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TRANSFER LEARNING BASED CNN FOR COVID 19

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Abstract - Covid-19 has significantly impacted individuals and health care systems on a global scale. Finding COVID-19 is difficult because there aren't manytesting kits available. A deep transfer learning-based CNN technique is used to recognize Covid 19 in chest CTimages. Chest CT scans from both Covid and non-Covid sources are included in the dataset used to train themodel. Computed tomography (CT) is a faster and more precise means of infection diagnosis when compared to x-ray imaging. This is because CT scan pictures show more potential infection indicators than x-rays, which explains why. X-rays do, however, release less ionizing energy than a CT scan. Deep transfer learning approaches can both train and fine-tune the weights of networks that have previously been trained using datasets, which is why they are effective for this. Inorder to evaluate pictures, deep learning in computer vision especially uses convolutional neural networks (CNNs). For the classification of CT scan pictures to manage the complex structure, deep architecture is needed. We hypothesize that using radiographical fluctuations of covid-19 in CT images, pre-trained deep transfer learning-based CNN models may be able to extract certain graphical properties of covid-19 and provide a clinical diagnosis. The main advantages oftransfer learning include reduced training time, improved neural network performance, and the absence of a large amount of data.

Key Words: Covid 19, CNN, ResNet101, Transfer Learning

1.INTRODUCTION

The COVID-19 epidemic has presented healthcare systems with an unprecedented challenge, highlighting the urgent need for effective and precise diagnostic methods. Application of deep learning techniques, in particular Convolutional Neural Networks (CNNs), for automated detection and diagnosis of COVID-19 from medical images such chest X-rays and computed tomography (CT) scans, is one promising strategy to address this difficulty. CNNs and other deep learning models have achieved astounding results in a variety of image recognition applications, including medical picture analysis. However, as there aren't many publically accessible medical pictures linked to COVID-19, training CNNs from scratch necessitates a sizable labeled dataset, which may be constrained for certain applications like COVID-19 detection. Deep neural network training from scratch can also be time- and computationally- intensive. Transfer learning saves the day in these circumstances. Transfer learning enables information to be applied to a comparable but smaller dataset (target task) after training on a large and diversified dataset (pre- training). A pre-trained CNN model, which was first trained on expansive image datasets like ResNet, can be specialized in recognizing COVID-19 from medical images with a manageably low number of COVID-19 instances. This procedure quickens the learning process and aids in enhancing performance even with scant data. Convolutional neural networks (CNNs) based on transfer learning havebecome a potent and successful method for COVID-19 identification from medical pictures. Transfer learning starts with a pre-trained CNN model that was learned on a sizable dataset (usually unrelated to COVID-19). The model may beretrained to detect COVID-19 because it has already learned general features from the initial dataset. Then, using a smaller dataset of COVID-19-related medical images, this pre-trained model is fine-tuned. The use of transfer learning- based CNNs for COVID-19 identification has a number of advantages, including less data needed, improved generalization, quicker training, and possibly state-of-the-art performance. Transfer learning makes it possible to build precise COVID-19 detection models with the little amountof data that is currently available by utilizing the information obtained from training on various datasets.

