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Dynamic Deep Learning Algorithm in Medical Diagnosis and Detection

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Abstract: The COVID-19 pandemic has had a profound global impact, necessitating effective diagnostic and treatment approaches. Diagnostic methods such as nucleic acid testing and chest CT scans, rely on COVID-19 imaging analysis. To address these challenges, deep learning, particularly Convolutional Neural Networks (CNN)have emerged. In our project, we developed a user-friendly prototype using CNNs, well-suited for image processing. By applying filters and downsampling techniques, we extract and classify features to enhance COVID-19 diagnosis. Our approach combines existing algorithms and post-processing analysis of chest X-rays to detect symptoms with impressive accuracy, reaching up to 96%. This innovation minimizes errors and aids medical workers in making treatment decisions.

Keywords: Four Deep learning, Covid-19, CNN, Chest X-rays

INTRODUCTION

The COVID-19 pandemic, caused by the new coronavirus SARS-CoV-2, has turned into a global problem, requiring early discovery and diagnosis to reduce its impact. Millions of cases are diagnosed each year in India alone, underscoring the importance of early detection and intervention utilizing Deep Learning [1]. This project seeks to create a platform that aids in the early detection and diagnosis of COVID-19, as well as Pneumonia [2], which exhibits similar symptoms and whose early detection is critical in treating the disease, minimizing errors and maximizing accuracy to assist healthcare professionals in choosing the best treatment. The platform will streamline the detection process by leveraging technology and medical developments, making it more accessible, efficient, and accurate.

MATERIALS AND METHODS

The deep learning-based CNN model employed in the study by N. S. Shadin, S. Sanjana and N. J. Lisa [3], demonstrates a unique characteristic by utilizing just two Convolutional layers. This deliberate choice offers advantages in terms of easier and faster experimentation while maintaining comparable efficiency to other CNN and deep CNN-based models used in similar studies. Notably, the CNN model itself achieves a commendable accuracy of 79.74%, highlighting its effectiveness in accurately classifying the data under consideration. The comparison between the InceptionV3 architecture and the CNN architecture reveals a clear distinction in terms of performance. The results unequivocally demonstrate that the InceptionV3 architecture outperforms the CNN architecture. This notable difference in performance signifies the superiority of the InceptionV3 model in achieving better results for the given task.

The dataset used by Foysal and Hossain [4] ensures variability among samples, improving representativeness. Its equilibrium aids in dependable and generalized study results. Using an ensemble model has numerous advantages, including fewer incorrect predictions and increased accuracy. This methodology combines different techniques, using individual talents to improve total performance. However, its implementation leads in a slight increase of around 10 milliseconds per image prediction when compared to a single model. This increase in execution time is caused by the complexity of integrating numerous modelsinside the ensemble.

M. H. Memon *et al.*,[5] advocate the use of Convolutional Neural Networks (CNNs) in the feature extractionstage to capture complex and abstract features from computerized tomography (CT) images that may not be easily recognizable by human experts. This allows for a more comprehensive analysis and understanding of the images. Furthermore, the LSTM network, known for its ability to learn temporal dependencies and patterns, is incorporated into the classification module. By integrating CNNs and LSTM, The proposed approach offers powerful and efficient approach for accurate infection detection and classification. The CNNs extract informative features from the CT images, while the LSTM network leverages its temporal modelling capabilities to capture

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the sequential patterns within the data. This combined approach enhances the model's ability to accurately classify infections, contributing to improved diagnostic outcomes and patient care. This research looked at the proposal and suggests using the Harmony, the search-based HyperparameterOptimization (HHO) algorithm is used to determine the best hyperparameter values for both the Convolutional Neural Network and the LSTM network. The suggested methodology uses the HHO algorithm to automate the process of hyperparameter tweaking, lowering the burden of manual selection and optimizingthe model's performance.

A study team lead by A. Panwar, R. Yadav, K. Mishra, and S. Gupta [6] investigated the use of various deep- learning models and machine-learning classifiers to classify COVID-19-infected, pneumonia-infected, or healthy chest radiographs. They extracted features from dataset photos using VGG16, VGG19, and Inception V3 models. These features were coupled with several machine learning classifiers for picture classification, as in, KNN, Tree, SVM, RF, NN, Nave Bayes, LR, and AdaBoost. The findings illustrate the utility of VGG models in the diagnosis of respiratory illnesses using chest radiography. Notably, when paired with a neural network classifier, the Inception V3 model attained an accuracy of 88.8%. This implies that the model has an 88.8% accuracy rate in identifying new images as COVID-19-positive, normal, or pneumonia-infected.

