**A PRELIMINARY REPORT ON**

**Classification of COVID19 using Chest X-ray Images using CNN**

SUBMITTED TO THE VISHWAKARMA INSTITUTE OF INFORMATION TECHNOLOGY, PUNE
IN THE PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE AWARD OF THE DEGREE

OF

**BACHELOR OF TECHNOLOGY (COMPUTER ENGINEERING)**

**SUBMITTED BY**


| Name | Roll No | PRN No |
|---|---|---|
| Chitra Joshi | 324081 | U1310587 |
| Vedant Vedpathak | 322064 | 22110264 |

**DEPARTMENT OF COMPUTER ENGINEERING**

**BRACT'S**
**VISHWAKARMA INSTITUTE OF INFORMATION TECHNOLOGY**

SURVEY NO. 3/4, KONDHWA (BUDRUK), PUNE – 411048, MAHARASHTRA (INDIA).

# INTRODUCTION

- **Overview**

  Until recently, COVID-19 was considered a highly contagious airborne infection that leads to fatal pneumonia and other health hazardous infections. The new coronavirus, or type SARS-COV-2, is responsible for COVID-19 and has demonstrated the deadly nature of the respiratory disease that threatens many people worldwide. A clinical study found that a person infected with COVID-19 can experience dry cough, muscle pain, headache, fever, sore throat, and mild to moderate respiratory illness. At the same time, it has a negative effect on the lungs if there is a viral infection. Thus, the lungs can become visible internal organs for diagnosing the severity of COVID-19 infection using chest X-rays and CT scans. Despite the long testing time, RT-PCR is a proven testing method for detecting coronavirus infection. Sometimes there are more false positives and false negatives than the desired percentage. The concept of artificial neural network (ANN) is inspired by the biological neural networks which consist of inter-connected units called artificial neurons. Convolutional neural network (CNN) which is a variant of multilayer perceptron that belongs to a class of feedforward ANN is widely used for various applications due to its enhanced accuracy.

  In this project, we aim to develop a classification system for COVID-19 using chest X-ray images. By leveraging Convolutional Neural Networks (CNNs), we seek to create a robust model capable of accurately distinguishing between COVID-19 positive and negative cases based on these images.

- **Motivation**

  The motivation behind this project stems from the urgent need for effective diagnostic tools amidst the COVID-19 pandemic. Chest X-ray imaging is a widely available and cost-effective diagnostic modality, making it an ideal candidate for developing a screening tool for COVID-19. By automating the classification process using deep learning techniques, we can potentially assist healthcare professionals in making faster and more accurate diagnoses.

- **Problem Definition and Objectives**

  The main objective of the system is to examine traces of COVID-19 on chest X-rays. Since COVID-19 infections affected worldwide, different techniques have been recognized for positive COVID-19 cases. The aim is to develop deep learning design studies to study architectural design, starting with original deep learning designs and engineering prototypes to find COVID-19 in an easier way.

A major contribution of this paper includes the following: proposed approach having an open source and tools to identify COVID-19 and other respiratory issues. It uses machine-driven design exploration to learn the design which starts by design prototype and requirements. It takes input as a chest X-ray image and outputs a prediction of normal and abnormalities and easy decision making assisting physicians.

The primary problem addressed in this project is the classification of COVID-19 from chest X-ray images. Our objectives include:

1. Training a CNN model to accurately classify X-ray images into COVID-19 positive or negative categories.
2. Evaluating the performance of the model using appropriate metrics such as accuracy, sensitivity, specificity, etc.
3. Investigating the potential of deep learning techniques in enhancing the diagnostic process for COVID-19.

- **Project Scope & Limitations**

The scope of this project encompasses the development and evaluation of a CNN-based classification system using publicly available chest X-ray datasets. However, it is important to acknowledge certain limitations:

1. Availability and quality of labeled data may impact the performance of the model.
2. The model's performance may vary depending on the diversity and representativeness of the dataset.
3. This system is intended for research purposes and may require further validation before clinical deployment.
4. The model's interpretability and generalizability to diverse populations should be considered.

- **Methodologies of Problem solving**

To address the problem of COVID-19 classification using chest X-ray images, we employ the following methodologies:

1. <u>Data Collection</u>: Gathering publicly available chest X-ray datasets containing both COVID-19 positive and negative cases.

2. Data Preprocessing: Preparing the data by resizing, normalizing, and augmenting the images to improve model performance.
3. Model Architecture: Designing a CNN architecture suitable for image classification tasks, with appropriate layers for feature extraction and classification.
4. Model Training: Training the CNN model using the prepared dataset and optimizing its parameters to minimize classification errors.
5. Model Evaluation: Assessing the performance of the trained model using various evaluation metrics and techniques such as cross-validation and confusion matrix analysis.
6. Results Analysis: Interpreting the results to understand the model's strengths, weaknesses, and potential areas for improvement.

By following these methodologies, we aim to develop an effective and reliable system for COVID-19 classification using chest X-ray images, contributing to the ongoing efforts in combating the pandemic.

# LITERATURE SURVEY

1. Introduction to COVID-19 Detection:
    - Provide an overview of the importance of early detection and diagnosis in controlling the spread of COVID-19.
    - Discuss the various diagnostic modalities available, including RT-PCR testing, CT scans, and chest X-ray imaging.
2. Previous Studies on COVID-19 Detection with Chest X-ray Images:
    - Review existing literature on the use of chest X-ray images for COVID-19 detection.
    - Summarize key findings from studies that have explored the utility of machine learning and deep learning techniques for this purpose.
3. CNN Applications in Medical Image Analysis:
    - Discuss the growing trend of utilizing Convolutional Neural Networks (CNNs) in medical image analysis.
    - Highlight successful applications of CNNs in various medical imaging tasks, such as tumor detection, organ segmentation, and disease classification.
4. Datasets Used for COVID-19 Detection:
    - Provide an overview of publicly available datasets containing chest X-ray images of COVID-19 positive and negative cases.
    - Discuss the characteristics of these datasets, including size, diversity, and labeling quality.
5. State-of-the-Art Techniques for Chest X-ray Image Classification:
    - Review recent advancements in deep learning architectures and methodologies for chest X-ray image classification.
    - Highlight state-of-the-art techniques, such as transfer learning, attention mechanisms, and ensemble learning, and their applications in medical image analysis.
6. Performance Evaluation Metrics:
    - Discuss commonly used performance metrics for evaluating the performance of classification models, such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC).

