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A Novel Computer-Aided Approach for Predicting COVID-19 Severity Using Hyperparameters in ResNet50v2 from X-ray Images

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Abstract: This research has been globally impacted by COVID-19 virus, which was a very uncommon, highly contagious & dangerous respiratory illness demanding early detection for effective containment and further spread. In this research, we proposed an innovative methodology that utilizes images of X-rays for COVID-19 detection at an early stage. By employing a convolution neural network, we enhance the accuracy performance via using ResNet50v2 using a hyperparameter. The methodology achieves a remarkable accuracy with an average accuracy of 99.12%. This accuracy surpasses other available models based on different deep learning models like VGG, Xception and DenseNet for COVID identification & detection with the help of X-ray images. X-ray scans are now preferably used modality for the identification & detection of COVID-19, given its widespread utilization and effectiveness. However, manual treatment & examination using X-ray images is very challenging, specifically in the field which is facing a limitation of skilled medical staff. Utilization of deep learning models has demonstrated significant potential and effective results in automating the diagnosis for timely identification of COVID with the help of X-ray films. The suggested architecture is specifically developed for timely prediction and analysis of COVID cases employing X-ray films. It firmly believes that this study holds significant potential in alleviating the workload of frontline radiologists, expediting patient diagnosis and treatment, and facilitating pandemic control efforts.

Introduction

Chest radiology is a frequently employed clinical imaging method for the early diagnosis of numerous diseases and as cheaper system. Many different available data and studies have shown X-Ray as a very important tool for identifying various infected diseases, that are very uncommon symptoms and found worldwide (Ju et al., 2024). The ability of computer-based systems to interpret and analyze X-ray images with different efficiency compared to practicing radiologists would be immensely beneficial. It has also been observed that attention towards the early detection of chest X-ray image features has been increased, with several algorithms developed & designed for pulmonary tuberculosis and pneumonia detection using machine learning and deep learning (Mohan et al., 2024). Additionally, deep learning techniques have found utility for timely identification and further advise.

Primary objective of this machine learning-based study is to identify early COVID symptoms with the help of multiple X-ray images. The unavailability of very large datasets in this field of medical imaging is a big challenge. Deep learning advancements have motivated for development of models to over cross performance of different medical professionals in various domains such as pneumonia detection, lung cancer screening and skin cancer classification.

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Algorithms specifically designed for detecting pneumonia from multiple chest X-rays outperform medical professionals. Moreover, some CNN models like AlexNet, VGG and DenseNet have shown very good results for the detection of multiple diseases with similar performance and parameters that we need for COVID-19 detection using X-rays (Yadav et al., 2024). Researchers have employed machine learning-based algorithms to detect and diagnose various life-threatening diseases. Some of them conducted research to analyze multiple chest X-ray scans to check COVID severity using deep learning. Deb et al. (2023) introduces a deep learning model, CoVSeverity-Net, for predicting COVID-19 severity from Chest X-ray scans. The Deep learning-based models showed satisfactory results, although the optimized and effective model incorporated non-image data and was trained specifically using X-ray images. (Hariri et al., 2023) Introduced one lightweight CNN-based model for the classification of images in pneumonia, COVID-19 and normal. The proposed research outperformed the performance of pre-trained models.

Furthermore, some computerized diagnosis systems using deep learning have already been employed to predict and analyze symptoms of tuberculosis in the chest or other body part X-rays. Deep learning can be used to detect different categories of pneumonia and other similar diseases through different X-ray clinical images (Dalvi et al., 2023). Deep learning-based predictive systems were developed to predict & forecast the threat of COVID-19 contraction. Furthermore, novel diagnostic systems employing many CNN models like VGG, Inception, DenseNet etc., have been suggested for timely identification and detection of different infections, especially for COVID using chest X-ray scans (Mann et al., 2023). These systems utilize various techniques, such as split-transform-merge blocks, region-homogeneity, and heterogeneity operations, to achieve favorable results in the early identification of COVID-19 and similar infections.

Significant limitations of previous research in the area of deep learning for chest images and CT scans are the focus on binary classification tasks and the availability of specific disease symptoms (Bhattacharjee et al., 2023; Liu et al., 2023). Lastly, evaluation of these models, like VGG, XGboost etc, has primarily relied on simple accuracy metrics, necessitating the use of effective detection models to find the severity or sensitivity of the disease (Narin et al., 2021). This research paper also aims to address these limitations and contribute to the area of deep CNNs using chest X-ray treatment and diagnosis. By implementing and comparing multiple models and training for seeking to identify and classify multiple pathology diseases accurately. Main objective of this research is to enhance the capabilities of deep learning in clinical image analysis, especially for chest X-ray analysis and to predict valuable insights for future study.

