Grenze International Journal of Engineering and Technology, June Issue

Challenges in COVID-19 Detection and the Imperative for Improved Methods

Manojeet Roy[1], Ujwala Baruah[2] and Santosh Rajak[3]
[1-3]National Institute of Technology Silchar /Computer Science and Engineering Department, Silchar, India
Email: manojeet_rs@cse.nits.ac.in, {ujwala@cse.nits.ac.in, santosh_rs@cse.nits.ac.in}@cse.nits.ac.in

***Abstract*— The pervasive impact of human-to-human disease transmission on society is evident in recent global pandemic out-breaks. Identifying and managing such diseases pose significant challenges, exacerbated by the absence of specific medications due to the extensive variants involved. Their similarities to pneumonia heighten the complexity of distinguishing these diseases. To address this, emerging machine learning (ML) and deep learning (DL) models offer promising solutions. This study delves into the potential of DL models, surpassing traditional ML, for more meaningful disease classification. Leveraging well-established models and lung-related X-ray images (CXR), we employ a transfer learning-based approach with meticulous hyper-parameter tuning. Our results demonstrate improved classification outcomes compared to previous attempts on the same dataset. Furthermore, our work highlights the optimization potential of existing modeling techniques, showcasing the feasibility of refining approaches with available resources for similar purposes.**

***Index Terms*— COVID-19 Classification, Deep Neural Networks, Radiography, Medical image classification, Computer Vision.**

I. INTRODUCTION

The COVID-19 outbreak has changed the complete perception of transformative disease in human life. This brings many challenges for identifying the correct disease among similar ones. It is quite appreciated that our medical fraternity has done a great job in identifying or classifying diseases. It has been seen that this disease has various variants with similarities with other disease lines, such as pneumonia, making the classification more challenging. Disease identification has become a focal point of research, with individuals from technical backgrounds actively contributing to support medical professionals through the application of Artificial Intelligence (AI). While ML models have made strides in this area, they encounter limitations in identifying the most pertinent features. Consequently, Deep Learning (DL) has emerged as a promising alternative, gaining popularity for its ability to address the challenges faced by traditional ML models. This shift reflects a growing recognition of the nuanced and complex nature of disease identification, prompting a shift towards more sophisticated AI approaches to enhance accuracy and efficacy in medical applications.
In all this, it has been observed that research also focuses on CXR images as they are available in open source. Attempts are being made to build the DL or ML model for classification purposes. DL always has the upper hand for feature identification with a lesser number of parameters, so an upsurge in DL-based work has been observed. If we compare it with the ML model where a limited set of features are recognized, it may not be sufficient for the

Grenze ID: 01.GIJET.10.2.243_1

classification problems.

Another observation that each DL model has its own capability for the defined problem. It can improve with proper model tuning. However, this work takes lots of time to identify the potential improvement with the domain characteristics.

Model tuning with proper hyper tuning or setting is generally used before training the model, which not only learns the features but also impacts the overall performance of the model significantly. Optimization is set to improve on the accuracy. The learning rate, is kept too low, it may lead to slow convergence, or the model may get stuck in some local minima. Tuning the learning rate is one of the significant and essential findings. Similarly, the batch size, fine-tuning, activation function, and adjustment of several neurons and epochs are some other aspects to be looked into.

- *Feature Learning:* It can extract the relevant feature automatically from the image, in comparison of ML model.
- *Representation Capability:* DL neural networks have multiple hidden models; we can increase their effectiveness based on customization by adding more layers depending on the problem, making it more versatile in applicability in other domains.
- *Scalability:* Whether one is dealing with a small or large dataset, the effectiveness of this approach remains consistent. In environments with dedicated processing units like GPUs or TPUs, the methodology operates with heightened efficiency, significantly enhancing the speed of computational tasks.
- *End-to-End Learning:* End-to-end learning capability makes this more popular among researchers. Apart from that, single it is also able to handle the complex tasks.
- *Transfer Learning:* Various fields, such as computer vision and natural language processing, extensively leverage a diverse range of networks. Technologies like Recurrent Neural Networks (RNNs), transformers, and CNNs are pivotal in advancing applications across these domains.
- *Industry Applications:* Successful applications in various industries, including medical care or healthcare (e.g., medical image analysis), autonomous vehicles drive, financial market (e.g., fraud detection), and e-commerce market (e.g., recommendation systems) of DL models have been observed.