The researchers D. Varshni, K. Thakral, *et al.* [7] evaluated various pre-trained CNN models and classifiers, ultimately selecting DenseNet-169 for feature extraction and SVM for classification based on their statistical findings. They demonstrated that tweaking hyperparameters during the classification step increased the model's performance. There are, however, some fundamental constraints to consider. For example, the evaluation method did not consider the medical history of the patient, which could have supplied crucial information for a more accurate diagnosis. Secondly, the study solely relied on frontal chest X-rays, disregarding the potential benefits of lateral view chest X-rays in diagnosis. In addition, due to the computational demands of the model's convolutional layers, high computational power is required, leading to potentially lengthy computation times. These limitations highlight the need for future research to incorporate patient history, consider additional X-ray views, and address computational efficiency to boost the effectiveness of the model.

METHODOLOGY

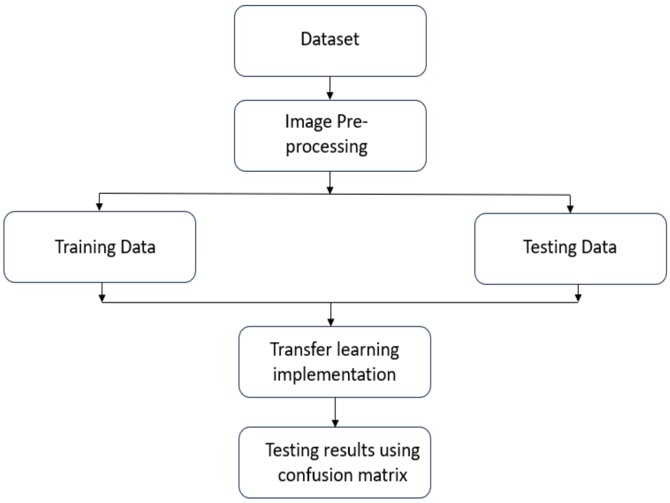

Figure 1: Block Diagram of Methodology

Scaling, normalization, and data separation into training and testing data are all part of the dataset preprocessing. Following that, the pre-processed data is input into the constructed CNN network, which is then subjected to transfer learning techniques.

Dataset

This dataset [8]-[11] includes posteroanterior (PA) chest X-ray images featuring individuals with Normal, Viral, and COVID-19 conditions. It comprises a total of 1,823 chest X-ray (CXR) images, with 536 images depicting COVID-19 cases, 619 displaying viral pneumonia, and 668 representing normal cases. The age range of COVID-19 cases within the dataset spans from 18 to 75 years.

Covid Detection

It takes place in 3 distinct steps

- Image Pre-processing
- CNN Network Developed
- CNN Network specifications with Transfer Learning Integration [12]

Image Pre-Processing

Separate the retrieved datasets into separate folders and save them somewhere accessible. All of the photos must be downsized to a standard common size in order for the model to extract features from all of the

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inputscan images to the same extent and produce better results. The images have been downsized to a standard 224x224 pixel size, a process that has been completed for over 1800 images. Following the correction of the dimensions, the data is put into the neural network for feature extraction and convolution.

CNN Network Developed

Input Layer: The model accepts photos with the size of (224, 224, 3) as input. These images have a height and width of 224 pixels and consist of three color channels (RGB).

Convolutional Blocks: The model is made up of three convolutional layer blocks. Convolutional layers with 32, 64, and 128 filters are applied to the input images in each block. The filters aid in the extraction of various features from photos. Activation functions (ReLU) are used to bring non-linearity into the model and improveits ability to learn complex patterns.

Max Pooling: Following each convolutional block, a max pool layer with a pool size of (2, 2) is applied. This technique decreases the spatial dimensions of the feature maps while retaining the most relevant features, allowing the model to concentrate on capturing the most important information.

Fully Connected Layers: A flatten layer is used after the convolutional and pooling layers to turn the multidimensional output into a 1D vector. This flattened representation is then transmitted through two dense layers, each with 1024 and 256 units. The thick layers learn high-level representations and patterns using the convolutional layers' retrieved features.

Output Layer: The final dense layer has three units, representing the three classes or categories in the classification problem (e.g., COVID-19, pneumonia, healthy). The SoftMax activation function is applied to produce probability distributions over the classes, allowing the model to predict the most likely class for a given input image. The model is compiled with the Adam optimizer, categorical cross-entropy loss function, and accuracy as the evaluation metric. This configuration sets the model up for training, where it learns to minimize the loss and optimize its parameters to make accurate predictions

CNN Network Specifications with Transfer Learning Integration

In our method, we begin by importing the MobileNet model via the 'tf.keras.applications.MobileNet' function, which comes pre-trained on the ImageNet dataset. To provide the expected input form for the model (224x224x3), we set the 'input_shape' parameter, which indicates compatibility with RGB images of 224x224 pixels. Furthermore, we freeze the layers of the MobileNet model, which protects the pre-trained weights and biases from being adjusted during subsequent training.

RESULTS

We have formulated an accessible approach to enhance our model's performance through training it across various supervised classification algorithms. Upon rigorous experimentation, it became evident that CNNs exhibit substantial promise in delivering superior outcomes. Our model now demonstrates competitive performance by employing deep and machine learning methodologies, achieving an accuracy rate of 96%. Furthermore, we meticulously fine-tuned the quantity of training cycles and epochs applied to our input ultrasound scan images, resulting in a notable reduction in errors and a commendable enhancement of the model's overall efficacy.