Related work

COVID detection and analysis have undergone extensive research. The initial section delves into different issues surrounding the utilization of different chest X-ray scans in combination with deep learning methods, has proven effective for timely COVID detection. The subsequent section of our paper examines sufficient and relevant literature to assess future possibilities and estimations for early identification and detection of COVID, further analysis & recovery. Chen et al. (2023) had worked on multi-disease detection from X-ray scans using deep learning techniques. The research has shown significant enhancement in multi-class disease detection. COVID-19 evolved into a worldwide pandemic because of the rapid transmission of the disease (Roychoudhury et al., 2021; Kaur et al., 2023; Bhosale et al., 2023; Rai et al., 2023; Vashist et al., 2023). Abayomi-Alli et al. (2022) study with the objective of developing model-based ensemble machine learning to improve the detection accuracy of COVID-19. Ahmed et al. (2023) discussed the importance of the detection of three different diseases COVID-19, pneumonia and tuberculosis, considering that patients can have multiple diseases simultaneously. The suggested model achieved over all 98.72% accuracy for all considered diseases. Detecting individuals who have been exposed to the virus poses a significant challenge since they may not exhibit immediate symptoms. Consequently, this is imperative to develop a single method for regularly estimating and calculating infected and partially infected individuals to implement appropriate measures. Artificial Intelligence (AI) presents an alternative, nontraditional, less time-consuming and less costly technique for screening individuals for COVID. Agrawal et al. (2023) suggest a modified model based on ResNet50 and Honnakasturi et al. for the classification of COVID-19 and Non-COVID-19. While numerous research studies have been done for different stages of COVID-19 patients, Kumar et al. (2023) research concentrates on EfficientNet XceptionNet for multi disease detection of COVID-19

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cases at the early stage and aid in subsequent treatment by examining chest X-rays.

Artificial Intelligence has found application in various research areas, including disease diagnoses in the healthcare sector. One noteworthy advantage of AI is its ability to be incorporated into a model that can be utilized for classification. In the research, we utilized artificial intelligence-based models for detecting COVID-19 symptoms by examining their respective chest X-ray images (Murugappan et al., 2023). Moreover, AI holds the potential for forecasting various phenomena, such as population growth over the next five years, through the utilization of existing evidence. Consequently, predicting future possibilities can assist authorities in adopting EfficientNet model with fine-tuned hyperparameters for the classification of lung diseases (Oh et al., 2023). Various other research was done using deep learning techniques for initial COVID-19 infection prediction based on images of chest X-rays. Sun et al. (2020) used deep-learning models and Support vector machines to achieve an appropriate 99% result accuracy (Yao et al., 2020; Abbasi et al., 2021) used machine learning model for COVID-19 detection using biomarkers, which detected 28 biomarkers related to consider images for COVID-19 risk estimation. Some studies utilized two-level thresholding & SVM to achieve an accuracy of 96.77% for COVID prediction by utilizing X-ray images. Different research students have used different supervised

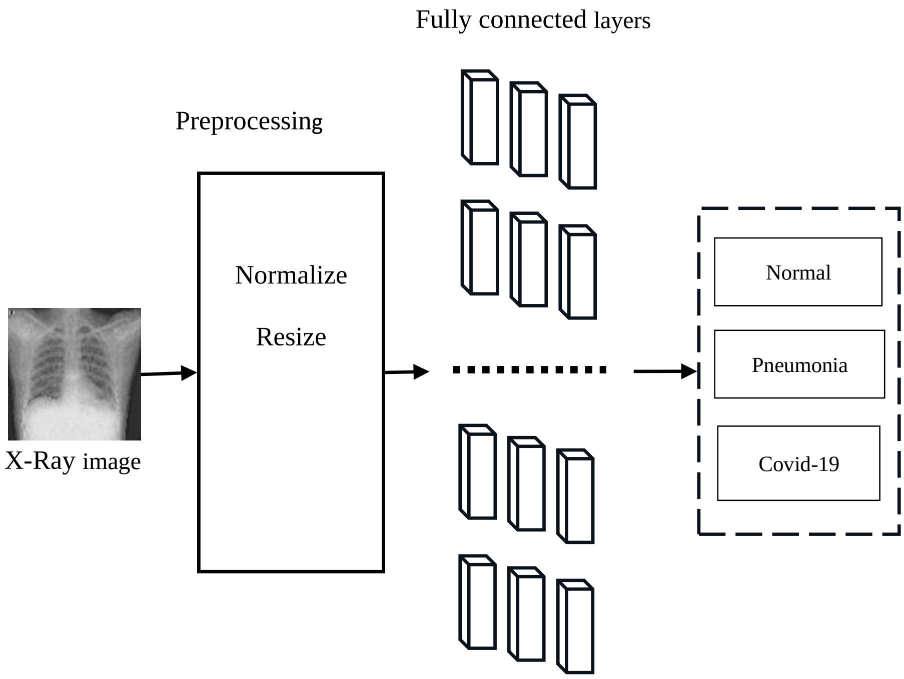

Figure 1. COVID-19 detection basic architectural diagram.

necessary measures. Some researchers focused on two key concepts: studies about COVID-19 diagnosis and studies concerning the prediction of future infection rates. The analysis of the research conducted revealed that most existing models exhibit inadequacies and biases. The authors recommended the use of UNet-based for research related to the detection of COVID-19 data to foster the development CNN based prediction models (Babaeipour et al., 2023). Machine learning has shown significant advancements, and deep learning, introduced in 2012, has become particularly influential. Convolutional neural networks based on Deep learning algorithms have given high accuracies in various applications, including computer vision tasks. For COVID-19 detection deep learning has emerged as a promising alternative against traditional and time-consuming costly methods. The research suggested a deep-learning-based model based on learning methods for the identification and detection of COVID-19-infected patients. Some researchers are achieving a sensitivity of 96.4% by utilising a modified network inception model to achieve better accuracy for the initial identification of COVID symptoms.