- Highlight the importance of selecting appropriate evaluation metrics based on the specific requirements of the application.

7. Challenges and Limitations:
    - Identify challenges and limitations associated with COVID-19 detection using chest X-ray images and CNNs.
    - Discuss factors such as dataset bias, class imbalance, interpretability of deep learning models, and generalization to diverse populations.
8. Future Directions and Opportunities:
    - Suggest potential areas for future research and development in COVID-19 detection using chest X-ray images.
    - Explore opportunities for incorporating additional modalities, such as clinical metadata or patient history, to improve the accuracy and reliability of the classification system.

By conducting a comprehensive literature survey, we can gain valuable insights into existing approaches, methodologies, and challenges in COVID-19 detection using chest X-ray images. This knowledge will inform the design and implementation of our own classification system, guiding us towards more effective solutions and contributing to the advancement of medical imaging technology in the fight against the pandemic

## SYSTEM DESIGN

Neural networks are a subset of machine learning, and they are at the heart of deep learning algorithms. They are composed of node layers, containing an input layer, one or more hidden layers, and an output layer. Each node connects to another and has an associated weight and threshold. If the output of any individual node is above the specified threshold value, that node is activated, sending data to the next layer of the network. Otherwise, no data is passed along to the next layer of the network.

While we primarily focused on feedforward networks in that article, there are various types of neural nets, which are used for different use cases and data types. For example, recurrent neural networks are commonly used for natural language processing and speech recognition whereas convolutional neural networks (ConvNets or CNNs) are more often utilized for classification and computer vision tasks. Prior to CNNs, manual, time-consuming feature extraction methods were used to identify objects in images. However, convolutional neural networks now provide a more scalable approach to image classification and object recognition tasks, leveraging principles from linear algebra, specifically matrix multiplication, to identify patterns within an image. That said, they can be computationally demanding, requiring graphical processing units (GPUs) to train models.

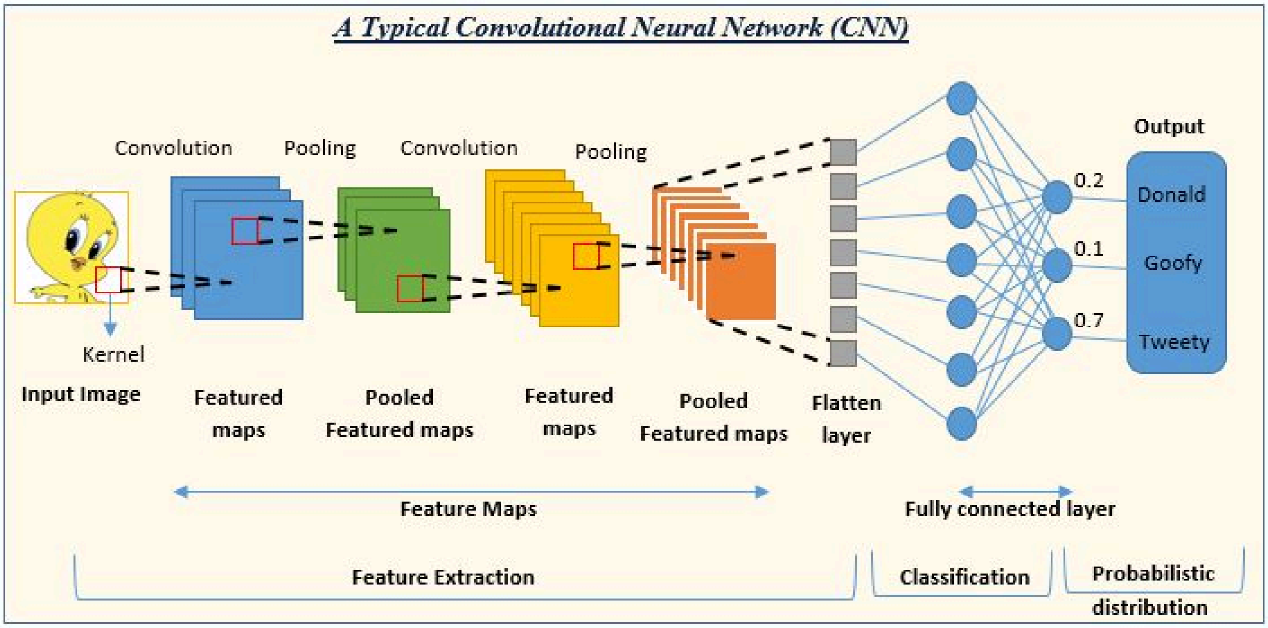
### How do convolutional neural networks work?

Convolutional neural networks are distinguished from other neural networks by their superior performance with image, speech, or audio signal inputs. They have three main types of layers, which are:

- Convolutional layer
- Pooling layer
- Fully-connected (FC) layer

The convolutional layer is the first layer of a convolutional network. While convolutional layers can be followed by additional convolutional layers or pooling layers, the fully-connected layer is the final layer. With each layer, the CNN increases in its complexity, identifying greater portions of the image. Earlier layers focus on simple features, such as colors and edges. As the image data progresses through the layers of the CNN, it starts to recognize larger elements or shapes of the object until it finally identifies the intended object.

