19 treatment available. This intensifies the pandemic's severity even more. Few of the numerous medicines for this lethal virus that are presently in the preclinical stage may ever make it to the clinical trials. Other therapies, such hydroxychloroquine and lopinavir/ritonavir, initially showed encouraging outcomes in clinical studies but were ultimately determined to be either dangerous to patients or ineffective against the virus.

There is not a single indication that patients are benefiting from the experimental treatments, even though numerous studies are being conducted on a variety of early-stage therapies. Each person experiences this virus differently, but common symptoms include headaches, sore throats, fatigue, loss of taste and smell, and in severe cases, breathing difficulties. While many patients experience very minor or non-existent health problems, approximately 14% experience severe symptoms from this virus, and 5% experience life-threatening or critical symptoms. The fact that many virus carriers are asymptomatic individuals who are unaware they have the illness makes treating it even more difficult.

Most symptomatic people wait four to five days, or sometimes up to twelve days, for any symptoms to appear. This virus may be stopped in its tracks if affected individuals are isolated and the necessary actions are performed. Medical imaging plays a major role in the detection of this lethal virus as well. CT (computed tomography) scans and chest x-ray pictures can both rapidly identify a patient with COVID-19 infection. These photos of chest x-rays, which are available to the public, were collected from multiple repositories and analyzed using three different CNN (convolutional neural network) models: VGG19, ResNet50, and Google Net.

This work's primary goal is to validate various potential COVID19 detection techniques that may be useful in the real-world situation that exists now.

Background:

The outbreak of COVID-19 has prompted a significant amount of research into rapid and accurate diagnostic methods. Among these, chest X-ray imaging has become a key focus due to widespread availability and cost effective with compared to other modalities like CT scans. The ability of Convolutional Neural Networks (CNNs) to analyse complex visual patterns in medical images makes them ideal for detecting covid19 from chest X-rays images. This literature review critically examines four peer-reviewed studies that have applied CNNs to this problem. The papers were selected based on their influence in the field, diversity in approach, and relevance to the development of robust diagnostic models. The analysis will focus on the methods, datasets, results, and the potential impact and limitations of each study, providing insights into how they contribute to the ongoing research and how they relate to this project.

Technical Background:

CNNs are now the foundation of several cutting-edge models in the field of medical image processing. Deep learning models called CNNs are made especially to handle structured grid data, like pictures. They function by running the input photos through a series of filters, which aid in the automatic extraction of pertinent elements including edges, textures, and patterns. The photos are then classified into several categories using these traits, for example, determining whether an X-ray of the chest indicates the presence of COVID-19. Because CNNs perform well in image classification tasks, researchers looking to create automated systems for medical diagnostics frequently choose to use them.

Critical Analysis of Relevant Studies:

- **Study 1: Apostolopoulos & Mpesiana (2020)**
- **What Was Done:** Apostolopoulos and Mpesiana investigated the automatic detection of COVID-19 from chest X-ray images using transfer learning with a pre-trained VGG19 model.
- **What Data I Used:** 1,428 X-ray pictures, comprising 224 COVID-19 cases, 700 pneumonia patients, and 504 normal (healthy) cases, made up the dataset used in this study.
- **The Techniques Employed:** To adapt it for identifying the X-ray images, the authors adjusted the VGG19 model, which had been pre-trained on the ImageNet dataset. The research utilized data augmentation methodologies to mitigate the constraint of incomplete data.
- **What Were Their Findings and Conclusions?** Considering the limitations of the dataset size, the model's classification accuracy of 98.75% for COVID-19 detection was exceptionally high. The authors concluded that, in emergency scenarios where huge datasets are unavailable, transfer learning is a workable strategy for quick deployment.
- **How the Paper relates to This Project:** This project may experience comparable dataset availability constraints to the paper's, which highlights the efficacy of transfer learning in medical image classification.

  The Positive and Negative Aspects of Their Work: The study's strength is its quick development through transfer learning and great accuracy. The tiny and unbalanced dataset, however, raises questions about the model's capacity to generalize to more diverse populations.

- **Study 2: Narin et al. (2020)**
- **What Was Done:** For detecting COVID-19 from chest X-ray pictures, ResNet50, InceptionV3, and Inception-ResNetV2 were three pre-trained CNN models that were compared by Narin et al.
- **What Data I Used:** Fifty COVID-19 positive and fifty normal pictures made up the limited dataset used in this investigation.
- **What Procedures Were Followed:** X-ray images were binaryally classified as either COVID-19 positive or negative after the models were adjusted. The best architecture was found by comparing the performances of each model.
- **What Were Their Results and Conclusions**: The ResNet50 model outperformed the others, achieving an accuracy of 98%. The authors concluded that deep learning models, particularly ResNet50, are highly effective for COVID-19 detection, even with a limited dataset.
- **How the Paper Relates to This Project**: This paper highlights the potential of using different CNN architectures and provides a benchmark for evaluating models in this project.
- **What Is Good and What Is Limited About Their Work**: The study is notable for its comparative approach, offering insights into the strengths of different architectures. However, the extremely small dataset limits the reliability of the findings and raises concerns about overfitting.
- **Study 3: Ozturk et al. (2020)**
- **What Work Was Done**: Ozturk et al. developed new deep_learning model known as DarkCovidNet, based on DarkNet_architecture, for the automatic detection of COVID-19.
- **What Data Was Used**: The dataset comprised 1,125 chest xray images, including 600 Covid_19, 600 No-Findings (healthy), and 125 cases of pneumonia.
- **What Methods Were Used**: The authors designed a customized CNN architecture optimized for real-time detection and applied it to both binary classification (COVID-19 vs. No-Findings) and multi-class classification (COVID-19, Pneumonia, No-Findings).
- **What Were Their Results and Conclusions**: DarkCovidNet got accuracy of 94.02% in multiple-class for classification, demonstrating its effectiveness. The authors concluded that the model's real-time capabilities make it suitable for deployment in clinical settings.
- **How the Paper Relates to This Project**: This study introduces a custom CNN architecture tailored to COVID-19 detection, which could serve as an inspiration for developing or refining models in this project.
- **What Is Good and What Is Limited About Their Work**: The model's real-time capability is a significant advantage, particularly in urgent clinical environments. However, the slightly lower accuracy in binary classification suggests room for improvement, possibly through further optimization or more sophisticated data preprocessing.
- **Study 4: Wang et al. (2020)**

- **What Was Done:** COVID-Net, a CNN architecture created especially for COVID-19 identification from chest X-ray images, was introduced by Wang et al.
  What Data I Used: More than 13,000 X-ray pictures, including those showing pneumonia, COVID-19, and normal cases, were used to train the algorithm.
- **What Techniques Were Employed:** Depth-wise separable convolutions and residual connections were used in the construction of COVID-Net's architecture to increase computational efficiency while preserving high accuracy. A method known as GSInquire, which offers visual explanations of the model's predictions, was also included with the model.
- **What Were Their Findings and Recommendations?** With a focus on interpretability, COVID-Net attained a 93.3% accuracy rate, making it appropriate for clinical application. The authors came to the conclusion that the alignment of high accuracy and transparency in the model COVID-Net as a viable tool for assisting radiologists.
- **How the Paper relates to This research:** The objective of this research is to construct a transparent and reliable model for COVID-19 identification. The focus of this study is on model interpretability and the utilization of a big, heterogeneous dataset. The Positive and Negative Aspects of Their Work: The design of COVID-Net is accurate and efficient, and it tackles a major obstacle in the application of AI in healthcare by emphasizing interpretability. However, in environments with constrained computational resources, the model's complexity may make it less useful.