2. LITERATURE REVIEW

As chest CT images in COVID-19-infected individuals exhibit a bilateral alteration, chest CT scans can be used for COVID-19 testing. To address issues with the noisy and unbalanced COVID-19 dataset, a top-2 smooth loss function with cost-sensitive attributes is also used. Comparing the proposed deep transfer learning-based COVID-19 classification model to other supervised learning models, experimental findings show that it produces effective results[1]. Radiologists can employ machine learning algorithms developed on radiography pictures as a decision support toolto help them complete diagnoses more quickly. They proposed a shallow CNN architecture and trained it from scratch in addition to using 12 commercial CNN architectures in transfer learning mode on 3 publically available chest X-ray databases to complete this goal. CNN models were fed chest X-ray pictures without any preprocessing in order to keep up with the several studies that used chest X-rays in this way [5]. Deep learning provides a quick and simple way to swiftly screen for COVID-19 and find likely high-risk individuals, which may be helpful for both the effective use of medical resourcesand for the early discovery of disease before patients experience severe symptoms. Using the external validation sets, the deep learning algorithm did a good job of differentiating COVID-19 from other types of pneumonia and viral pneumonia. The successful categorization of patients into high- and low-risk groups whose hospital stays varied significantly (p=0.013 and p=0.014, respectively) was another achievement of the deep learning system. Without the requirement for human involvement, the deep learning algorithm automatically focused on anomalous locations that shared characteristics with the recorded radiological results [6]. The suggested methodology uses transfer-learning pre-trained models to categorize COVID-19 (positive) and COVID-19 (negative) patients. They explain the creation of a deep learning framework called KarNet that is based on pre-trained models (VGG16, ResNet50V2, and MobileNet). Each model was trained on original (i.e., unaugmented) and altered (i.e., enhanced) datasets in order to thoroughly test and assess the framework [7]. Thoracic X-ray imaging, MRI, CT, and other types of chest X-ray imaging are among the mostefficient and affordable diagnostic radiological methods for lung illness. Additionally accessible in hospitals, they subject people to lower doses. Since both disorders show similar geographic characteristics on X-ray images, including lung disease, it can be difficult to tell the difference between pneumonia and COVID-19 even for highly qualified and experienced practitioners. Many studies have focused on COVID-19, pneumonia analysis, and detection using various techniques. The bulk of healthcare applications are becoming more and more popular because to key features supported by artificial intelligence (AI), machine learning, and deep learning.[10][11][12]. However,the bulk of solutions rely on a single result prediction made by the model, which may or may not be accurate. To obtain a judgment, a special ensemble technique combines the strengths of various deep neural network architectures. Using Lung CT Scan images, a variety of pre-trained models, such as VGG16, VGG19, InceptionV3, ResNet50, ResNet50V2, InceptionResNetV2, Xception, and MobileNet, are utilized to refine them. All of these trained models are combined into an effective ensemble classifier to produce the final prediction [15].

3. DATASET

Lung CT scans will be used in the experiment to detect COVID-19. This dataset intends to advance research and the creation of deep learning methods that can assess a person's CT scans to see if they have SARS-CoV-2. Because the lung region is the area that is often affected by the virus, medical imaging modalities like X-ray and Computed Tomography (CT) are typically taken into account in orderto assess the severity of the infection. X-ray imaging techniques are often used for COVID-19 diagnosis due to their extensive availability, quick turnaround, and low cost. However, CT imaging techniques are preferred since they offer in-depth details on the affected area. A lung CT scan image collection [1] with two groups, COVID and non-COVID, was constructed by collecting actual patient CT scans from the hospitals in Sao Paulo, Brazil. Total CT-scan images utilized for training and testing are 2481. 1252 CT scans from patients who tested positive for COVID-19 and 1229 CT scans from patients who tested negative for COVID-19 are both included in the SAR-CoV-2 CT-scan dataset.

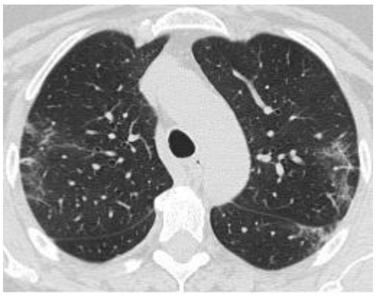

Fig 1. Covid

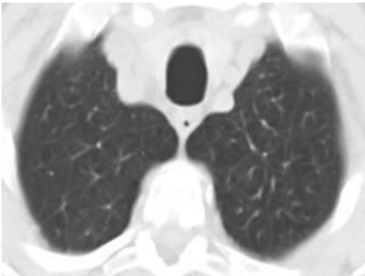

Fig 2. Non - Covid

4. PROPOSED WORK

1) Data Preprocessing and Visualization

Medical imaging is the practice of taking pictures of the inside of the body to diagnose different problems. The two medical imaging modalities that are mostfrequently used for identifying COVID-19 are X-ray and CTimaging. However, because of the pictures' low intensity and contrast, it is difficult to tell where the boundaries and margins of the images are, which might result in a mistaken illness diagnosis. In order to improve the model's performance, it is necessary to pre-process medical pictures to extract the crucial information and eliminate the extraneous data [10]. The process of enhancing the picture quality of raw medical data for further analysis is known as medical image processing. In order to enhance the visual information of the input picture, a variety of pre-processing techniques such as image resizing, image transformation etc. are employed in medical imaging applications. Then visualization of the same is performed.