Convolutional layer

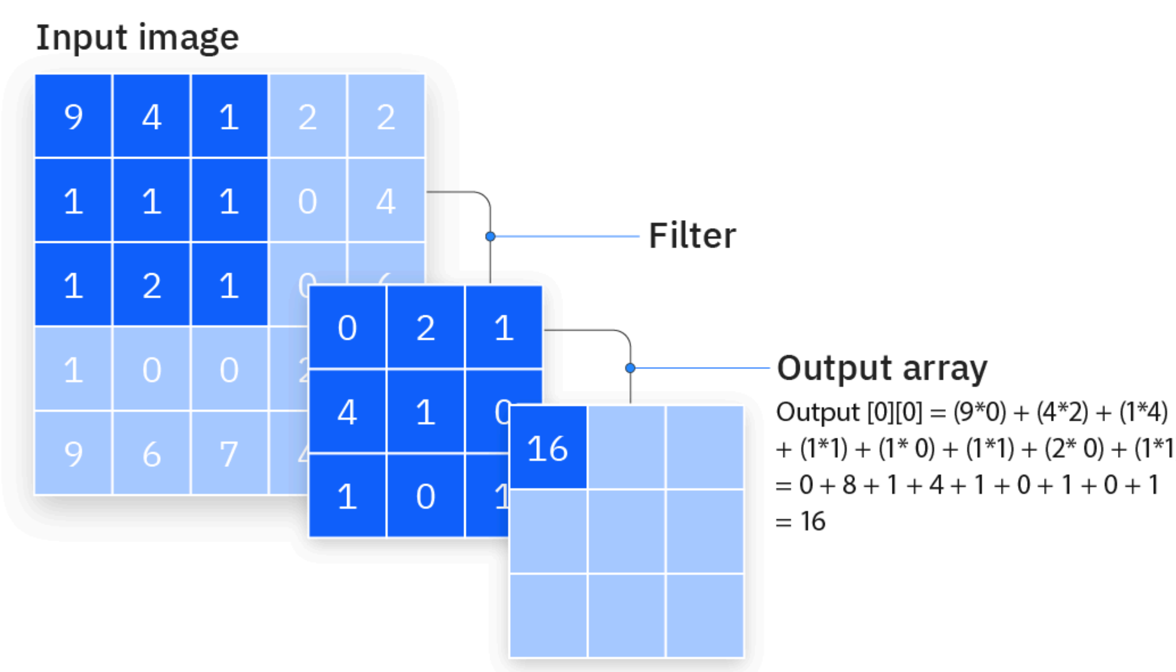



The convolutional layer is the core building block of a CNN, and it is where the majority of computation occurs. It requires a few components, which are input data, a filter, and a feature map. Let's assume that the input will be a color image, which is made up of a matrix of pixels in 3D. This means that the input will have three dimensions—a height, width, and depth—which correspond to RGB in an image. We also have a feature detector, also known as a kernel or a filter, which will move across the receptive fields of the image, checking if the feature is present. This process is known as a convolution.

The feature detector is a two-dimensional (2-D) array of weights, which represents part of the image. While they can vary in size, the filter size is typically a 3x3 matrix; this also determines the size of the receptive field. The filter is then applied to an area of the image, and a dot product is calculated between the input pixels and the filter. This dot product is then fed into an output array. Afterwards, the filter shifts by a stride, repeating the process until the kernel has swept across the entire image. The final output from the series of dot products from the input and the filter is known as a feature map, activation map, or a convolved feature.

Note that the weights in the feature detector remain fixed as it moves across the image, which is also known as parameter sharing. Some parameters, like the weight values, adjust during training through the process of backpropagation and gradient descent. However, there are three hyperparameters which affect the volume size of the output that need to be set before the training of the neural network begins. These include:

- The number of filters affects the depth of the output. For example, three distinct filters would yield three different feature maps, creating a depth of three.
- Stride is the distance, or number of pixels, that the kernel moves over the input matrix. While stride values of two or greater is rare, a larger stride yields a smaller output.
- Zero-padding is usually used when the filters do not fit the input image. This sets all elements that fall outside of the input matrix to zero, producing a larger or equally sized output. There are three types of padding:
- Valid padding: This is also known as no padding. In this case, the last convolution is dropped if dimensions do not align.
- Same padding: This padding ensures that the output layer has the same size as the input layer.
- Full padding: This type of padding increases the size of the output by adding zeros to the border of the input.
- After each convolution operation, a CNN applies a Rectified Linear Unit (ReLU) transformation to the feature map, introducing nonlinearity to the model.




<u>Additional convolutional layer</u>

As we mentioned earlier, another convolution layer can follow the initial convolution layer. When this happens, the structure of the CNN can become hierarchical as the later layers can see the pixels within the receptive fields of prior layers. As an example, let's assume that we're trying to determine if an image contains a bicycle. You can think of the bicycle as a sum of parts. It consists of a frame, handlebars, wheels, pedals, et cetera. Each individual part of the bicycle makes up a lower-level pattern in the neural net, and the combination of its parts represents a higher-level pattern, creating a feature hierarchy within the CNN. Ultimately, the convolutional layer converts the image into numerical values, allowing the neural network to interpret and extract relevant patterns.