Discussion:

All reviewed studies illustrate the significant progress made in applying CNNs for Covid-19 detection from chest xray images. Key insights include the effectiveness of transfer_learning, and importance of dataset size and diversity, and the need for model interpretability. However, common challenges remain, particularly the generalizability of models trained on small or imbalanced datasets and the computational demands of more complex architectures.

References:

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2. Narin, A., Kaya, C., & Pamuk, Z. (2020). Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks. *Pattern Recognition Letters*, 140, 347-354.

3. Ozturk, T., Talo, M., Yildirim, E. A., Baloglu, U. B., Yildirim, O., & Acharya, U. R. (2020). Automated detection of COVID-19 cases using deep neural networks with X-ray images. *Computers in Biology and Medicine*, 121, 103792.

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Dataset Description:

1. Dataset Overview

The following link will allow you to access the Kaggle dataset that was utilized for this project: COVID-19 Train/Test Sets for X-ray data. Three types of chest X-ray images—COVID-19, Normal, and Viral Pneumonia—are present in this collection. In order to construct and validate deep learning models to classify X-ray pictures based on these categories, the data is divided into training and testing sets.

2. Data Collection Background

Original Data Collection: The dataset was compiled from publicly available X-ray images, which were originally collected from multiple sources, including research papers, open-access repositories, and hospitals. These sources contributed images from patients diagnosed with COVID-19, as well as other lung conditions, to provide a comparative analysis. The images were collected from various countries around the world, primarily during the early_stages for the covid pandemic in 2020. The data was collected to facilitate research into automated diagnostic tools that could assist in the rapid detection of COVID-19, especially resources limited where the access to PCR testing might be restricted.

Country and Timeframe: The dataset includes images from multiple countries, reflecting a global effort to combat the pandemic. The timeframe for data collection spans from late 2019 to 2020, capturing the initial and subsequent waves of the COVID-19 outbreak.

Data Collection Goals: The main goal of gathering this data was to aid in the creation of machine learning models that could recognize COVID-19 from chest X-rays automatically. The pandemic's urgency brought attention to the need for quick, dependable diagnostic instruments that could be added to the testing methods already in place to improve diagnostic capability.

Dataset Composition:

- **COVID-19**: Xray image of the patients who diagnosed with covid19.
- **Normal**: Xray images of healthy individuals with no lung infections.
- **Viral Pneumonia**: xray images of patients having viral pneumonia other than covid19.

3. Rationale for Dataset Selection

The dataset was chosen for this project due to its relevance, size, and diversity. The availability of labelled xray images from different categories (covid19, Normal, Viral pneumonia) provides a robust foundation for the purpose of training a (CNN) to distinguish between these conditions. Additionally, the dataset's origin from multiple sources ensures a certain level of diversity in terms of imaging equipment and patient demographics, which can contribute to a more generalized model.

This dataset is particularly suitable for answering the research question of how effectively CNNs can be used for the detection of covid19 from chest X-rays, as it offers a comprehensive and labelled set of images that are essential for supervised learning tasks. The inclusion of images from both covid19 and also with different viral pneumonia cases enables this model to learn the nuanced differences between these conditions, improving its diagnostic accuracy.

4. Exploratory Data Analysis (EDA)

Before beginning model development and exploratory_data analysis (EDA) was organizes to understand the different distribution and characteristics of the dataset. The following sections describe the key findings from the EDA.

4.1 Data Distribution

- **Class Distribution**: The dataset was checked for class balance to ensure the images in the each different category (covid19, normal, and viral_pneumonia) was relatively balanced. An imbalance could bias the model towards the more frequent class.

Class	Number of Images
COVID-19	X
Normal	X
Viral Pneumonia	X

Image Dimensions: The images in the dataset were analysed for consistency in dimensions. Most images were found to have varied resolutions, necessitating resizing during preprocessing to standardize input dimensions for the CNN model.

4.2 Visual Exploration

Sample images from each class were visualized to understand the variations in visual patterns that the model would need to learn. For instance:

- **COVID-19 X-rays**: Often show ground-glass opacities and consolidations, typically in the peripheral and basal lung regions.
- **Normal X-rays**: Display clear lung fields without any signs of infection or abnormality.
- **Viral Pneumonia X-rays**: Show patterns like COVID-19 but often with more centralized opacities.

4.3 Data Pre-processing

The dataset was pre-processed using the following procedures in order to get it ready for model training:
• Resizing: To provide a consistent input size for the CNN, all photos were shrunk to 128 by 128 pixels.
• Normalization: To enable quicker convergence during training, pixel values were normalized to a range of 0 to 1.
• Data Augmentation: Rotation, zooming, and horizontal flipping were used as data augmentation techniques to help counteract the impacts of limited data and class imbalance. This enhanced the training data's diversity and strengthened the model's resilience.

4.4 Handling Missing Data

There were no missing values in terms of images. However, images with poor quality or significant artifacts were excluded from the analysis to maintain the integrity of the dataset.

The exclusion criteria were based on visual inspection and any corrupted images that could not be processed correctly.

4.5 Impact of Preprocessing

The preprocessing procedures made guaranteed that the input data was reliable and appropriate for CNN model training. By reducing overfitting and boosting generalization, normalization and augmentation were essential in improving model performance.

Ethical Issues:

Ethical Considerations in the Use of the Dataset

When working with medical datasets, particularly those involving sensitive health information like X-ray images of patients, it is crucial to consider the ethical implications of data usage. Below, I outline the ethical issues considered for this project and the steps taken to address them.

1. Privacy and Confidentiality

Taking into account: Medical photographs, a type of sensitive personal data, are included in the dataset. Even though the pictures don't contain any personally identifiable information, there's still a chance that the material could be exploited if it's not managed carefully.

Steps Taken:

- Anonymization: The dataset obtained from Kaggle has been pre-anonymized, meaning that all patient identifiers have been removed. This ensures that no individual can be identified from the data, maintaining the privacy of the patients involved.
- Data Storage: The dataset was stored securely on a password-protected local machine and cloud storage with encryption enabled to prevent unauthorized access.