Machine learning-aided COVID-19 Infection Prediction methods, particularly predictive models, have been utilized to assess the potential COVID-19-infected patients and predict the trajectory of the outbreak (Chu et al., 2020; Prabha et al., 2023). Raise the requirement to develop a prediction model using ML-based algorithms and estimate the highest level of COVID-19 burst worldwide, especially in China, with results matching real-world data. Different suggested model (Ozturk et al., 2020; Ge et al., 2020) for early COVID prediction spread in the 15 most infected countries was used by some researchers, providing valuable insights for decisionmakers. A group of researchers (Rao et al., 2022; Khanday et al., 2020; Sharma et al., 2020) put a Convolution neural network to the data to calculate different numbers of reported COVID cases in China, showing promising predictive efficiency. Overall, computer-based Artificial Intelligence-based methods using deep learning techniques for identifying COVID patients and shown very promising & favourable results (Albahli et al., 2021; Hussain et al., 2020). These technologies have the potential and strength to aid healthcare staff and skilled professionals in diagnosing COVID-19 infections accurately and provide valuable insights to policymakers for better decision-making in managing the pandemic. Nonetheless, further research and data sharing are necessary to develop more robust and unbiased models for better disease detection and prediction.

Materials and Methods

The CNN-based proposed approach for COVID-19 detection involves a multi-step process, as depicted in Figure 1. This approach has the following five key steps:

Step 1: Data Collection

The chest X-ray image dataset used in this research is from Kaggle, which provides an image repository for advanced research (https://www.kaggle.com/datasets/prashant268/chest-xray-covid19-pneumonia). Kaggle image dataset used in this study is organised with two main folders named as test and train. Both respective folders are structured in three categories: COVID-19, Normal and pneumonia, with a total number of 6432 images. This dataset includes different images collected from both COVID patients and individuals without any infection to facilitate robust model training and evaluation.

Step 2: Data Augmentation

For improved diversity and database size, it employs different augmentation methods. Specifically, this generates an additional 1000 X-ray images, which helps improve the generalization ability of different deep-learning methods.

Step 3: Features Representation & Deep Learning

The next step involves the transformation of these images into a feature-rich space. Subsequently, employ modern machine learning methods to explore meaningful important features and different patterns from given X-rays.

Step 4: Data Splitting

To achieve improved reliability, we split the dataset into two separate sets for comprehensive examination,

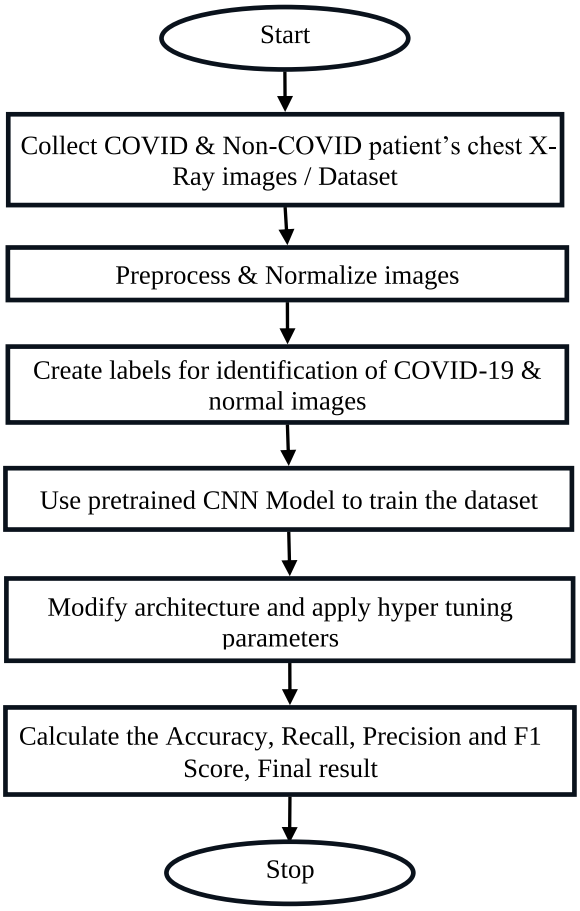

Figure 2. Framework of the methodology.

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where one set will be used for training and the other one for validation. By splitting the dataset into two sets training and validation model is preventing overfitting and ensuring robustness.

Step 5: Hyperparameter Tuning

Hyperparameter optimization plays an important role in enhancing the performance of machine learning models, specifically for image classification tasks. Hyperparameter tuning plays a key role in improved performance, accuracy and computational efficiency of the model.