- **Image Resizing:**

The data set must be standardized because it was collected from several locations and different scanners, eachof which may have a different size. To improve the CNN model's classification performance, every image in the dataset is generalized to a fixed dimension via image scaling. Here we set the dimensions of all the image as 224 × 224 which is nothing but square.

- **Image Transformation:**

Image transformation is essential for easy training of the models, reduce the computational demand and to improve the image quality. Here we use keras image generator to transform the image. We make use of the horizontal flip parameter of the keras image generator whichbasically flips the pixels of both rows and columns horizontally.

- **Visualization:**

After the preprocessing steps visualization of the dataset is done to ensure whether the dataset is clean and of highquality and contains expected size and features. Here we visualize some samples of covid and non-covid images by annotating them with labels such as covid and non-covid.

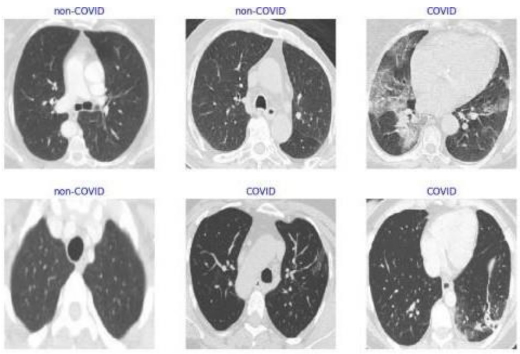

Fig 3. Visualization of Dataset

2) Transfer Learning

When it comes to image categorization tasks like covid identification, transfer learning is a potent tool in machine learning and deep learning. It entails using the information gained from one job to enhance the performance of another task that is related. The suggested approach uses transfer learning to create apowerful image classifier.

Transfer learning has various benefits, including:

- **Faster Training**: Compared to starting from scratch, we can train models more quickly since they have already been taught.
- **Better Generalization**: Because transfer learning allows models to learn from a larger dataset, they frequently generalize effectively even with little amounts of training data.
- **Improved Accuracy**: Pre-trained models, which have absorbed complicated characteristics, can provide models that perform better, particularly in difficult tasks like image classification.

A base model that has already been trained serves as the beginning of transfer learning. The basis model in this instance is the ResNet101 architecture, which was pre- trained using a large ImageNet dataset. This pre-trained model is a superior feature extractor since it has previously mastered the recognition of a wide range of characteristics from images.

The pre-trained model's layers are kept, up to and including the global max-pooling layer. A feature extractoris provided by these layers. These layers are used throughout training, and although the model's weights change, the knowledge from ImageNet is preserved by keeping them frozen. In order to classify the input images, the model collects pertinent attributes from the images. A customized Dense layer is put on top of the pre-trainedlayers. This new layer is in charge of figuring out which classes to assign the characteristics that the underlying model extracted. The model adjusts its expertise to the current classification challenge by adding this layer. After that, the model is trained using the provided unique dataset. The custom classification layer's weights are learnt based onthe new dataset whereas the pre-trained layers' weights are not modified (they are "frozen") during training. This gives the model the opportunity to specialize in identifying the distinctive patterns and traits of your data.

In essence, transfer learning is a powerful tool for different machine learning and deep learning tasks, including image classification, since it enables you to take advantage of the experience of models trained on substantial and varied datasets.

3) Structure of the Model

As a foundational model for transfer learning in the detection of covid, our proposed study uses the ResNet101 architecture. Convolutional layers, pooling layers, and other important elements make up ResNet101's architecture, which is broken down into its constituent parts. Deep convolutional neural network ResNet101 is well known for its capacity to train extremely deep networks by inserting residual connections, which assist counteract the vanishing gradient issue. The following describes its intricate architecture:

- **Input Layer:**

The image shape is defined as (224, 224, 3). This corresponds to an image with a width and height of 224 pixels and 3 color channels (RGB).