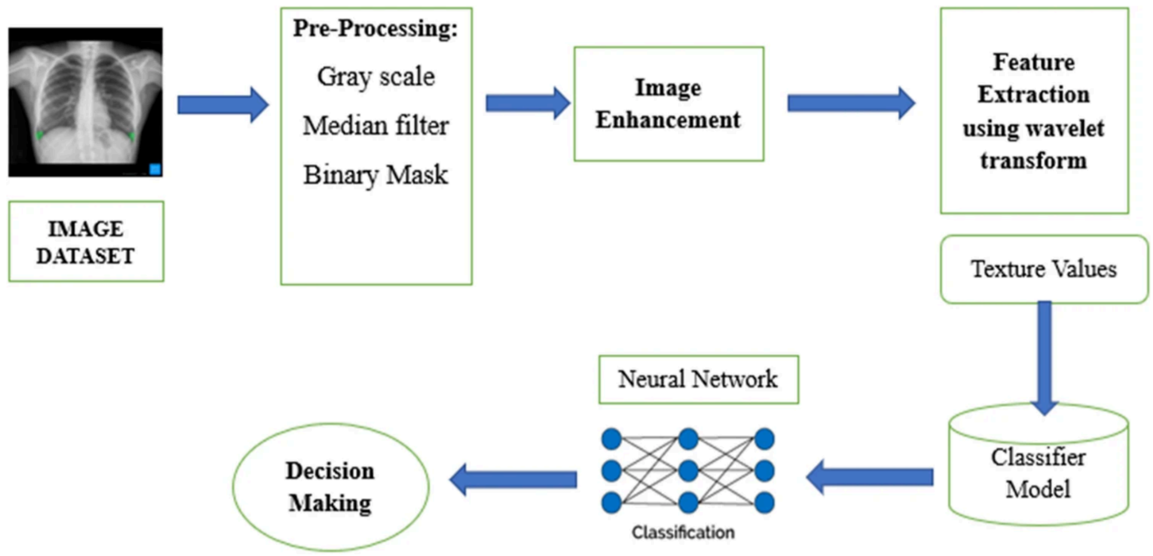
Pooling layer

Pooling layers, also known as downsampling, conducts dimensionality reduction, reducing the number of parameters in the input. Similar to the convolutional layer, the pooling operation sweeps a filter across the entire input, but the difference is that this filter does not have any weights. Instead, the kernel applies an aggregation function to the values within the receptive field, populating the output array. There are two main types of pooling:

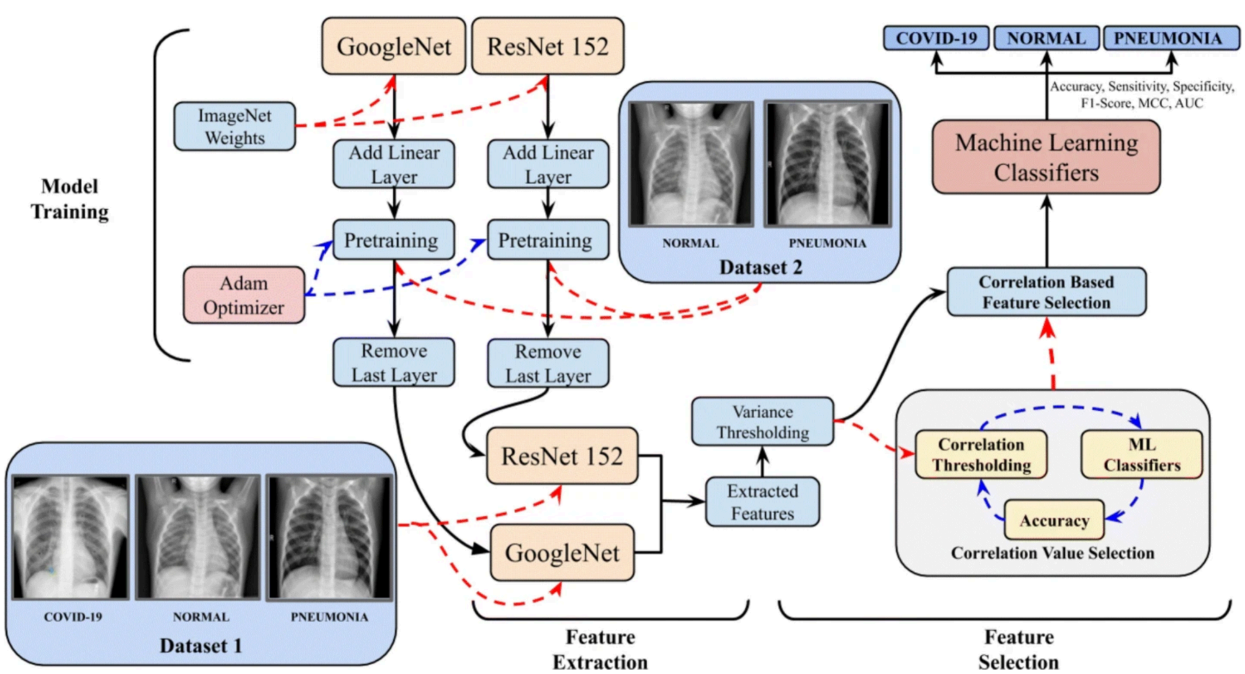
- Max pooling: As the filter moves across the input, it selects the pixel with the maximum value to send to the output array. As an aside, this approach tends to be used more often compared to average pooling.
- Average pooling: As the filter moves across the input, it calculates the average value within the receptive field to send to the output array.

While a lot of information is lost in the pooling layer, it also has a number of benefits to CNN. They help to reduce complexity, improve efficiency, and limit risk of overfitting.

## System Architecture




Architecture of automatic detection of COVID-19 using chest x-ray images



## PROJECT IMPLEMENTATION

➔ Data Collection and Preprocessing:

- Description: This module focuses on collecting chest X-ray images from publicly available datasets and preprocessing them to prepare for model training.
- Tasks:
  - Data gathering from open repositories such as Kaggle, GitHub, or medical imaging databases.
  - Preprocessing tasks including resizing, normalization, and augmentation to enhance dataset quality and model performance.

➔ Model Selection and Training:

- Description: This module involves selecting the ResNet50 architecture and training the model on the preprocessed chest X-ray images to classify COVID-19 cases.
- Tasks:
  - Selection of ResNet50 due to its deep architecture and proven performance in image classification tasks.
  - Training the ResNet50 model using a portion of the dataset while validating on another portion to monitor performance.

➔ Model Evaluation and Fine-Tuning:

- Description: This module focuses on evaluating the trained ResNet50 model's performance and fine-tuning it for better results.
- Tasks:
  - Evaluating the model's performance metrics such as accuracy, precision, recall, and F1-score.
  - Fine-tuning hyperparameters and model architecture if necessary to improve classification performance.