Step 6: Performance Evaluation

The final and most important phase of the considered model includes evaluating the efficiency of the COVID-19 detection method with the validation data. Rigorous validation tests are employed to calculate model's accuracy, sensitivity, specificity and other key performance indicators.

The proposed research model incorporates a comprehensive and systematic approach for early COVID-19 detection by integrating augmentation deep learning dataset splitting and precise performance evaluation. Thorough assessment of the proposed model's capabilities is ensured by utilizing both original and augmented datasets.

Data augmentation is a widely recognized artificial intelligence method that can be used to counter the challenge related to the collection of COVID chest X-rays and provide robustness to the machine-learning model. Data augmentation is also used to expand and diversify labeled training datasets. This process involves generating multiple variations of the existing samples within a dataset, thus increasing its size and diversity.

The application of data augmentation serves several essential purposes in machine learning:

Addressing Class Imbalance: Data augmentation aids in mitigating class imbalance issues that can arise when dealing with imbalanced datasets. In this case, it helps ensure a balanced representation of healthy and COVID-19 cases.

a) **Reducing Overfitting:** The most common challenge of deep learning is overfitting. Data augmentation reduced risk overfitting is achieved by implementing variability with training data and enhancing the model's generalization capabilities.

b) **Improving Convergence:** Augmented data can lead to improved model convergence during the training process. This, in turn, contributes to more effective and efficient model training.

The methodology employed for implementation is illustrated in Figure 3. To ensure reliable results, several steps are needed to generate a robust and accurate model. Initially utilized dataset is obtained from the Kaggle COVID-19 radiography database. Considered dataset was made constructed by accumulating clinical images and data from various publicly available resources. The dataset is structured with two main categories: train and test, each containing three folders: COVID-19, Pneumonia and Normal. In total, there are 5144 X-ray images with the test data comprising 25% of the complete dataset.

Proposed model steps

Step 1: start
Step 2: Collect/ select chest X-Ray image dataset of COVID patients.
Step 3: Preprocess the chest X-Ray images
Step 4: Normalize, resize, rotate and fill by near pixels etc.
Step 5: Use CNN model ResNet50v2 to train the dataset.
Step 6: Hyper tune the parameters.
Step 6: Apply SVM for classification of images.
Step 7: stop

The images used in the model were resized first to a dimension of 224 × 224 × 3. To achieve this resizing, employ the Nearest-Neighbour interpolation technique. Following the interpolation process, the image pixel values were normalized to adjust for the standard range of pixels 0 to 1, ensuring consistent & standardized data representation.

For this model, we have used ResNet50v2 to train the database. The considered dataset is widely utilized for object categorization tasks, making it a suitable source for transfer learning. By leveraging transfer learning, the model could effectively learn from the specific characteristics of the dataset. To modify the pre-trained model for the purposes of different pooling index layers with a standard size of 2 × 2 and subsequently flattened output. For optimize the training process and facilitate faster convergence, we employ hyperparameter tuning. This widely used optimization method adapts the learning rate dynamically, resulting in improved efficiency and accuracy during training.

Further evaluation of the reliability and accuracy of CNN based covid detection model with several performance-based metrics, including different accuracy and precision parameters with Score. Comprehensive insights provided by metrics into the model's effectiveness in classifying the different X-ray chest images accurately.

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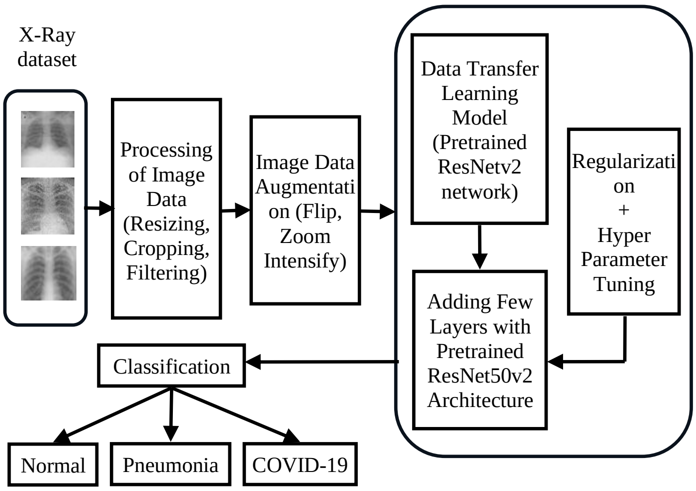

Figure 3. X-Ray's based Covid detection model.