In conclusion, while both ML and DL have their positive aspects, DL succeeds when the work at hand involves a higher level of knowledge and complexities. Its inherent capacity to acquire and represent characteristics from raw data, along with its scalability and breadth of usage, make DL an important tool for numerous different and complicated jobs. Furthermore, when tackling tasks that require a combination of strengths from numerous models, embracing the use of hybrid models, which integrate the capabilities from various deep learning architectures, can be the key to outperforming just one model in classification performance. However, it is essential to recognise that, in addition to all of these advantages, some other limitations always exist when it comes of the availability of reliable image data and its source.

II. Literature Review

We meticulously investigated a range of approaches in this comprehensive review of the literature, commencing with classical ML methods, progressing into the area of DL, and concluded with new fusion-based techniques. This investigation reveals how these various approaches differ in the context of disease classification, with a special focus on the challenging issue of multi-class classification.

In the study by [1], SVM served as a method to identify pneumonia. The authors have worked with Local Binary Pattern (LBP) to demonstrate fine details in lung images. The detection model presented a multi-scale texture segmentation technique aimed at cleansing up lung images, effectively determining lung abnormality-affected areas. The modification affected the texture, displaying numerous overlapping blocks. In addition, these researchers used ridge border identification with Sobel Edge detection to determine carry out sick regions, particularly those with discrepancies.

Considering the level of difficulty of the COVID classifications task, we determined that multi-class classification offers a more formidable challenge than binary classification. Our study caters specifically to the complexities of multi-class classification, corresponding to the complexities of categorising multiple COVID-related scenarios in the actual world.

A deep learning model was used to apply to a huge image dataset covering chest CT scans in an additional endeavour, as explained in [2]. This effort aimed to separate COVID-19 symptoms from instances of pneumonia and other lung diseases in individuals.

Proceeding further, [3] introduced the COVID-RENet model, that is intended for the gathering of features, comprising edges and region-based characteristics, using Convolutional CNN towards classification. CNN was utilized in the feature extraction method, while SVM was utilized to enhance the accuracy of classification. Using a dataset carefully selected for COVID-19, this approach accomplished a thorough 5-fold cross-validation process. The proposed approach could be useful, particularly for healthcare professionals seeking early detection of COVID-19 in people with the infection.

A separate investigation, conducted by [4], thoroughly analysed 21 chest CT scans among COVID-19 patients in Wuhan, China. The present investigation focused on clarifying the symptoms of COVID-19 on human lung tissue and its consequences. A further investigation, apparently reported in [5], used a dataset of 123 front-view CXR images to detect COVID-19 patients. This dataset played a critical role in facilitating the creation of diagnostic approaches.

In the work presented in [6], the authors explored the utility of chest CXR in the identification of lung abnormalities. Their findings suggest that the medical community may increasingly rely on CXR due to its wide accessibility and reduced infection control concerns.

The authors studied the effectiveness of chest CXR in confirming the presence of lung abnormalities in their research that was reported at [7]. Their findings indicate that healthcare professionals may rely more on CXR due to its simplicity of application and lower prevention of infection concerns.

Another research investigation, released in [8], included the extraction of two subsets of regions, sized 16x16 and 32x32, using a dataset comprising 150 CT scans and 3,000 images, all specifically labelled for COVID-19. To enhance the efficiency of their proposed technique, the researchers used fusion and ranking algorithm design. SVM was applied to classify the information that was processed, and transferred learning with a CNN model was additionally used. Unexpectedly their findings demonstrated that set 2 exceeded set 1 with respect to accuracy.

Moreover, the authors of [9] studied the role of AI tools in the medical field, providing insight on the hurdles connected with integrating AI tools on prohibited publically available imaging databases. The authors created an extensive set of data by combining CXR and CT scans from multiple sources, and subsequently used DL and transfer learning algorithms to recognise COVID-19. They used a pre-trained AlexNet model coupled with a modified CNN model, and their outcomes were remarkable. The correctness of the pre-trained model was 98.1%, while the accuracy of the revised CNN model was 94.1%.

Synthesis: Several factors are associated with multi-class classification. It is crucial to consistently consider how existing models create differences in terms of classification. A thorough investigation, coupled with experimentation, is necessary to identify the potential deep architectures that may perform well for the classification problem.

III. Data Set And Techniques Proposed

In this section, we have given a detailed description of a well-known dataset and the proposed approach named `TransDL," which is a fusion of transfer learning and deep learning models.