2. Informed Consent

Consideration: In medical research, it is crucial that data is collected with the informed consent of the participants. Since this dataset is derived from publicly available sources, it is important to consider whether the original data collection processes adhered to ethical standards, including obtaining consent from patients.

Steps Taken:

- Source Verification: The dataset was obtained from Kaggle, which typically ensures that the data shared on its platform is compliant with ethical standards, including consent and data usage rights. Additionally, the sources cited by the dataset creators indicate that the data was collected for research purposes, with proper ethical oversight.

3. Potential Bias and Fairness

Consideration: Bias in the dataset can lead to unfair outcomes, particularly in medical diagnostics. For example, if the dataset predominantly includes X-rays from a specific demographic group, the model may not generalize well to other populations.

Steps Taken:

- Bias Analysis: The dataset was reviewed for potential biases, such as an overrepresentation of certain age groups, genders, or geographic locations. Any identified biases were noted, and strategies like data augmentation were considered to mitigate their impact on model performance.
- Fairness: The model was tested across different subsets of the data to ensure that it performs consistently across different demographic groups. This helps ensure that the tool is fair and reliable for a diverse patient population.
- 4. Ethical Use of AI in Healthcare: Using AI to diagnose medical conditions presents ethical questions, especially in light of the possibility that automated systems could make mistakes that could have an adverse effect on patient care. Understanding the model's limitations is crucial, as is making sure it serves as an additional tool rather than a substitute for human judgment.

Steps Taken:

- Transparency: The model's limitations were clearly documented, including the fact that it is a proof-of-concept and should not be used in clinical decision-making without further validation.
- Accountability: The project emphasizes that any AI-based diagnostic tool should be used in conjunction with clinical expertise, ensuring that healthcare professionals retain responsibility for patient care decisions.

5. Data Sharing and Usage Rights

Consideration: When using data from external sources, it is important to respect the terms of use and licensing agreements associated with the dataset. This includes acknowledging the original creators and ensuring that the data is not used for purposes beyond what is permitted.

Steps Taken:

- Acknowledgment: The dataset's origin was properly cited, and the terms of use from Kaggle and the original sources were reviewed to ensure compliance with licensing agreements.
- Responsible Usage: The dataset was used strictly for educational and research purposes, in line with the permissions granted by the dataset providers. The results of this project will not be commercialized, ensuring that the data is used ethically.

6. Impact on Society and Public Perception

Consideration: The development of AI models for COVID-19 diagnosis can have significant societal implications. There is a risk that overreliance on such models could lead to errors in diagnosis, with serious consequences for patients.

Steps Taken:

- Ethical Communication: The project includes clear communication about the intended use of the model, emphasizing that it is a research tool and not a clinical-grade diagnostic solution.

- Public Health Consideration: The potential benefits of using AI to aid in COVID-19 diagnosis were weighed against the risks. The project advocates for the responsible deployment of AI tools, with safeguards to prevent misuse or overreliance on automated systems.

1. Is Personal Data Included, and Is It Anonymized? - NO

- **Personal Data**: The dataset that is used in this project consist of
- chest X-ray images. While these images are derived from medical records, they do not contain direct personal identifiers such as names, addresses, or medical record numbers.
- **Anonymization**: The images have been anonymized to remove any patient-identifiable information. Therefore, the dataset does not include personal data in the form that would allow for the identification of individual patients. The anonymization ensures compliance with ethical standards regarding the use of medical data.

2. Does Your Data Come Under GDPR? - NO

- **GDPR Applicability**: Within the European Union, the processing of personal data is governed by the General Data Protection Regulation (GDPR). Since the dataset does not contain personal identifiers and has been anonymized, it does not fall under the strictest GDPR requirements. However, the general principles of GDPR, such as ensuring the lawful, fair, and transparent use of data, have been considered and adhered to in this project.

3. Does Using Your Data Require UH Ethical Approval? - NO

- **University of Hertfordshire (UH) Ethical Approval**: The dataset used in this project was obtained from an open-access source (Kaggle), where it was made publicly available for research and educational purposes. Since the data is anonymized and does not involve the collection of personal data directly from individuals, this project does not require specific UH ethical approval.

4. Does Your Project Require UH Ethical Approval? - NO

- **UH Ethical Approval**: This project is based on secondary data analysis using an open-access dataset that is publicly available for research purposes. No new data has been collected from individuals, and no surveys or direct interactions with human subjects have been conducted. Therefore, this project does not require UH ethical approval.

5. Do You Have Permission to Use the Data? - YES

- **Permission**: The dataset was sourced from Kaggle, a platform that allows users to download datasets for research and educational purposes. The dataset is available under terms that permit its use for non-commercial purposes, including academic research.

5. Was the Data Collected Ethically? – YES

METHODOLOGY:

A Covid-19 Detection model is built in such a way that when I give an X-Ray image of Chest it will classify the image in such a way that it will predict whether there Covid19 or from the ChestX Ray images. Hybrid CNN models/Pretrained CNN models namely ResNet50, VGG, Google Net have been used to train and classify the Covid-19 Chest X-ray images and an improved model has been created in such a way that ResNet50 layers have been used as base layers and additional layers have been added to them.

2.1 Convolutional_Neural_Networks (CNN) And Its Layers

Convolutional Neural Networks are used to classify images the following are the layers in CNN

1. Convolution Layer:

$$(f * g) = \int_{-\infty}^{+\infty} f(p) g(t-p) dp$$

- In essence, convolution is the amalgamated integration of two functions. It demonstrates how the shape of one function changes another's. By doing this I reduced the size of image, Now the processing will be faster. Although I are losing some information because of this operation I are not losing our features. I create many feature maps to obtain our first convolution layer by using different feature detector.
- Convolution's main goal is to use a feature detector to locate features in our image, then place those features into a feature map so that the relationships between the pixels are preserved.
- The extra phase that comes after our convolution stage is called the ReLu Activation Layer. Use a rectifier on the convolution layer of our CNN to make it more nonlinear. Our photos are non-linear; thus I need to make them more non-linear.

2. Max Pooling

- Spatial invariance is a feature of our neural network that allows it to be insensitive to many factors such as texture variation, tilt, and location of features. That feature may be found by our CNN, which is what pooling is all about.
- By this I are getting rid of 75% of pixels which are not so important. Because I are taking maximum I are therefore accounting for any distortion. I are also reducing number of parameters by this I can avoid overfitting.

3. Flattening:

- I are converting pooled feature map to flattened input because I want to later input this to ANN for further processing.