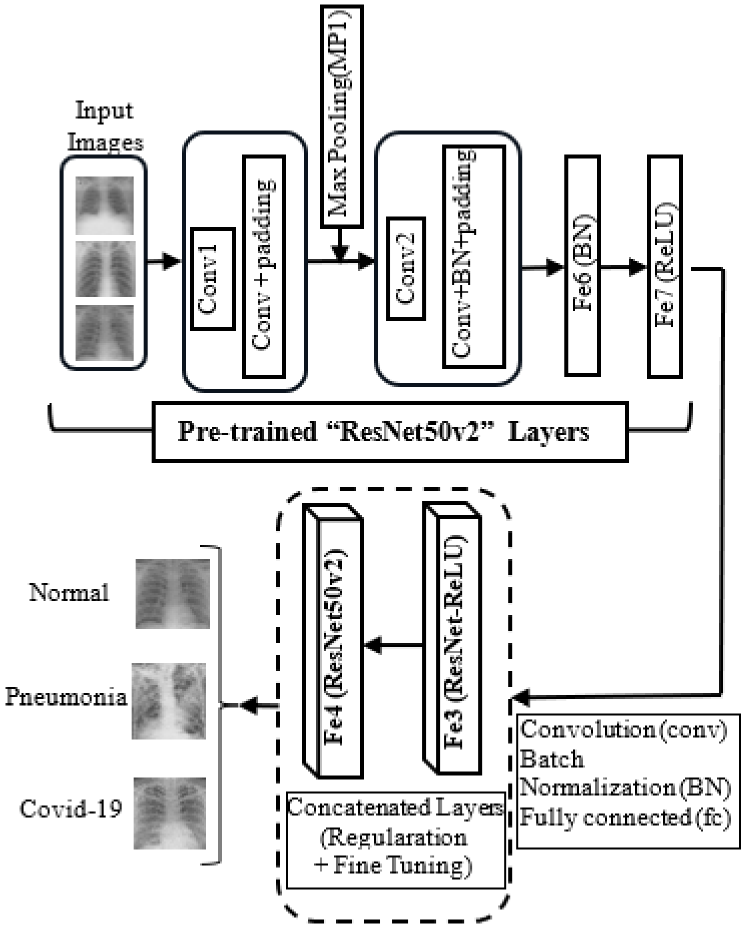

Figure 4. Updated ResNet50v2 architecture.

This model adopted a set of well-established evaluation metrics consistent with the methodology utilized by (Ahmed et al., 2013). These metrics include precision, F1 score, recall, correlation coefficient, (RMSE) Root Mean Square Error and accuracy. Each of these metrics provides a distinct performance perspective of the adopted model and the ability to perfectly identify positive COVID cases.

Root Mean Square Error: RMSE calculates the gap between real and predicted values in case of confirmed COVID-19-positive cases, covid recovered patients and patients deaths due to COVID. It penalizes larger predicted errors more severely. The RMSE formula is:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \check{x}_i)^2} \quad \text{......................(i)}$$

Here x_i represents real values, $\check{x}_i$ for predicted values and N for number of instances.

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Correlation Coefficient

The correlation coefficient is commonly used to evaluate prediction algorithm performance. It is calculated as:

$$CC = \left(1 - \frac{1}{N}\sum_{i=1}^{N} |\, x_i - \check{x}_i \,|\right) * 100\% \text{...............(ii)}$$

Resnet trained Hypermeters

In the field of deep learning, the ResNet50 architecture has established itself as an effective and flexible tool for a generous array of computer vision tasks. This research delves into the meticulous optimization of hyperparameters specific to ResNet50, aiming to unravel the intricacies of fine-tuning that contribute to heightened model performance. The exploration encompasses various key parameters, along with their respective formulas, to provide a comprehensive understanding of the optimization process.

learning rate (α)

learning rate is basically a pivotal parameter, determining step size during the next weight update. Finding an optimal learning rate (α) is essential for stable and efficient training. Learning rate schedules, such as time-based decay or adaptive methods like Adam, are often employed. The formula for weight update can be expressed as:

$$w_{n+1} = w_n - \alpha \cdot \nabla L(w_n) \text{.................................(iii)}$$

Here, in the formula, $L(w_n)$ is the loss function, and the gradient of loss is represented by $\nabla L(w_n)$ with respective weights.

Depth of ResNet50 (N):

ResNet50 is basically a pre-trained convolutional neural network architecture with 50 layers of depth. Formula D=3×N+1 can be used to calculate the total depth of ResNet50. More intricate features can be captured by using more deeper network considering overfitting aspects. The overall aim is to achieve optimal balance by ensuring improved performance.

Batch Size (B):

Batch size is an important parameter affecting both convergence speed and computational efficiency. It also determines the total number of data points to be processed in each iteration. Following is the formula for updating weights:

$$W_{t+1} = W_t - \frac{\alpha}{\beta}\sum_{i=1}^{\beta} \nabla L(W_t; x_i, y_i) \text{....................(iv)}$$

Here x_i, y_i represent input and respective labels of the i^{th} data point in the mini-batch.

Batch size: 32
Convolution 3 : [4,8]
Convolution 4 : [3, 24, 39]
Pooling : [‘avg’, ‘maz’]
Learning rate : [0.001, 0.01, 0.1]
Optimizers : [‘adam’, ‘rmsprop’, ‘sgd’]

In case of ResNet50 optimization of hyperparameters is crucial for unlocking its full potential in deep learning tasks. The process of fine-tuning involves different parameters like careful balance of learning rates, batch sizes, model depth and regularization techniques with the objective of achieving optimal performance while maintaining robust generalization capabilities.