A. DATA SET

Enhancing disease diagnostic and prognosis precision, especially when dealing with the context of a pandemic like COVID-19, starts out with demanding data collecting. In reaction to the problem of limited data availability in medical research, there has been a significant increase in the usage of openly releasing datasets. Several researchers [10-14] have submitted varying datasets, the majority of which are focused on CXR images, each customized for different characteristics and purposes. The collaborative effort to make datasets accessible has significantly accelerated progress in the field, promoting advances in disease understanding and prediction.

A dataset mentioned in [10] for example, includes frontal CXR images illustrating cases of Covid-19, Pneumonia, and Normal states. Another large dataset featured in [11] contains 15,264 chest CXRs for training and 400 images for testing. This dataset incorporates both positive and negative Covid-19 cases. The authors introduced a dataset of approximately 137 curated images of Covid-19 in a related paper [12] In addition, the dataset contains 317 normal chest CXR images of viral pneumonia, which are organized into test and train directories. Furthermore, in an another study, investigators used the frontal chest CXR dataset described in [15] to carry out multi-class classification. This dataset is a significant resource for exploring alternative labelling procedures, with the goal of addressing the difficulties and costs associated with getting labelled data [12]. [13] was a retrospective cohort of children with medical conditions from Guangzhou Women and Children's Medical Centre in Guangzhou, China, who had anterior-posterior CXR scans included in their usual clinical care. This dataset can help with the diagnosis and treatment of a variety of diseases. Furthermore, a part of this dataset was used in [16], where an AI system was constructed to precisely categories images of macular degeneration and diabetic retinopathy.

Table:1 provides an overview of some widely recognized open-source datasets in medical imaging. While these datasets stimulate innovation in AI algorithms for medical image analysis, they come with notable challenges. Variability in image quantity and quality, limited clinical data and metadata, and the presence of outdated or low-quality images, inadequately curated or labeled data, and small sample sizes are among the challenges associated with open-source datasets. Furthermore, it's important to note that many of these datasets are intended solely for non-commercial (research) usage.

We used the image dataset cited in [11], as shown in Figure:1, 2 and 3. This collection contains representative images of pneumonia, normal circumstances, and COVID-19. This dataset is widely recognized and has previously been used in different research endeavors, making it a useful resource.

TABLE I. OPEN-SOURCE MEDICAL CXR DATASETS

Sl.No.	Medical Imaging Data Set			
	Dataset	**Image Type**	**Patients**	**Ground Truth**
1	Chester AI [10] Radiology Assistant	CXR	6432	2D Imaging
2	University of Waterloo [11]	CXR	15264	2D Imaging
3	University of Montreal [12]	CXR	517	2D Imaging
4	Cell Press Journal [13]	CXR	5863	2D Imaging

Furthermore, we did a comparison of our efforts with those of other scholars that worked on this dataset.

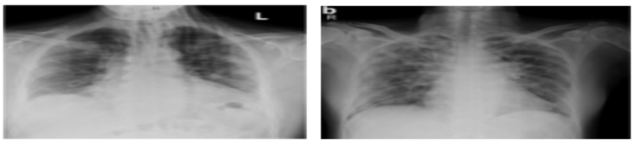

Figure 1: Frontal PA view of Covid-19

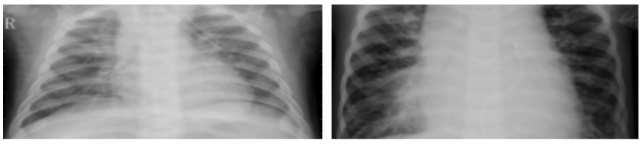

Figure 2: Frontal PA view of Pneumonia

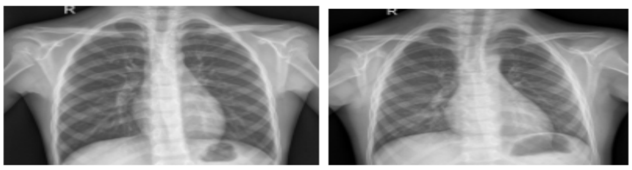

Figure 3: Frontal PA view of Normal

B. Techniques Proposed

In our methodology, pre-trained models' "PT", also known as deep networks, serve as the foundation, and our study reveals their effective performance, particularly on medical images such as CXR. Each pre-trained model encapsulates a unique feature vector. These models have been initially trained on a diverse set of images, with ImageNet alone incorporating around 1,281,167 images for training purposes [17,18]. Utilizing the Keras functional API, which comes equipped with valuable functions for classification tasks, we seamlessly acquire model weights by downloading them and saving them in our local directory, specifically ``keras/models/''.