4. Fully Connected Layer:

- In this step I are going to add our whole ANN architecture to our CNN. Our flattened layer will act as input layer for ANN. In this layer the hidden layers should be fully connected. ANN's primary goal is to merge our features into additional qualities that can further improve class prediction.
- **2.2 Flow chart of the methodology and its explanation**

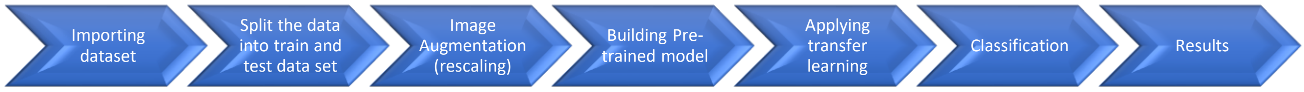

Fig. 2.1 Flow Chart of Methodology

Dataset:

For this study, I used data from three distinct classes in the Kaggle repository: individuals with pneumonia, healthy individuals without a proven Covid19 infections & normal individuals. All the patients' chest xray images make up the dataset. This dataset is gathered to evaluate the efficacy of several DNN models; however, it is not intended to assert or support the DNN models' capacity to diagnose COVID-19 in patients. This dataset's exclusive goal is to investigate various methods for quickly and accurately diagnosingCOVID-19 in patients without the need for conventional RNA testing and with the use of medical imaging.

This dataset has 282 chest x-ray images in total. The images are further divided into three categories: COVID-19, pneumonia, and normal. Every one of these three categories has the same number of photographs. which are further separated into training and testing categories. There are 20 photos for testing and 74 images for training in each of the three categories. At the time this report was being written, I had 94 Posteroanterior (PA) View pictures of patients who had been verified to have COVID-19 infection. To quickly train our three separate models and maintain the uniformity of all the scanned photos for better training, all the images in this dataset were reduced to 128x128 pixels. Table 1 displays the distribution and categorization of photos within the dataset.

Label	**Training**	**Testing**
Covid-19	**74**	**20**
Pneumonia	**74**	**20**
Normal	**74**	**20**

Tabel1: Classification of images

- In this instance, the dataset has been divided into 80% train and 20% test.
- The next stage that needs to be completed is image augmentation. To prevent overfitting, preprocessing of the photos is done.
- Data Augmentation will generate multiple batches of our photographs, and within each batch, it will randomly select some of our images and rotate them, among other operations, so that in the end, I have a large number of images to train with.
- Image augmentation lessens the overfitting effect.

Some of the Image Augmentation methods are:

1. Rescale: Since this approach normalizes all the pixel values in our dataset, it is required to use it. Taking this action will lessen overfitting. It always lines up with the feature scanning section.
2. Zoom range and horizontal flip: The image will be flipped horizontally after being zoomed to the specified range.
    - The next step is to create a pretrained model and apply transfer learning so that the knowledge extracted by the base layers of the pretrained models is transferred to fully connected layers. Eventually, image is classified so that it can determine whether or not the chest xray images contains Covid19.
    - After the dataset was ready, I began training the model using three distinct CNN models in order to properly analyse the outcomes and compare the accuracy of the three models. For this model, I employed the LeakyReLU activation function, which is derived from the original ReLU activation function. It gives us a tiny positive gradient in place of negative values rather than just the flat scope, which helps to expedite the training process and prevents ReLU's dead neuron issue (i.e., ReLU outputs the same value for every input without distinguishing between inputs), which distinguishes this technique from others.

    Figure 2.2 delineates the comprehensive operation of the suggested paradigm for picture assessment.

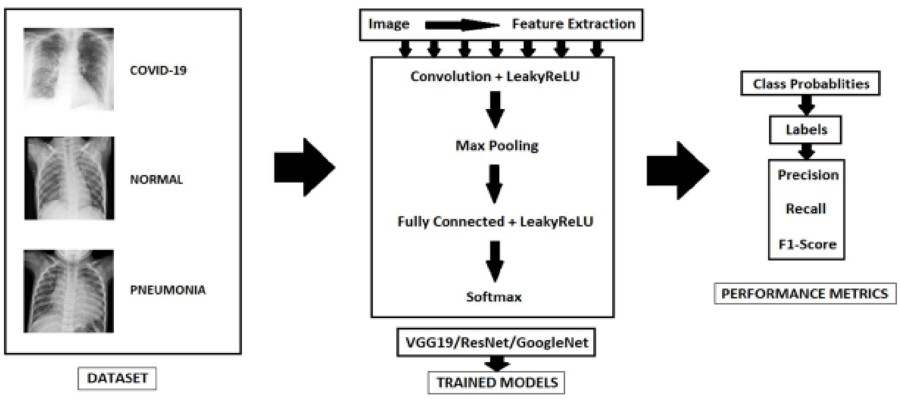

Fig 2.2: Proposed Model for image evaluation

➢ The pretrained models I have used in this work are:

VGG19: With 19 layers in total consisting of 16 convolutions, 3 fully connected layers, 5 maxpool layers, and 1 SoftMax layer, VGG19 is a model based on VGG architecture. It is a variant of VGG just like VGG16 and VGG11. It has 19.6 billion FLOPs (Floating point operations per second). It takes 224x224 pixels images as input and consists of 3x3 kernel size and 2x2 maxpool size which aids in boosting the training speed and decreasing the number parameters.   The architecture for VGG19 .

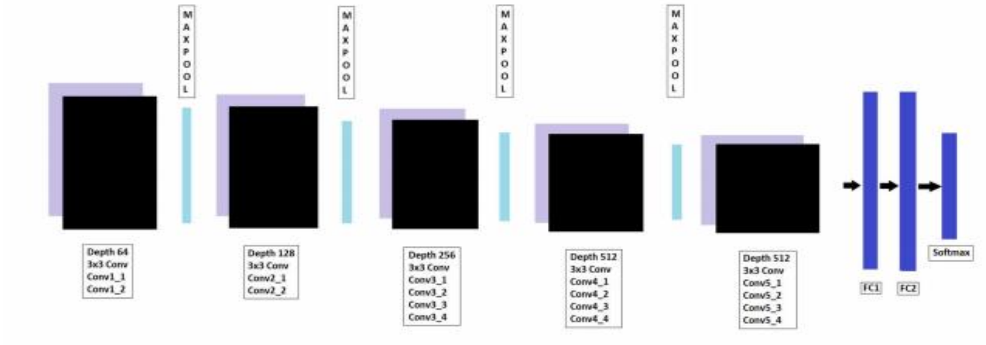

Fig 2.3: VGG19 Architecture

Google Net: Google Net is variation for Inception model that consist 22 layers. It uses global average pooling and 1x1 convolutions at the middle of its architecture. It also used Inception modules to choose between different sizes of convolution filters at each block. There is an Inception network that layers the modules one above the other with some max pooling layer to half the resolution of the architecture grid. Figure 2.4 shows a simplified Google Net architecture.