- **Initial Convolution and Pooling:**

A max-pooling layer follows the initial convolutional layer in ResNet101. These layers extract minute details from the source images.

- **Residual Blocks:**

The residual blocks are the foundation of the ResNet design. ResNet101 is made up of 101 layers, which are divided up into various residual blocks. Usually, batch normalization, ReLU activations, and many convolutional layers are present in each residual block.

In order to improve gradient flow during training, residual connections, sometimes referred to as skip connections or shortcut connections, enable the model to learn residuals (the discrepancy between the desired output and the actual output) and add them back to the input. This makes it possible to train incredibly deep networks.

- **Pooling layer:**

"pooling =Max" has been applied in this instance. This suggests that global max-pooling is used at the ResNet101 architecture's very conclusion. The most crucial characteristics for classification are retained while the spatial dimensions are reduced thanks to global max-pooling.

- **Fully Connected Layer (Dense Layer):**

For classification, a fully connected (Dense) layer is placed after the convolutional and pooling layers. The high-level characteristics that were retrieved bythe preceding layers are mapped to the variety of output classes in this layer. The Dense layer uses the softmax activation function, which is typical for multi- class classification issues. As a result, class probabilities are produced.

- **Output Layer:**

There are as many units in the model's outputlayer as there are classes in your dataset. The final output of the model is translated into class probabilities using the activation function, softmax..

- **Training and Compilation:**

Adamax optimizer and categorical cross-entropy loss, which are popular options for deep learning classification applications, were used in the model's construction. During training, accuracy is employed as a monitoring metric.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 resnet101 (Functional)      (None, 2048)              42658176

 dense (Dense)               (None, 2)                 4098

=================================================================
Total params: 42,662,274
Trainable params: 42,556,930
Non-trainable params: 105,344
_________________________________________________________________
```

Fig 4. Structure of the Model

A deep convolutional neural network called ResNet101 has a lot of layers and residual connections that make training efficient. As a result of its capacity to identify intricateelements in pictures, it is frequently employed for image classification jobs. Our proposed approach takes advantage of pre-trained weights from ImageNet and adds a new classification layer for the selected COVID dataset to exploit this architecture for transfer learning.

4) Evaluation of the model

A key component of transfer learning is model assessment, which makes it easier to adapt previously trained models to new tasks and ensures their efficacy and dependability across a range of domains.

Three different datasets—the training set, the validation set,and the test set—are used to evaluate our model. Loss and accuracy, the two key performance indicators for the model,are the main metrics used for evaluation.

To compute the dataset's size, the dataset's length must first be calculated. The appropriate batch size for assessment is thus determined dynamically. Here, a batch size of 16 is used. The goal is to handle the test data effectively while avoiding processing it in overly large batches. It then determines, using the selected batch size, how many steps are needed to process the complete test dataset. Afterward, the model is assessed to see how well it performs. It uses the test_steps that were previously calculated as well as the generators for training, validation, and test data. For each dataset, the function provides loss and accuracy scores. Calculating loss and accuracy are the two main measures used in this study.

The train loss and accuracy: This metrics show how well the model matches the training set of data. The model is capable of precisely fitting the training data, as seen by the astonishingly minimal training loss and the high training accuracy of 1.0. Although great training accuracy isfrequently anticipated, it's crucial to make sure that thisperformance also applies to previously unobserved data.

Validation Loss and Accuracy: The validation dataset serves as a stand-in for unobserved data to evaluate the generalizability of the model. The model is doing remarkably well on data that it hasn't encountered before during training, as seen by a validation loss of 0.0597 and a validation accuracy of 0.9879. Strong generality is indicatedby this encouraging indicator.

Test Loss and Accuracy: These metrics offer a practical evaluation of the model's effectiveness on untested data. The model retains high accuracy on brand-new, independentdata, as seen by test accuracy of 0.9558 and test loss of 0.1558. This may indicate that the model has discovered significant patterns in the training data and is able to predict outcomes for comparable but previously undiscovered data points.

In conclusion, the model has done surprisingly well in the testing stage. On the training set of data, it performs with almost flawless accuracy, demonstrating a good match. More importantly, it demonstrates great generalization, as seen by the validation and test datasets' high accuracy and minimal loss. These outcomes show that the model has effectively discovered pertinent patterns in the training data and is capable of making precise predictions. It illustrates the model's efficacy and dependability, which is a noteworthy accomplishment.