Training and Validation Loss and Accuracy Graphs

The loss and accuracy graphs are divided into parts, specifically before and after implementation of Transfer Learning.

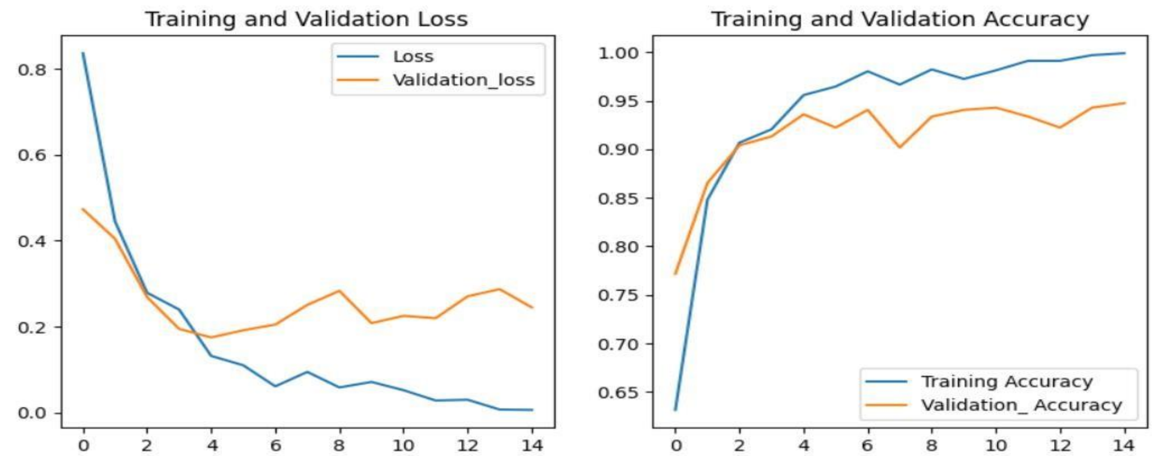

Figure 2: Training and Validation Loss and Accuracy Graph, CNN

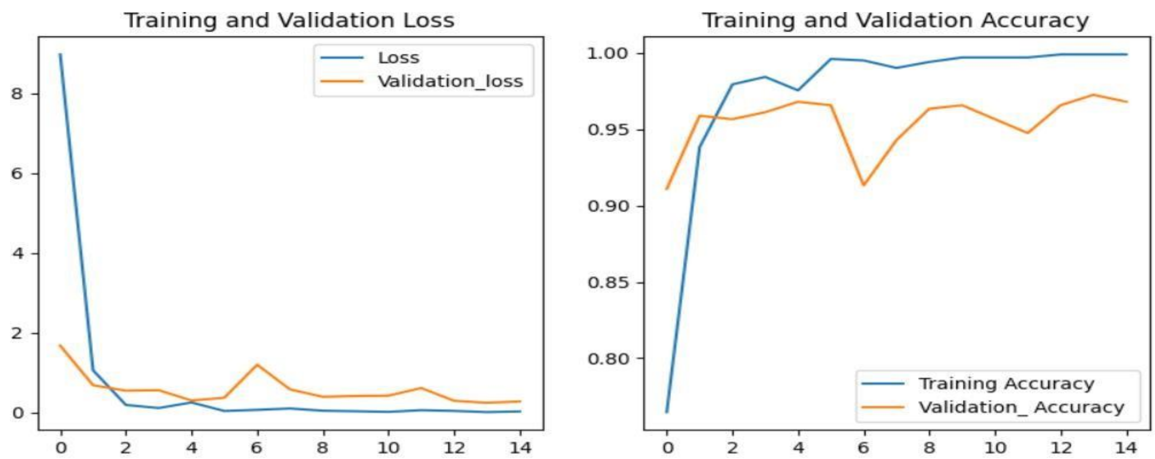

Figure 2: Training and Validation Loss and Accuracy Graph, CNN with Transfer Learning

Confusion Matrix

The confusion matrix are separated into two sections, prior to and following the use of Transfer Learning, and the total amount of false negatives is reduced after Transfer Learning.

	covid	normal	virus
covid	105	3	0
normal	2	121	6
virus	2	8	118

	covid	normal	virus
covid	106	2	0
normal	0	127	2
virus	1	6	121

Figure 2: Confusion Matrix pre and post Transfer Learning implementation

CONCLUSION

With the help of medical professionals, we hope to improve the accuracy of pneumonia and COVID-19 stagepredictions. We identified Convolution Neural Networks (CNN) as a promising solution by employing user- friendly approaches and multiple supervised classification algorithms. Our model outperformed numerous previous models with an outstanding accuracy rate of 96%. Furthermore, our optimization efforts, such as fine-tuning the number of epochs and training cycles for ultrasound scan images, improved overall model performance. This method has the potential to greatly assist medical practitioners in making more accurate diagnostic and treatment decisions.

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