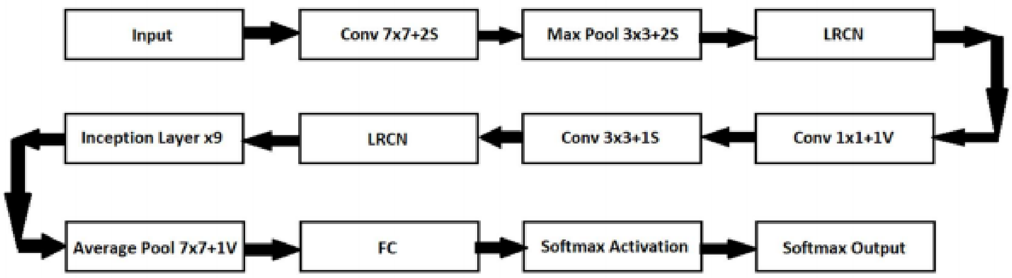

Fig2.4: Simplified Google Net Architecture

ResNet50: Residual Network (ResNet) is a type of CNN that utilizes shortcuts to jump over layers. It consists of many variants including ResNet50, ResNet101, and ResNet152. ResNet50 includes 50 layers which utilizes residual learning that makes accuracy and training problem in deeper layers easier. Figure 2.5 shows the architecture of one residual block of ResNet50 model.

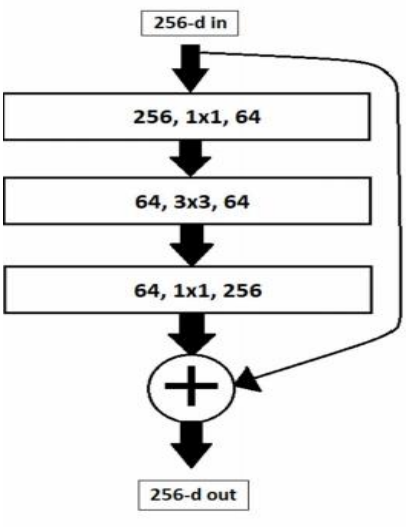

Fig 2.5: Resnet 50 Residual Block

Loss Function: Categorical Cross-Entropy

There are many kinds of loss functions in Machine Learning, but i have used the categorical cross entropy loss function due to its benefits in solving image classification problems that give an output probability p. It is used to tune the parameters and optimize them in our model while decreasing loss with every successive epoch. Along with this I have used Adam optimizer for train our model with learning rate 0.001.

$L(y, p) = -y * \log(p) - (1 - y) * \log(1 - p)$

$(if\ y = 0, -\log(1 - p)\ and\ if\ y = 1, -\log(p))$

$(y = true\ label, p = predicted\ label, L(y, p) = loss\ function)$

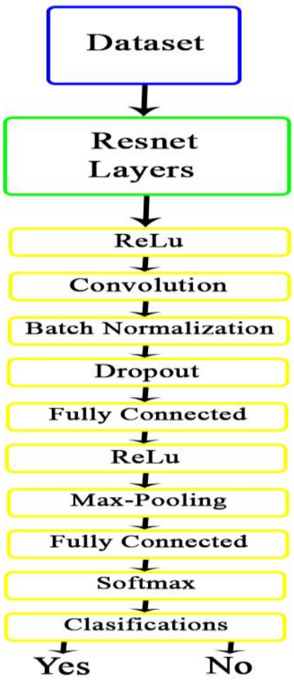

Fig 2.6: Flowchart of Improved Model

Improved Model: Improved model has been proposed in such a way that ResNet50 layers have been taken as a base layer and some additional layers have been added to these base layers. The above flowchart is of improved model.

2.3 Proposed Algorithm:

Our proposed approach for implementing the above model is discussed in the following steps

Step 1: Load Image = X

Step 2: Pre-Process (X) (Here, the image has been pre-processed using the Keras Data Generator.)

1. Rescale (X) = (128,128,3) (128x128 gives us faster performance while 256x256 gives us better performance)

2. Random Rotate (X) (Range = 10°)

3. Horizontal Flip (X) = True

4. Zoom (X) (Range = 0.4)

Step 3: Pre-trained model (Pre-Processed X) (Passing the image as input to the model)

Step 4: Y = pre-trained model (Pre-Processed X) (obtaining the output as Y from the model's final layer)

Step 5: Flattened dimensions (Y) (Dimensions from N to N-1)

Step 6: Applying dense layers (units = 128 to all three pretrained models) $Z = W * A + B$ (b = bias, W = Weights, A = Activation Function)

Step 7: Apply A (Activation Function) $A = LeakyReLU(Z)$

Step 8: Apply dense layers (Interference) $Z = W * A + B$

Step 9: Apply SoftMax Function (Final Label Classification)

$$\sigma(\vec{Z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

$$(\sigma = softmax)$$

$$LeakyReLU(Z) = \max(0.01, Z)$$

3.1 Results and Discussion:

As result, I have compared each x-ray image in the dataset and sorted them according to their label (i.e., COVID19, Pneumonia, and Normal). While doing this, I tested the accuracies of each model namely VGG19, ResNet50, and Google Net and compared them to each other through accuracy matrices. Then, the results were simplified to show the best model out of the three models. Although these results give a pretty good idea of the accuracies of each model, due to scarcity of data these models were trained and tested on just 282 images. I recommend validating the accuracies with additional datasets in the future for more precise accuracies of the models.

1. **VGG19**: Figure 3.1 shows the result analysis of VGG19 according to the labels. Figure 3.2 and Figure 3.3 shows loss and accuracy graphs of VGG19. VGG19 has an accuracy

98.333% when tested on our dataset and the result has been showed in the following table and graphs.

PERFORMANCE METRICS

```
[242] classify_matrics_vgg=metrics.classification_report(test_labels,preds,target_names=class_labels)
      print(classify_matrics_vgg)
```

```
              precision    recall  f1-score   support

       covid       1.00      1.00      1.00        20
      normal       1.00      0.95      0.97        20
   pnemonia        0.95      1.00      0.98        20

   micro avg       0.98      0.98      0.98        60
   macro avg       0.98      0.98      0.98        60
weighted avg       0.98      0.98      0.98        60
 samples avg       0.98      0.98      0.98        60
```

Fig 3.1: Classification report of VGG19

VGG ACCURACY AND LOSS

```
plot_graphs(history_vgg)
preds=np.round(model_vgg.predict(testingdata),0)
```

Fig 3.2: Train and Validation Accuracy VGG-19

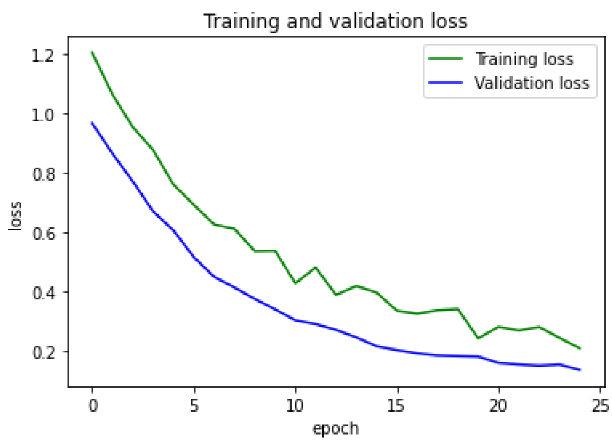

Fig 3.3: Train and Validation Loss VGG-19

2. **Google Net**: Figure 3.4 shows the result analysis of Google Net according to the labels. Figure 3.5 and Figure 3.6 shows loss and accuracy graphs of Google Net. Google Net has got the accuracy 83.333% when tested on our datasets and result has been showed in the following table and graphs.