```
Train Accuracy:  1.0
--------------------
Validation Loss:  0.059687867760658264
Validation Accuracy:  0.9879032373428345
--------------------
Test Loss:  0.15575243532657623
Test Accuracy:  0.9558233022689819
```

Fig. 5 Result

5. RESULTS AND DISCUSSION

Following training, the model is assessed usingdistinct datasets from the training, validation, and test sets. Notably, it has outstanding performance across all three sets.The training accuracy is astoundingly high at 99.55%, while the training loss is extraordinarily low at 0.0147, demonstrating a robust fit to the training data. The model's capacity to successfully generalize to new data is demonstrated by the validation loss (0.0760) and accuracy (97.18%). Finally, the model's ability to accurately categorize CT scan images as COVID-19 or non-COVID-19 is demonstrated by the test loss (0.1213) and accuracy (95.18%).

A confusion matrix and classification report offer additional insights. The model achieves great precision and recall for both COVID-19 and non-COVID-19 situations, according to the confusion matrix. For COVID-19 instances, recall (sensitivity) is 0.94, suggesting that 94% of genuine COVID-19 cases are accurately detected, and precision is 0.97, meaning that 97% of cases categorized as COVID-19 are true positives. Similar performance is shown by the non-COVID-19 class, with precision and recall at 0.94 and 0.97, respectively. The f1-score, precision, and recall metrics in the classification report demonstrate the model's balanced and accurate performance in identifying both COVID-19and non-COVID-19 cases.

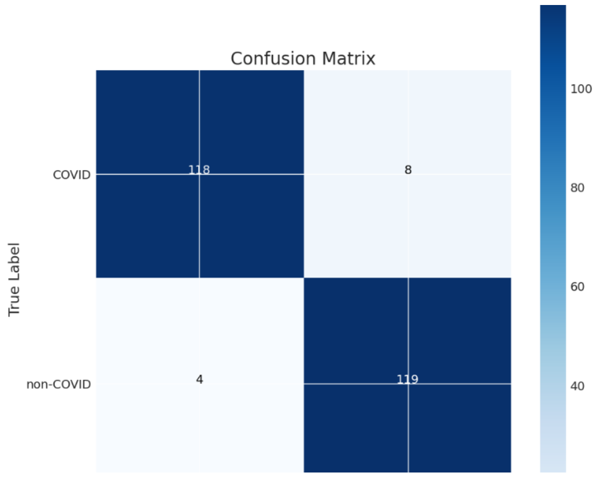

Fig 6. Confusion Matrix

6. CONCLUSION

With an emphasis on transfer learning utilizing a pre-trained ResNet101 model, this study provides a thorough investigation of deep learning methods for image categorization. Data collection, preprocessing, and dataset splitting were done at the beginning of the project to lay a solid basis for model building. A good place to start was by using the ResNet101 architecture, a well-known convolutional neural network. To adapt the model to the particular image classification job, the model architecture has to be customized by creating a unique classification layer. The model's suitability for training was assured by the hyperparameters used in its construction.Multiple training epochs were used to undertake extensive experimentation, and the training process including loss and accuracy metrics was carefully observed. The model performed exceptionally well, with high accuracy and low loss values, when thoroughly evaluated on the validation and test datasets, demonstrating the model's prowess in spotting patterns in previously unobserved data.

The model was improved further by hyperparameter adjustment and a final combined training step. The model's viability for practical applications was ultimately established through thorough testing on a dedicated test dataset. The results of this study highlight the significance of data preparation, model architecture design, and hyperparameter tuning in obtaining remarkable model performance, providing useful insights for practitioners and researchers in the fields of computer vision and deep learning. The experiment also demonstrates the potential for transfer learning to hasten and improve the creation of image classification models, opening the door to a wide range of applications in diverse fields, from autonomous systems to healthcare. Overall, this research adds to the body of deep learning knowledge and emphasizes the practical use of transfer learning in current machine learning research.