Bayesian optimization (BO)

Bayesian optimization is used to optimize parameters in the case of black box function. Bayesian optimization method can be very helpful for image processing and deep learning problems as these cases are based on black box optimization. Bayesian optimization can be very useful in case of limited number of samples are available. Bayesian optimization method uses Bayes theorem and applied machine learning to fine-tune the hyperparameter to improve results.

$$P(S|O) = \frac{P(O|S) \text{ X } P(S)}{P(S)} \text{..................................(v)}$$

Before model training, hyperparameters like k_1, k_2, and k_3 in the configuration space K need to be set, where K is initialized as

$$K = k_1 x\ k_2\ x\ k_3 \text{.......................................(vi)}$$

Setting appropriate hyperparameters is critical as they significantly impact the model's performance. An incorrect learning rate, for instance, might cause the model to miss important patterns. The right combination of hyperparameters improves model efficiency and accuracy while minimizing the loss function. Therefore, tuning hyperparameters is essentially an optimization problem.

Table 1. Bayesian optimization hyperparameters range.

Hyperparameters	Ranges
Learning Rate	[0.001, 1]
Depth	[1, 4]
Momentum	[0.65, 0.97]
Drop out	[0.0, 0.75]
Activation function	RELU, tanh

In our work, we utilized Bayesian optimization to fine-tune the hyperparameters, aiming to enhance efficiency and minimize loss. The specific hyperparameters we optimized included learning rate, depth, momentum, L2 regularization etc. Details of these parameters are shown in Table-2. This optimization process ensures that the model achieves optimal performance by systematically selecting the best hyperparameter values.

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For any recently trained ResNet50 architecture, features are extracted from the average pooling layer, yielding 2048 features. On a similar pattern for the recently trained Inception model, features are obtained from the global average pooling layer.

Feature fusion combines multiple features into a single vector, significantly enhancing the performance of image processing applications because of unique attributes. To handle multi-dimensionality and redundancy, these fused features were processed using canonical correlation analysis (CCA). This method ensures a more efficient and accurate feature representation.

testing and training features $W_N^{f1}, W_N^{f2}, W_N^{f3}, W_N^{f4}$ obtained from the trained ResNet50 model, resulting in fused vectors of size N × F

$$W_{\text{fused}}^{\text{train}} = \begin{pmatrix} W_N^{f1} \\ W_N^{f3} \end{pmatrix}_{i=1}^{n} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{(vii)}$$

$$W_{\text{fused}}^{\text{train}} = \begin{pmatrix} W_N^{f2} \\ W_N^{f4} \end{pmatrix}_{i=1}^{n} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{(viii)}$$

Feature selection is basically a method to get the optimized and favourable features by deleting the unnecessary features so features so feature selection enhances accuracy and takes less compile time. Bayesian optimization utilizes the Gaussian process at each step to compute the belief. Afterward, a heuristic is used to choose the next decision. The Gaussian process that computes this belief is called a Surrogate Function, while the heuristic is known as an Acquisition Function. The process can be outlined as follows:

1) Compute Posterior Belief $\mu(x)$ uses a surrogate Gaussian process to estimate the mean and the standard deviation $\sigma(x)$, describing the uncertainty.
2) Calculate an acquisition function $\alpha(x)$ that indicates the benefit of sampling the next point from the range of values.
3) Identify the point where this acquisition function is maximized and sample at that location.

$$x_t = arg_x max\, \alpha_t(x) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{(ix)}$$

This will be repeated with multiple iterations, known as the optimization budget, to find a sufficiently good solution. The main acquisition functions are:

Probability of Improvement (PI): The acquisition function value is proportional to the probability of improvement at each point, characterized by the upper-tail CDF of the surrogate posterior.

$$\alpha_t(x) = \int_{-\infty}^{y_{opt}} N\big(y \big| \mu(x), \sigma(x)\big)dy \ldots\ldots\ldots\ldots\ldots\ldots\text{(x)}$$

Expected Improvement (EI): The value is proportional not only to the probability but also to the magnitude of potential improvement from that point.

$$\alpha_t(x) = \int_{-\infty}^{y_{opt}} N\big(y \big| \mu(x), \sigma(x)\big)[y_{opt} - y]dy \ldots\ldots\text{(xi)}$$

Upper Confidence Bound (UCB): This function controls exploration through the deviation and a tunable control parameter while exploiting the mean values of the posterior to determine the next sampling point.

$$\alpha_t(x) = -\mu(x) + \beta\sigma(x) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{(xii)}$$

Maximizing the acquisition function involves another non-linear optimization problem. However, since these functions are analytic, they can be differentiated, ensuring at least local convergence. To achieve global convergence, the process starts from multiple points within the domain, increasing the likelihood that the algorithm's maximum is close to the global optimum.

In summary, the proposed methodology encompasses the following key steps: dataset selection and through rotation, image resizing, pixel value normalization, utilization of a pre-trained ResNet50v2 model with hyperparameter tuning and optimization using Bayesian optimizer. These steps collectively contribute to systemically developing a robust and realistic model for image classification, specifically for chest X-rays.