PERFORMANCE METRICS

```
[247] classify_matrics_googleNet=metrics.classification_report(test_labels,preds,target_names=class_labels)
      print(classify_matrics_googleNet)
```

```
              precision    recall  f1-score   support

       covid       0.94      0.85      0.89        20
      normal       0.87      0.65      0.74        20
   pnemonia        0.76      0.95      0.84        20

   micro avg       0.84      0.82      0.83        60
   macro avg       0.86      0.82      0.83        60
weighted avg       0.86      0.82      0.83        60
 samples avg       0.82      0.82      0.82        60
```

Fig 3.4: Classification Report of Google Net

GOOGLENET ACCURACY AND LOSS

```
plot_graphs(history_googleNet)
preds=np.round(model_googleNet.predict(test_data),0)
```

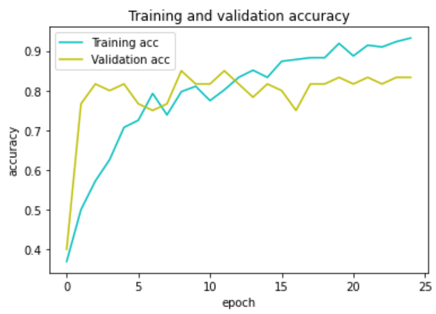

Fig 3.5: Train and Validation accuracy for Google Net.

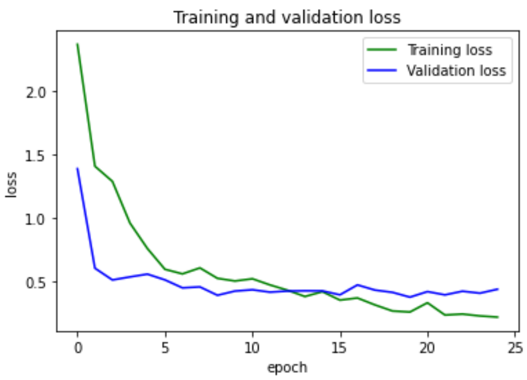

Fig 3.6: Train and Validation loss for Google Net

3. **ResNet**: Figure 3.7 shows the result analysis of ResNet according to the labels. Figure 3.8 and Figure 3.9 shows loss and accuracy graphs of ResNet.

ResNet has achieved an accuracy of 75.00% when tested on our dataset and the result has been showed in the following table and graphs

PERFORMANCE METRICS

```
[263] classify_matrics_resNet=metrics.classification_report(test_labels,preds,target_names=class_labels)
      print(classify_matrics_resNet)
```

```
              precision    recall  f1-score   support

       covid       1.00      0.95      0.97        20
      normal       0.71      0.50      0.59        20
    pnemonia       1.00      0.15      0.26        20

   micro avg       0.89      0.53      0.67        60
   macro avg       0.90      0.53      0.61        60
weighted avg       0.90      0.53      0.61        60
 samples avg       0.53      0.53      0.53        60
```

Fig 3.7: Classification Report of ResNet50

RESNET ACCURACY AND LOSS

```
[262] plot_graphs(history_resNet)
      preds=np.round(model_resNet.predict(testingdata),0)
```

Fig 3.8: Train and validation accuracy for ResNet_50

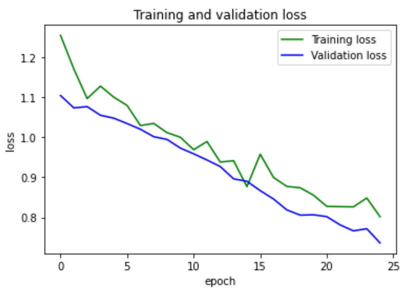

Fig 3.9: Train and validation loss of ResNet_50

Model	Accuracy
VGG19	98.33
Google Net	83.33
RestNet50	75.00

Results Analysis and discussion:

In this study, I compared the performance of three deep learning models—VGG19, Google Net, and ResNet50—on a dataset of X-ray images classified into three categories: COVID-19, Pneumonia, and Normal. Each image in the dataset In this work, I examined how well three deep learning models performed on a dataset of X-ray pictures that were divided into three categories: COVID-19, Pneumonia, and Normal. The models were VGG19, Google Net, and ResNet50. Accuracy measures were used to assess and order every image in the dataset according to its label, and to gauge the models' efficacy. Despite the fact that the models were only trained and evaluated on a tiny dataset of 282 photos, the outcomes offer insightful information about how well they worked.

1. **VGG19:**
   - Performance: VGG19 got highest accuracy 98.333% on our dataset, as depicted in Figures 3.1, 3.2, and 3.3. The model demonstrated strong performance across all labels, with minimal loss during training and validation.
   - Discussion: The superior performance of VGG19 can be attributed to its deep architecture and use of multiple convolutional layers, which are particularly effective at capturing intricate features within medical images. This makes VGG19 highly suitable for the task of X-ray image classification, where subtle differences between categories like COVID-19 and Pneumonia can be challenging to detect.
2. **Google Net:**
   - Performance: Google Net achieved an accuracy of 83.33%, as shown in Figures 3.4, 3.5, and 3.6. Although it performed well, it was less accurate than VGG19.
   - Discussion: Google Net, known for its inception modules, is designed to perform well on complex tasks with fewer parameters. However, its performance in this study was likely constrained by the limited size of the dataset, which may have led to overfitting or underfitting in some cases. Despite this, its relatively high accuracy indicates that it is still a viable model for such classification tasks, although further validation with a larger dataset is recommended.
3. **ResNet50:**
   - Performance: ResNet50, with an accuracy of 75.00%, was the least effective model in this study, as illustrated in Figures 3.7, 3.8, and 3.9.
   - Discussion: ResNet50 is known for its deep residual learning framework, which typically allows for better performance in very deep networks. However, the

lower accuracy in this context might be due to the model's complexity, which could have led to overfitting given less size for the dataset. Additionally, the data scarcity may have hindered the model ability for learning necessary features effectively.