REFERENCES

[1]. Y.Pathak., Deep Transfer Learning Based Classification Model for COVID-19 Disease. IRBM Volume 43, Issue 2, April 2022, Pages 87-92

[2]. Kushwaha S., Bahl S., Bagha A.K., Parmar K.S., Javaid M., Haleem A., Singh R.P. Significant applications of machine learning for COVID-19 pandemic. *J Integrat Manage.* 2020;5(04):453–479

[3]. Nirmala Devi K., Shanthi S., Hemanandhini K., Haritha S., Aarthy S. *2021 5th International Conference on Electronics, Communication and Aerospace Technology (ICECA)* IEEE; 2021. Machine learning based twitter sentiment analysis on COVID-19; pp. 1745–1749

[4]. Tilve A., Nayak S., Vernekar S., Turi D., Shetgaonkar P.R., Aswale S. *2020 International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE)* IEEE; 2020. Pneumonia detection using deep learning approaches; pp. 1–8.

[5]. T Majeed, R Rashid, D Ali, A Asaad - Medrxiv, 2020, Covid-19 detection using cnn transfer learning from x-ray images

[6]. Wang S., Zha Y., Li W., Wu Q., Li X., Niu M., Wang M., Qiu X., Li H., Yu H., Gong W. A fully automatic deep learning system for COVID-19 diagnostic and prognostic analysis. Eur Respiratory J. 2020;56(2)

[7]. Arpita Halder and Bimal Datta 2021 Mach. Learn.: Sci. Technol. 2 045013, COVID-19 detection from lung CT-scan images using transfer learning approach.

[8]. Xiao L.S., Li P., Sun F., Zhang Y., Xu C., Zhu H., Cai F.Q., He Y.L., Zhang W.F., Ma S.C., Hu C. Development and validation of a deep learning-based model using computed tomography imaging for predicting disease severity of coronavirus disease 2019. *Front bioeng biotechnol.* 2020:898.

[9]. Berrimi M., Hamdi S., Cherif R.Y., Moussaoui A., Oussalah M., Chabane M. *2021 International Conference of Women in Data Science at Taif University (WiDSTaif)* IEEE; 2021. COVID-19 detection from Xray and CT scans using transfer learning; pp. 1–6.

[10]. Rajakarunakaran Surya Abisek, Lourdu Arun Raja, Muthusamy Suresh, Panchal Hitesh, Alrubaie Ali Jawad, Jaber Mustafa Musa, Ali Mohammed Hasan, Tlili Iskander, Maseleno Andino, Majdi Ali, Masthan Ali Shahul Hameed. Prediction of strength and analysis in self-compacting concrete using machine learning based regression techniques. *Adv Eng Software.* 2022;173

[11]. Majdi Ali, Alrubaie Ali Jawad, Al-Wardy Alia Haider, Baili Jamel, Panchal Hitesh. A novel method for indoor air quality control of smart homes using a machine learning model. *Adv Eng Software.* 2022;173

[12]. Shanthi S., Aruljyothi L., Balasundaram M.B., Janakiraman A., Nirmaladevi K., Pyingkodi M. Artificial intelligence applications in different imaging modalities for corneal topography. *Survey of Ophthalmol.* 2021

[13]. Kaur T., Gandhi T.K. Classifier fusion for detection of COVID-19 from CT scans. *Circuits, syst signal processing.* 2022;41(6):3397–3414.

[14]. Pathak Y., Shukla P.K., Tiwari A., Stalin S., Singh S. Irbm; 2020. Deep transfer learning-based classification model for COVID-19 disease.
[15]. Shaik N.S., Cherukuri T.K. Transfer learning based novel ensemble classifier for COVID-19 detection from chest CT-scans. *Comput Biol Med.* 2022;141