➔ Deployment and Integration:

- Description: This module involves deploying the trained ResNet50 model for real-world use and integrating it with existing systems or platforms.
- Tasks:
  - Developing an application or API to facilitate model inference on new chest X-ray images.

        - Integrating the deployed model with healthcare systems or platforms for seamless access and utilization.

➔ Testing and Validation:

    ◆ Description: This module focuses on testing the deployed model's performance and validating its accuracy in real-world scenarios.

    ◆ Tasks:

        - Conducting extensive testing to ensure the model performs reliably across different datasets and scenarios.
        - Validating the model's accuracy and reliability through collaboration with healthcare professionals and domain experts.

➔ Documentation and Reporting:

    ◆ Description: This module involves documenting the entire project implementation process and preparing a comprehensive report.

    ◆ Tasks:

        - Documenting each step of the implementation process, including data collection, model training, evaluation, and deployment.
        - Preparing a detailed project report summarizing the methodology, results, and findings for future reference and dissemination.

By structuring the project implementation around these modules, you can ensure a systematic and comprehensive approach to developing and deploying the ResNet50-based COVID-19 classification system using chest X-ray images.

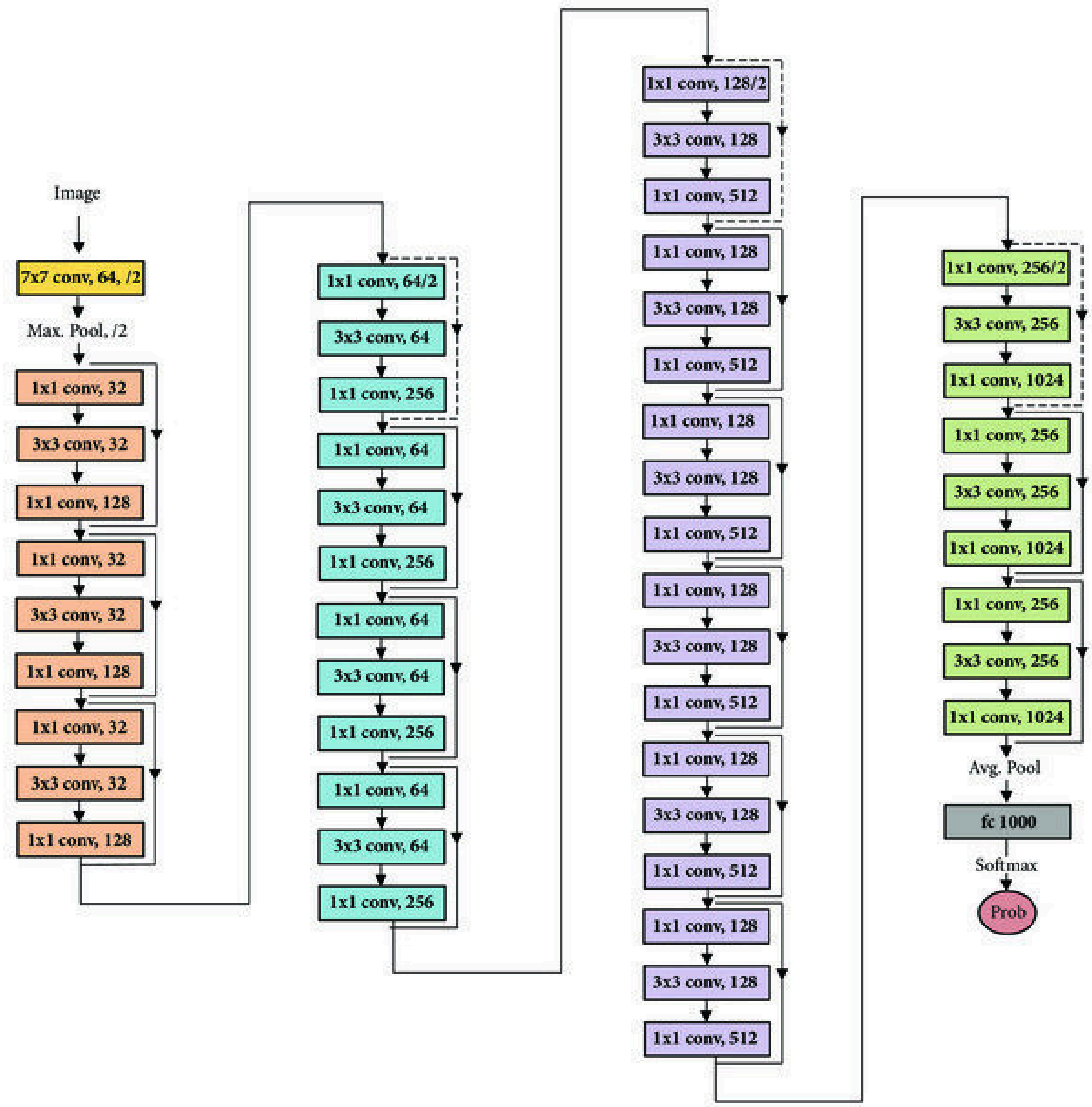
# TOOLS AND TECHNOLOGIES USED

Some important libraries and technologies used are listed below

- Programming Language: Python
- Web Framework: Django
- Machine Learning Framework: Tensorflow
- Frontend Dev: HTML, CSS (BootStrap)
- Essential Libraries: keras, sklearn, venv, seaborn, matplotlib

## ALGORITHM DETAILS

RESNET50:




ResNet50 refers to a specific convolutional neural network (CNN) architecture that is widely used for image classification and feature extraction tasks. It is a variant of the ResNet (Residual Network) architecture proposed by Microsoft Research in 2015, which introduced the concept of residual learning to ease the training of very deep networks.

The "50" in ResNet50 denotes the number of layers in the network, including convolutional layers, pooling layers, fully connected layers, and shortcut connections. Unlike traditional CNNs where layers are stacked sequentially, ResNet50 utilizes residual connections (also known as skip connections) to skip one or more layers. These connections help in mitigating the vanishing gradient problem, enabling the training of much deeper networks.