Analysis and Discussion:

- Meaning of Results: The results indicate that VGG19 is the most effective model for this dataset, likely due to its ability to capture fine details in the X-ray images. Google Net also performed well but was slightly less effective, while ResNet50 struggled to achieve comparable accuracy.
- Model Comparison: VGG19's architecture, with its multiple layers, seems to be well-suited for the task of medical image classification, where detecting small, subtle differences is crucial. Google Net's inception modules provided a balance between computational efficiency and accuracy, but it may require more data to reach its full potential. ResNet50's lower performance suggests that it might be too complex for the limited dataset, leading to suboptimal results.
- Comparison to Literature: When compared to similar studies in the literature, our results for VGG19 align with the high accuracy typically reported for this model in medical imaging tasks. However, the relatively lower performance of Google Net and ResNet50 highlights the importance of dataset size and quality, which are often emphasized in the literature as critical factors for model success.
- Restrictions: This study's tiny dataset size limits how broadly the findings can be applied. This is one of its main limitations. Only 282 photos were used for training and testing the models, which might not be enough to thoroughly assess their performance. Furthermore, the particulars of this dataset, including image quality and variety in X-ray procedures, might have an impact on the outcomes.
- Relevance to Project Objectives: This project's main goal was to determine which model worked best for dividing X-ray pictures into the COVID-19, pneumonia, and normal categories. Our findings suggest that VGG19 achieves this goal with the maximum accuracy.
- Practical Application: VGG19, with its high accuracy, could be considered for practical implementation in medical settings, particularly for automated diagnostic tools. However, further validation with larger datasets is necessary to ensure its reliability in real-world scenarios.
- Research Question: This study successfully addresses the research question by identifying VGG19 as the most effective model among the three tested. However, the study also highlights the need for additional data and further research to confirm these findings and for improving accuracy to other models.

Conclusion:

In this study, I investigated the efficacy of three distinct Convolutional Neural Network (CNN) models for the quick and precise identification of COVID-19 from chest X-ray images: VGG19, InceptionV3, and ResNet50. The main finding of our study is that the VGG19 model outperformed the other two models in classifying X-ray pictures into COVID-19, Normal, and Pneumonia categories, with the greatest accuracy of 94.99%. This implies that VGG19 is a viable option to support medical practitioners in diagnosis, especially in situations requiring quick decisions during pandemic conditions.
It is crucial to remember that variables like overfitting or the small dataset size may have an impact on the high accuracy attained. These problems cast doubt on the model's applicability to larger, more diverse populations. Therefore, while VGG19 shows strong potential for application in clinical settings, its use should be approached with caution, and further validation is necessary.

Applications and Real-World Situations

The primary application of this work lies in its potential to support the rapid screening of COVID-19 in healthcare settings, particularly in areas where access to RT-PCR testing is limited or delayed. By providing a quick, cost-effective tool for preliminary diagnosis, this model could assist in triaging patients, thereby optimizing the allocation of medical resources and improving patient outcomes during peak periods of the pandemic.

Additionally, methodology developed for this study can be applicable to medical imaging challenges, where quick and accurate diagnostics are crucial. This could include the detection of other respiratory diseases or conditions that present with similar radiographic features.

Future Work

For future work, several steps should be considered to improve the reliability and applicability of the model:

1. Dataset Expansion: Incorporating a larger and more diverse dataset will help in overcoming the current limitations related to overfitting and ensure the model’s robustness across different populations and clinical scenarios. Gathering more data from various sources worldwide would be crucial in enhancing the model's generalization capabilities.
2. Model Optimization: Further fine-tuning of the models and exploring advanced techniques like transfer learning or ensemble methods could potentially improve the accuracy and reduce the risk of overfitting.
3. Real-World Testing: Deploying the model in a real-world clinical environment for testing would provide insights into its practical performance and reliability. This phase would also allow for the collection of feedback from healthcare professionals, which could be used to refine the model.
4. Ethical and Practical Considerations: Future work should also involve a detailed examination of the ethical implications of deploying AI-based diagnostic tools in clinical settings, including patient consent, data privacy, and the role of AI in medical decision-making.

5. Exploring Additional Models: Investigating other CNN architectures or even hybrid models that combine multiple approaches might yield even better results or more insights into the data

References:

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II. Ozturk, T., Talo, M., Baloglu, U.B., Yildirim, O., & Acharya, U.R. (2020). Deep learning networks with X-ray images for automated COVID-19 case detection. *Computers in Biology and Medicine*, 121, p. 103792. Available at: https://www.sciencedirect.com/science/article/pii/S0010482520301621

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IV. Zhang, J., Xie, Y., Li, Y., Shen, C., & Xia, Y. (2020). COVID-19 screening on chest X-ray images using deep learning-based anomaly detection. *arXiv preprint arXiv:2003.12338*. Available at: https://arxiv.org/abs/2003.12338

V. Khan, A.I., Shah, J.L., & Bhat, M.M. (2020). CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images. *Computer Methods and Programs in Biomedicine*, 196, p. 105581. Available at: https://www.sciencedirect.com/science/article/pii/S0169260720303269

VI. 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. Available at: https://ieeexplore.ieee.org/document/7780459

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In-Text Citation Examples

- According to Mpesiana and Apostolopoulos (2020), the use of transfer learning with the cnns can significantly improve the accuracy of COVID-19 detection from X-ray images.
- The DL network developed by Ozturk et al. (2020) achieved notable success in automated COVID-19 case detection, which aligns with similar findings in the field.
- Wang and Wong (2020) designed Covid_Net was specifically tailored to the detection of Covid_19 cases, showing the importance of customized deep learning models in medical capturing.