Result and Discussions

In our research work, we employ the CNN-based ResNet50v2 model for timely prediction of COVID using X-Ray images. By utilizing a trained CNN model hyper-parameter tuning & optimization technique to develop a workable model for initial COVID detection. Initially learning rate value will be set as 0.01 and the training steps consist of 40 epochs with a batch size of 32. COVID detection will be performed using both X-rays and CT scans chest images. Although, CT scans are often costly and not easily accessible to all patients. Therefore, this model has focused on utilizing X-ray scans to develop an economically viable model.

Before feeding the X-rays into pre-trained architecture, the images underwent a pre-processing step. They were resized to dimensions of 224×224×3. This resizing ensured consistency in the input image size. The trained CNN model extracts features from chest X-ray scans. Illustrated model, as shown in Figure 3 was composed of several layers that were specifically built to extract features from the images at both low and high levels. Following the completion of 40 epochs of training. Figure 5 illustrates the accuracy of different models after training as epoch numbers are increasing, further validating the model's learning capabilities.

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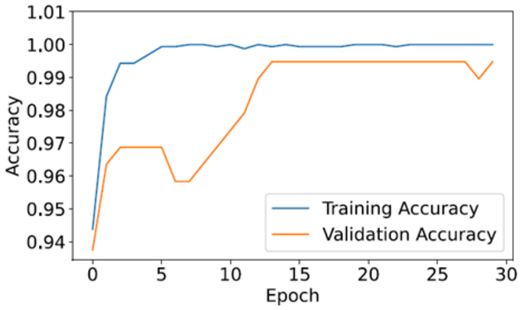
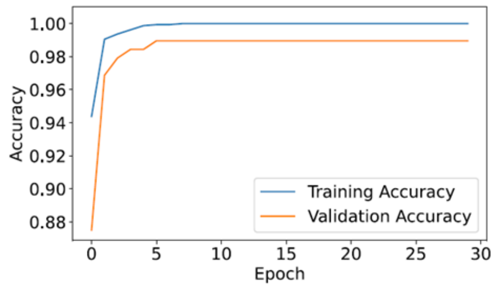
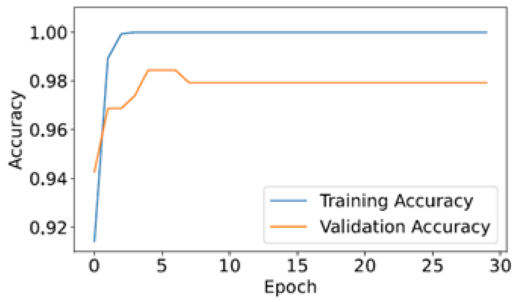


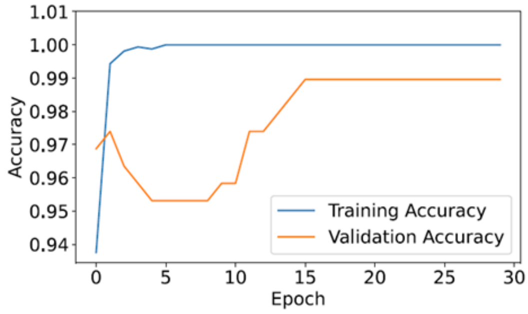
(a). VGG



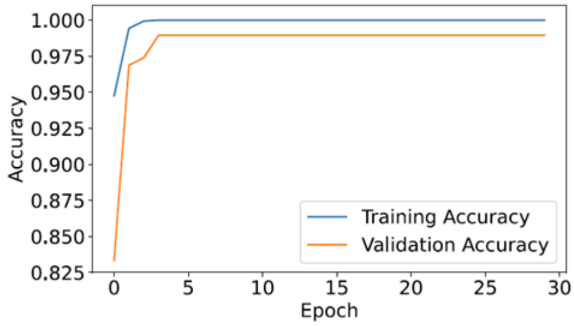
(b). Xception



(c). DenseNet



(d). ResNet50



(e). ResNet50v2

Figure 5. Training process of the models.

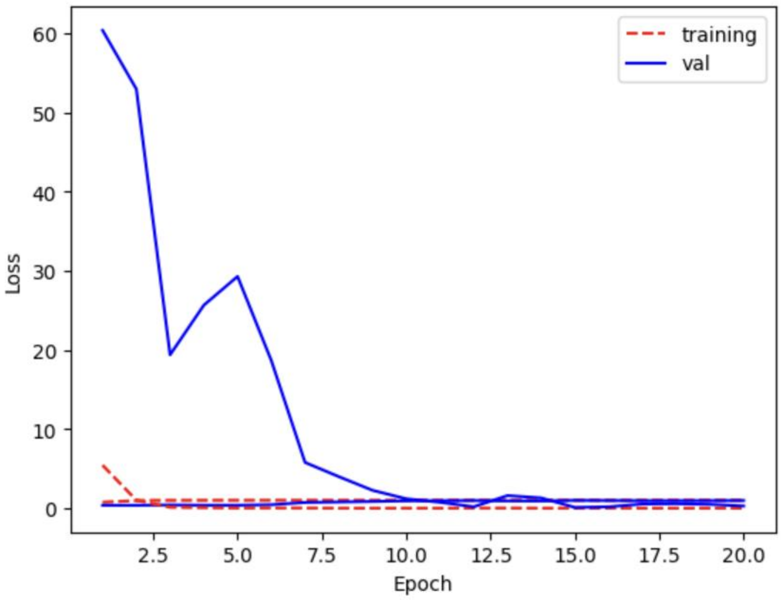


Figure 6. Graph showing training values as loss.