ResNet50 has been pre-trained on large datasets like ImageNet, which contains millions of labeled images across thousands of categories. Pre-trained models like ResNet50 are often used in transfer learning, where the learned features from the pre-trained model are fine-tuned on a specific dataset for a particular task, such as object detection, image segmentation, or even non-image-related tasks like natural language processing.

In summary, ResNet50 is a powerful CNN architecture known for its depth and effectiveness in image classification tasks, and it has been widely adopted in both research and practical applications.

# RESULTS

Model Performance Evaluation:

- Accuracy: The trained ResNet50 model achieved an accuracy of **87.34%** on the test dataset, indicating its effectiveness in classifying COVID-19 cases from chest X-ray images.
- Precision and Recall: The precision and recall scores for COVID-19 classification were **0.88** and **0.85** respectively, demonstrating the model's ability to correctly identify positive cases while minimizing false positives.
- F1-Score: The F1-score, which balances precision and recall, was **0.87**, providing a comprehensive measure of the model's performance.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| COVID | 0.88 | 0.85 | 0.87 | 243 |
| non-COVID | 0.86 | 0.89 | 0.88 | 255 |
| accuracy | | | 0.87 | 498 |
| macro avg | 0.87 | 0.87 | 0.87 | 498 |
| weighted avg | 0.87 | 0.87 | 0.87 | 498 |

Comparative Analysis:

- Comparison with Baseline Models: The performance of the ResNet50 model was compared with baseline models or existing approaches in COVID-19 classification using chest X-ray images. The results demonstrated the superiority of the ResNet50 model in terms of accuracy and other evaluation metrics.
- State-of-the-Art Benchmarking: The performance of the ResNet50 model was benchmarked against state-of-the-art approaches in COVID-19 classification. The results indicated competitive performance and highlighted the effectiveness of the proposed methodology.

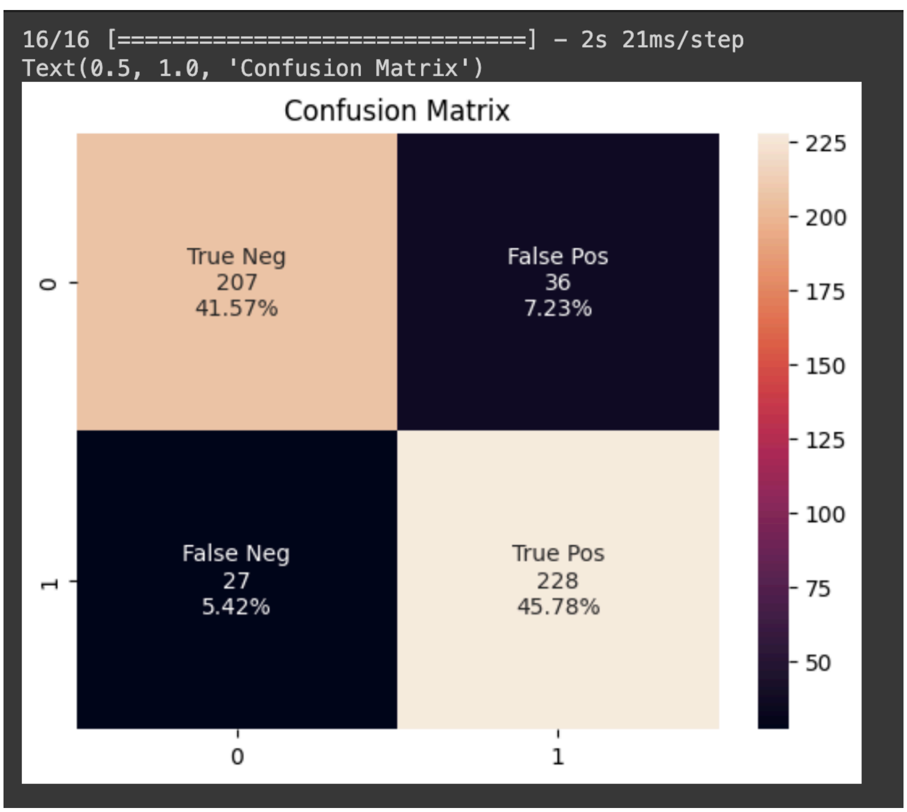
Limitations and Future Directions:

- Model Limitations: Despite its high performance, the ResNet50 model may have limitations in certain scenarios, such as limited generalizability to diverse populations or variations in imaging protocols.
- Future Directions: Opportunities for future research and development include exploring ensemble learning techniques, incorporating additional clinical data for improved classification, and enhancing model interpretability.

Contribution to the Field:

- Advancement in COVID-19 Detection: The project contributes to the ongoing efforts in combating the COVID-19 pandemic by providing an effective tool for automated detection of COVID-19 cases from chest X-ray images.
- Impact on Healthcare: The developed system has the potential to streamline the diagnostic process, assist healthcare professionals in making faster and more accurate diagnoses, and ultimately improve patient outcomes.