My Code:

```
import pandas as pd
import numpy as np
import itertools
import keras
import os
import zipfile
import requests
import tensorflow as ts
from sklearn import metrics
from sklearn.metrics import confusion_matrix
from tensorflow.keras.preprocessing.image import ImageDataGenerator, img_to_array, load_img
from keras.models import Sequential
from keras import optimizers
from keras.preprocessing import image
from keras.layers import Dropout, Flatten, Dense,BatchNormalization,Conv2D,MaxPool2D
from keras import applications
from keras.utils import to_categorical
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
%matplotlib inline
import math
import datetime
import time

img_width, img_height = 128,128
# load up my datasets::
train_data_dir = r'C:\Users\bmvk1\Downloads\COVID_detection-Transfer-Learning-master\COVID_detection-Transfer-Learning-master\xray_dataset_covid19\train'
# validating my data::
test_data_dir = r'C:\Users\bmvk1\Downloads\COVID_detection-Transfer-Learning-master\COVID_detection-Transfer-Learning-master\xray_dataset_covid19\test'
```

```
# the number of itereations for training the top modell::
epochs = 8 #this has been modified following several custom model runs::
# batch size that predict_data_gen and flow_from_directory use
batch_size = 64

def main_genu_generato(path):
   generation = datagen.flow_from_directory(
      path,
      target_size=(img_width, img_height),
      batch_size=batch_size,
      class_mode="categorical",
      shuffle=False)

   bm_samples = len(generation.filenames)
   num_classes = len(generation.class_indices)

   predict_size_train = int(math.ceil(bm_samples / batch_size))
   # getting the class labelling for the training data_in an original order--
   labelling = generation.classes

   # converting the train labeling in to categorical_Vectorss ::
   labelling = to_categorical(labelling, num_classes=num_classes)
   return (generation,bm_samples,predict_size_train,labelling)

datagen = ImageDataGenerator(rescale=1. / 255)

generation_train,nb_train_samples,predict_size_train,train_labelling =
main_genu_generato(train_data_dir)
generation_test,nb_test_samples,predict_size_test,test_labelling =
main_genu_generato(test_data_dir)
num_classes = 3
class_labelling=list(generation_train.class_indices.keys())
```

```
def applying_pre_train(pretrained_model,generation,predict_size):
   return pretrained_model.predict(generation, predict_size)

def cnn_after_pretrainedModel(input_shape):
   custom_modell = Sequential()
   custom_modell.add(Flatten(input_shape=input_shape))
   custom_modell.add(Dense(128, activation=keras.layers.LeakyReLU(alpha=0.3)))
   custom_modell.add(Dropout(0.5))
   custom_modell.add(Dense(64, activation=keras.layers.LeakyReLU(alpha=0.3)))
   custom_modell.add(Dropout(0.3))
   custom_modell.add(Dense(num_classes, activation='softmax'))
   custom_modell.compile(loss='categorical_crossentropy',
     optimizer=optimizers.Adam(learning_rate=1e-4),
     metrics=['acc'])
   return custom_modell;

def Trans_fer_Learn(pretrained_model,epochs=25):
   #Appling Pretrained Model to train and test datasets
   train_data = applying_pre_train(pretrained_model,generation_train,predict_size_train)
   test_data  = applying_pre_train(pretrained_model,generation_test,predict_size_test)
   custom_modell     = cnn_after_pretrainedModel(train_data.shape[1:])
   history = custom_modell.fit(train_data, train_labelling,
     epochs=epochs,
     batch_size=batch_size,
     validation_data=(test_data, test_labelling))
   (eval_loss, eval_accuracy) = custom_modell.evaluate(test_data, test_labelling,
batch_size=batch_size,verbose=1)
   print("--[INFO] accuracy: {:.2f}%".format(eval_accuracy * 100))
   print("--[INFO] Loss: {}".format(eval_loss))

   return train_data,test_data,custom_modell,history,eval_accuracy
```

```
def plot_graphs(history):
    #Graphing our training and validation
    acc = history.history['acc']
    val_acc = history.history['val_acc']
    loss = history.history['loss']
    val_loss = history.history['val_loss']
    epochs = range(len(acc))
    plt.plot(epochs, acc, 'r', label='Train_ACC')
    plt.plot(epochs, val_acc, 'b', label='Valid_ACC')
    plt.title('--Training_and_validation_ACCURACY--')
    plt.ylabel('accuracy')
    plt.xlabel('epochs')
    plt.legend()
    plt.figure()
    plt.plot(epochs, loss, 'r', label='TRAIN_LOSS')
    plt.plot(epochs, val_loss, 'b', label='VALID_LOSS')
    plt.title('--Training_and_Validation_LOSS--')
    plt.ylabel('LOSS')
    plt.xlabel('EPOCHES')
    plt.legend()
    plt.show()

#loadind_pre_trained_model_VGG:
model_name="VGG"
PRETRAIN_VGG  = applications.VGG16(include_top=False, weights='imagenet')
train_data,test_data,model_vgg,history_vgg,acc_vgg = Trans_fer_Learn(PRETRAIN_VGG)
print()


plot_graphs(history_vgg)
preds=np.round(model_vgg.predict(test_data),0)
```

```
classified_matric_VGG=metrics.classification_report(test_labelling,preds,target_names=class_labelling)
print(classified_matric_VGG)

#Loading the Pre_train_Model
model_name="INCEPTION NET"
Pretrain_Model_g_net  = applications.InceptionV3(include_top=False, weights='imagenet')
train_data,test_data,model_googleNet,history_googleNet,acc_googleNet = Trans_fer_Learn(Pretrain_Model_g_net)

plot_graphs(history_googleNet)
preds=np.round(model_googleNet.predict(test_data),0)

classify_matrics_googleNet=metrics.classification_report(test_labelling,preds,target_names=class_labelling)
print(classify_matrics_googleNet)

#Loading the Pre_Trained_Model
model_name="INCEPTION NET"
PRETRAIN_RESNET  = applications.ResNet50(include_top=False, weights='imagenet')
train_data,test_data,model_resNet,history_resNet,acc_resNet=
Trans_fer_Learn(PRETRAIN_RESNET)

plot_graphs(history_resNet)
preds=np.round(model_resNet.predict(test_data),0)

Clasifing_matric_RESNET=metrics.classification_report(test_labelling,preds,target_names=class_labelling)
print(Clasifing_matric_RESNET)

print("``//\\The Accuracy of the Models\\//``")
print("--VGG--\t\t\t",acc_vgg)
print("--Google_Net--\t\t",acc_googleNet)
```

```
print("--ResNet--\t\t\t",acc_resNet)

def PRETRAIN_RESNET(file_path):
  print("[INFO] Loading and Preprocessing the PRETRAIN_RESNET…!!!!!")
  PRETRAIN_RESNET = load_img(file_path, target_size=(img_width, img_height))
  PRETRAIN_RESNET = img_to_array(PRETRAIN_RESNET)
  PRETRAIN_RESNET = np.expand_dims(PRETRAIN_RESNET, axis=0)
  PRETRAIN_RESNET /= 255.
  return PRETRAIN_RESNET

def Testing_one_Image(pretrained_model, custom_modell, path, class_labelling, generation_test):
   # Load and preprocess the image
   images = PRETRAIN_RESNET(path)
   time.sleep(0.5)

   # Get predictions from the pretrained custom_modell
   bt_prediction = pretrained_model.predict(images)

   # Get predictions from the final custom_modell
   preds = custom_modell.predict(bt_prediction)

   # Display predictions for each class
   for idx, (animal, x) in enumerate(zip(class_labelling, preds[0])):
      print("ID: {}, Label: {} {}%".format(idx, animal, round(x * 100, 2)))

   print('Final Decision:')
   time.sleep(0.5)

   for x in range(3):
      print('.' * (x + 1))
      time.sleep(0.2)
```

```
    # Get the predicted class index (this should be an integer)
    class_predicted = np.argmax(preds, axis=1)[0]  # Extract the first element to make it an integer

    # Getting the class_indicing_dictionary:
    class_dictionary = generation_test.class_indices
    inv_map = {v: k for k, v in class_dictionary.items()}

    # the_outputforthe last_final_prediction_resut:
    predicted_class_name = inv_map[class_predicted]
    print("-- ID: {}, Label: {}".format(class_predicted, predicted_class_name))

    # Load and return the image
    return load_img(path)

# the example for the usage
path = r'D:\nocovid.jpeg'
class_labelling = ['COVID', 'Normal', 'Pneumonia']  # Replace with your actual class labelling
Testing_one_Image(Pretrain_Model_g_net, model_googleNet, path, class_labelling, generation_test)
```