The trained/tested loss and accuracy are shown in figure 5, 6. The results yielded accuracy quantifies the proportion among X-ray scans for further categorization in the category of COVID and non-COVID class or

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category related to the total images considered in the model. Precision gives a ratio of accurately identified images of COVID cases out of the total images in the model. The metric recall denotes the proportion of photos accurately identified as being positive among the entire population of individuals who are truly COVID-19-positive. The metric F1 score quantifies model performance using a harmonic average of recall and accuracy, thus offering a well-balanced evaluation.

The results depicted in Figure 6 show a downtrend in the loss of train data as and when the number of epochs increases, indicating our model's ability to learn and improve its predictions. Confusion matrix Figure 7 illustrates performance of the considered classification model for early COVID prediction. Comparative Tables 2 and 3 show the performances of the parameters based on the classes to show the high accuracy results we have achieved.

Table 2. Accuracy, Precision, Recall and F1 score of proposed and other models.

Model (DL)	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
VGG	95.75	95.7	95.75	95.65
Xception	96.55	96.65	96.65	96.7
DenseNet	96.7	96.75	96.65	96.6
ResNet50	96.75	96.8	96.75	96.79
ResNet50V2	99.12	98.85	98.76	98.90

Table 3. Evaluation Results of proposed models of 5 repeated experiments.

Number of Folds	Accuracy (2-class)
First Fold	99.14 %
Second Fold	99.12 %
Third Fold	99.04 %
Forth Fold	99.11 %
Fifth Fold	99.17 %
Average	99.12%

Table 4. Parameters compared with class-wise performances.

Model	Method	Image (Dataset)	Performance (Accuracy %)
VGG	VGG	X-Ray	95.75
Xception	Xception	X-Ray	96.55
DenseNet	DenseNet	X-Ray	96.7
ResNet50	ResNet50	X-Ray	96.75
ResNet50V2	ResNet50V2 + HT	X-Ray	99.12

Additionally, it compares the results obtained from other available deep learning models applied with the same dataset and training parameters, as presented in Table 1. The accuracy achieved using Xception, Inception, DenseNet, ResNet50 and ResNet50v2 was 96.55%, 95.75%, 96.7%, 96.75% & 99.12%. The table indicates that the ResNet50v2 model outperforms the other models, exhibiting superior accuracy. Additionally, quantitative evaluation results using other indices, accuracy, precision, recall and F1-score, are presented in Tables 2.

In conclusion, this study successfully implemented and evaluated a CNN model using X-Ray for initial detection and prediction of COVID, trained through transfer learning, demonstrated significant precision, accuracy, F1 Score and recall. The results highlight the effectiveness of our proposed methodology and the superiority of the CNN architecture compared to other models.

Conclusion

The proposed architecture presents a powerful and lightweight deep learning model and solution for computer-based COVID-19 severity prediction using chest X-rays. Model demonstrates its potential as a valuable tool in assisting medical professionals in making efficient and accurate severity assessments with X-rays. The lightweight nature of the proposed architecture contributes to computational efficiency, making it well-suited for real-time applications. Through continued research and refinement, this methodology holds promise for improving disease management and patient outcomes in the ongoing fight against the global COVID-19 pandemic. The study presents a very effective development of a methodology utilizing the Convolutional Neural Network (CNN) model for early COVID detection. Remarkable results were produced by

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employing a pre-trained ResNet50v2 model. They showed very good results with an accuracy of 99.12%, which outperformed the results of other available models like Xception, DenseNet etc.

The suggested approach incorporates CNN to extract comprehensive representations from the original images, enhancing the image information for accurate disease classification. Moving forward, future work will focus on incorporating attention modules into the model to emphasize important features. We will also plan to explore deep learning-based unsupervised segmentation models to accurately identify other features and diseases. This will enable better utilization of pre-processed images for model training and lead to improved overall model performance. Additionally, it gathers a larger and more diverse clinical dataset to further train and validate the model, enhancing its capability for clinical diagnosis. The research has presented a robust methodology for early COVID-19 identification by using chest X-rays, leveraging the power of the CNN model, hyper-parameter tuning and optimization. The achieved positive results and the comparative analysis with other models demonstrate the efficacy and superiority of the approach. By continuing to refine and expand the methodology, contribute to the medical science field for image analysis & provide valuable support for clinical diagnosis and decision-making.

Conflict of Interest

The authors declare that they have no conflict of interest related to the manuscript.

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