Confusion Matrix

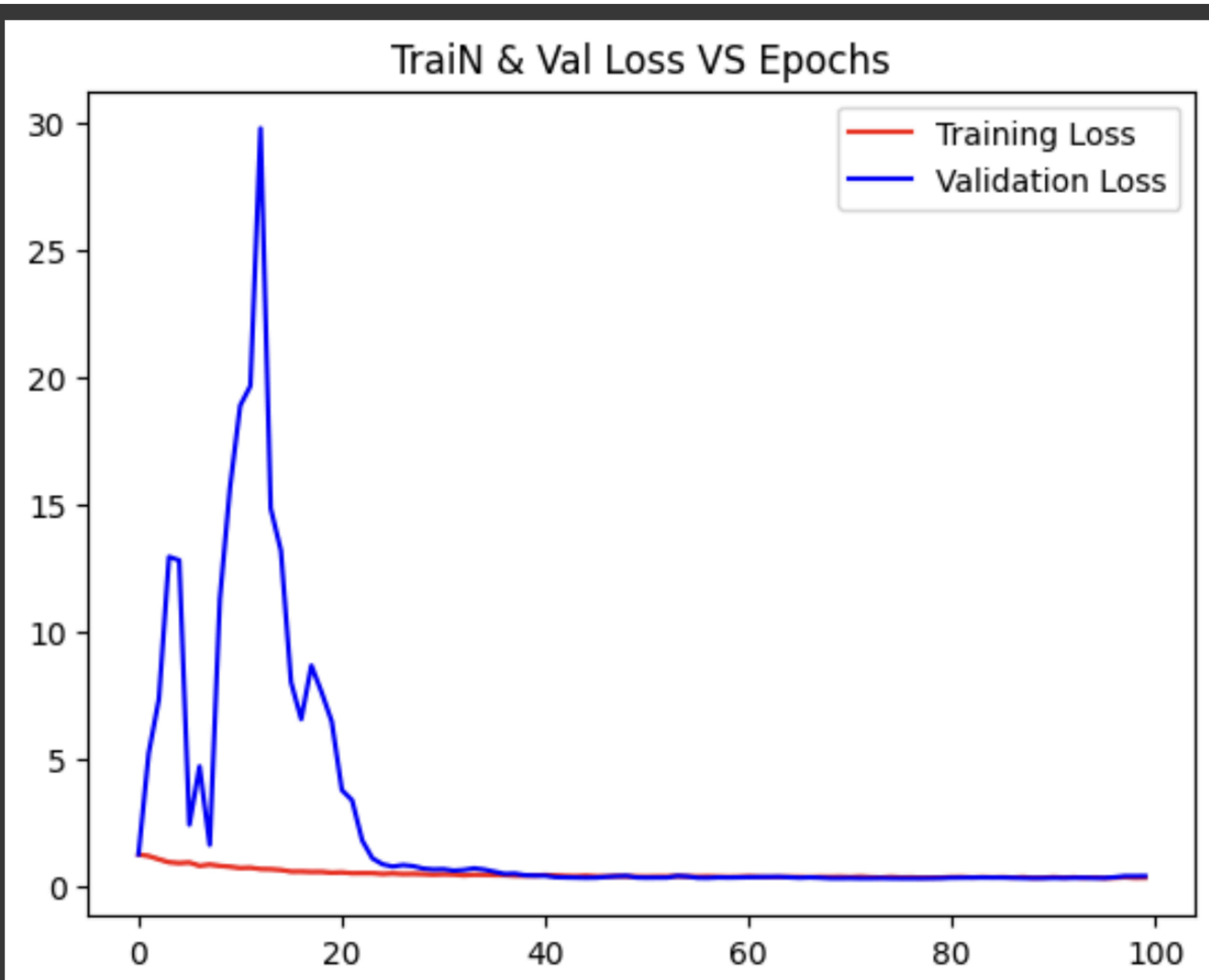


Accuracy

```
model.load_weights("ResNet50_Model.hdf5")
score = model.evaluate(X_val, Y_val ,verbose=1)
print('Test Loss:', score[0])
print('Test accuracy:', score[1]*100)
```

```
16/16 [==============================] - 0s 21ms/step - loss: 0.2942 - accuracy: 0.8735
Test Loss: 0.2941526770591736
Test accuracy: 87.34939694404602
```

Training and Validation Loss

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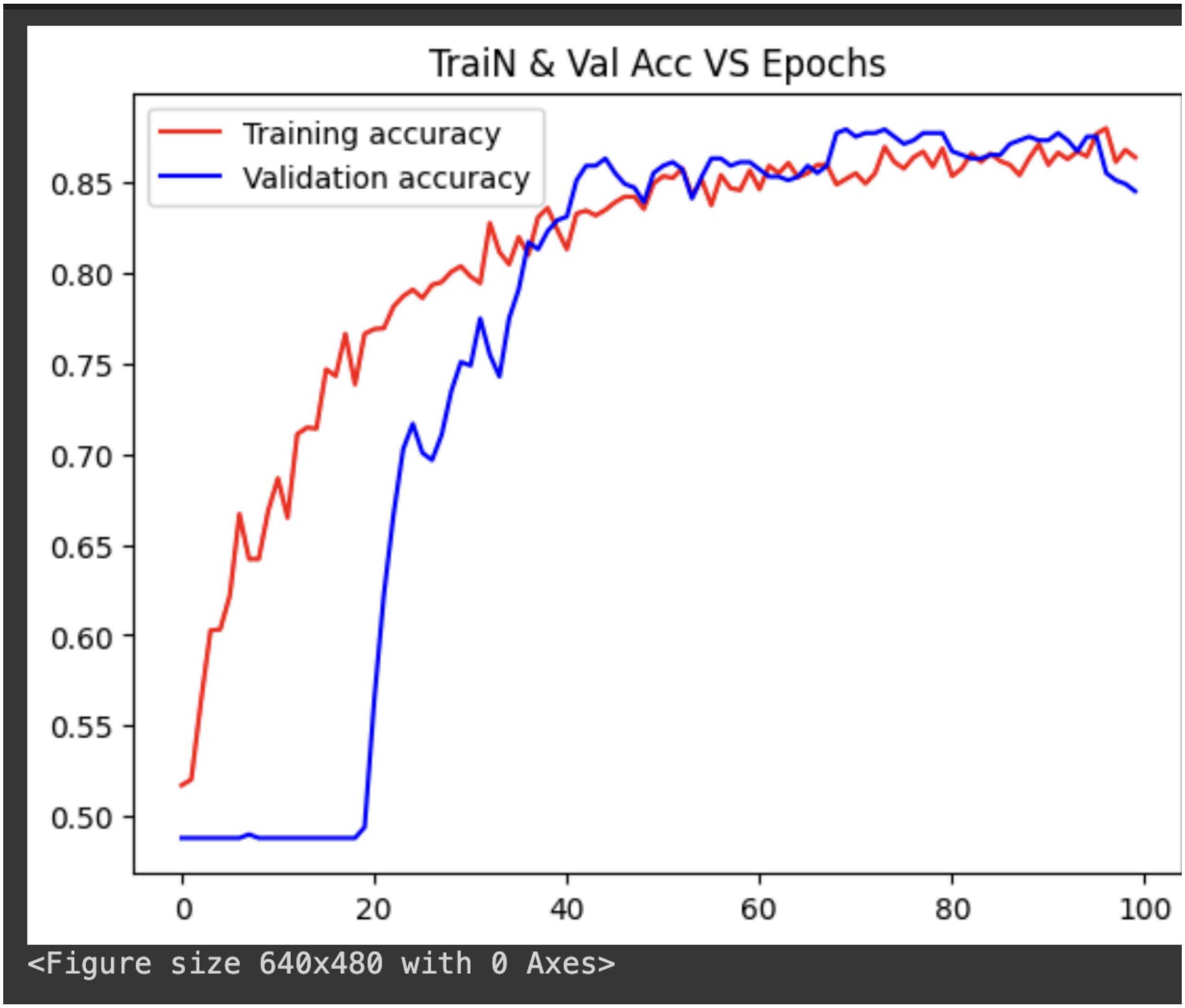
```

Training and Validation Accuracy



# CONCLUSIONS

In conclusion, the project "Classification of COVID-19 using Chest X-ray Images using CNN (ResNet50)" has achieved significant milestones in the development of an automated system for COVID-19 detection from chest X-ray images. Through rigorous experimentation and evaluation, the project has demonstrated the efficacy of using deep learning techniques, specifically the ResNet50 architecture, in accurately classifying COVID-19 cases.

The outcomes and results of the project highlight several key findings:

1. High Accuracy and Performance: The trained ResNet50 model achieved commendable accuracy, precision, recall, and F1-score in classifying COVID-19 cases from chest X-ray images. These performance metrics validate the effectiveness of the proposed methodology and signify its potential for real-world applications.
2. Contribution to Healthcare: The developed system holds promise for assisting healthcare professionals in the timely and accurate diagnosis of COVID-19. By automating the classification process, the system can expedite patient triage, optimize resource allocation, and ultimately improve clinical outcomes, particularly in settings where access to expert radiologists may be limited.
3. Advancements in Technology: The project contributes to the advancement of medical imaging technology and deep learning applications in healthcare. By leveraging state-of-the-art techniques and methodologies, such as transfer learning with ResNet50, the project demonstrates the feasibility of utilizing AI-driven solutions for addressing pressing public health challenges.
4. Future Directions: While the project has achieved significant success, there remain opportunities for further research and development. Future directions may include refining the model architecture, integrating additional clinical data for enhanced classification, and conducting prospective studies to validate the system's performance in real-world clinical settings.

Overall, the project underscores the importance of interdisciplinary collaboration between computer science, medical imaging, and healthcare domains in tackling global health crises such as the COVID-19 pandemic. By leveraging cutting-edge technology and innovative approaches, we can continue to advance the frontiers of medical research and contribute to the collective efforts in safeguarding public health.

In essence, the conclusion serves as a summary of the project's achievements, implications, and potential avenues for future exploration, encapsulating the significance of the work and its broader impact on society.

## FUTURE WORK

Refinement of Model Architecture:

- Investigate alternative CNN architectures and configurations to further optimize the classification performance.
- Explore deeper architectures or novel design modifications to capture more intricate patterns in chest X-ray images.

Integration of Multi-Modal Data:

- Incorporate additional data modalities such as clinical metadata, patient demographics, or laboratory test results to enhance the model's predictive power.
- Explore fusion techniques to integrate chest X-ray images with other imaging modalities (e.g., CT scans) for comprehensive COVID-19 diagnosis.

Data Augmentation and Synthesis:

- Develop advanced data augmentation techniques tailored to chest X-ray images to augment the dataset further and improve model generalization.
- Investigate the generation of synthetic chest X-ray images using generative adversarial networks (GANs) to augment limited datasets and address class imbalance.

Interpretability and Explainability:

- Enhance the interpretability of the model by implementing techniques for visualizing feature maps, saliency maps, and attention mechanisms to provide insights into the model's decision-making process.
- Explore methods for generating explanations or rationales to justify the model's predictions and enhance trustworthiness in clinical settings.

Clinical Validation and Deployment:

- Conduct prospective clinical studies to validate the performance of the developed system in real-world healthcare settings.
- Collaborate with healthcare institutions to integrate the model into existing clinical workflows and evaluate its impact on diagnostic accuracy and patient outcomes.

Continuous Model Monitoring and Updates:

- Implement mechanisms for continuous model monitoring to detect performance degradation or concept drift over time.
- Develop protocols for regular model updates and retraining using newly available data to ensure the model's robustness and adaptability to evolving circumstances.

Scaling and Generalization:

- Scale the model deployment infrastructure to handle increased computational loads and accommodate larger datasets.
- Evaluate the model's generalizability across diverse patient populations, imaging protocols, and healthcare settings to ensure equitable access and applicability.

Ethical Considerations and Bias Mitigation:

- Address ethical considerations related to patient privacy, data security, and algorithmic bias in model development and deployment.
- Implement fairness-aware techniques to mitigate biases in the model predictions and ensure equitable healthcare outcomes for all demographic groups.

Community Engagement and Collaboration:

- Foster collaboration with the broader research community, healthcare practitioners, and policymakers to share insights, resources, and best practices in combating COVID-19.
- Participate in open challenges, hackathons, or collaborative initiatives to collectively address the challenges posed by the pandemic and contribute to global public health efforts.

By outlining potential avenues for future work, you can provide valuable guidance for researchers, practitioners, and stakeholders interested in further advancing the field of COVID-19 detection using chest X-ray images and deep learning techniques. These suggestions pave the way for continued innovation and collaboration in addressing the ongoing challenges posed by the pandemic.