Notably, we introduced modifications to the layer configuration by excluding certain output layers. In our specific case, we opted to utilize the ImageNet weights "Wt" with the top layer "Tl" parameter set to ``False'' during the model loading phase. This strategic choice allows us to train the final layer with our dataset while omitting the fully connected output layers primarily designed for prediction purposes. Here we have applied common setting for each deep network, for example, in the case of the Xception Net deep network, the arguments are utilized as follows:

BL = PT (Wt='ImageNet', Tl=False, Shape=Tensor)

Features = BL.output

Further, in pre-processing of all raw CXR images involved standardizing their size to 299 * 299 pixels. Subsequently, the Xception base model processed the input image, resulting in a 10 * 10 * 2048 feature map. Similarly, the ResNext50 base model produced a feature map of the same size. In the case of Inception, the feature map dimensions were 8 * 8 * 2048. To ensure consistency across these feature maps, we applied zero padding to the Inception-based feature map. Given that all three models generated feature maps of identical sizes, we fused the features from both the Inception and ResNext models to enhance the quality of semantic features. We have presented the flow diagram as a key component of one of the most effective approaches, illustrated in Figure 4. However, alternative approaches are also viable.

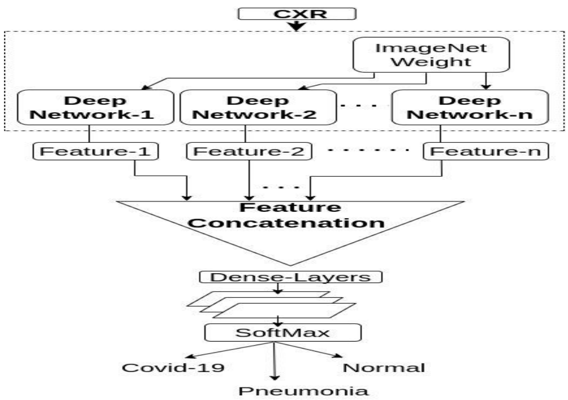

Figure 4: Flow diagram

This feature concatenation was succeeded by the application of a convolutional layer with 1024 layers. To further reduce feature dimensionality, a max-pooling layer was introduced. The features underwent flattening using a Flatten layer and were subsequently passed through densely connected layers with reduced sizes of 1024, 512, and 256, each employing the Rectified Linear Unit (ReLU) activation function. To address potential false positives, a dropout rate of 0.5 was applied. The integrated features then traversed a final fully connected layer, with the activation function set as Soft max, facilitating classification into one of the three classes: Covid-19, Pneumonia, or Normal. The parameters used for the proposed model are listed in Table: 3.

The model training process incorporated several key hyper parameters, outlined comprehensively in Table:6. Notable training parameters encompassed a learning rate set at 0.0001, utilization of a categorical cross-entropy loss function, and the application of the RMS prop optimizer, all operating on the input CXR images.

Our fine-tuning techniques encompassed diverse approaches, such as feature extraction from pre-trained models, random initialization of weights to facilitate the retraining of the model architecture, and partial training involving some layers while concurrently freezing others across multiple epochs. These strategic fine-tuning methods were instrumental in optimizing the model's performance and tailoring it to the nuances of our specific dataset. We have shown the generated output shape from the different layer in Table 2. With this we have also mentioned the best possible hyper parameter for this approach shown in Table 3.

IV RESULTS & DISCUSSION

In this section we have compared with the existing model in terms of corpus of data related to same diseases with the overall performance measured in accuracy and epochs to train the model. We observed that the author of [19] had previously employed this combination model. Based on its applicability and effectiveness, we fine-tuned the model with our parameters, resulting in improved classification performance.

We have conducted a comparison of Precision, Recall, and F1-score for the classification, as illustrated in Figures 6, 7 and 8. In terms of future prospects, this method can be extended to classify other diseases, exploring parameter selection, model layer configuration, and weight selection, providing opportunities for further research in this domain. We have been shown the confusion matrix on test data in Figure 9.

TABLE II. PROPOSED APPROACH LAYER AND OUTPUT SHAPE

Layer	Output Shape
Deep Network-1 InceptionV3 Layer	8*8*2048
Deep Network-2 Xception Layer	10*10*2048
Deep Network-3 ResNext50 Layer	10*10*2048
Max Pooling Flatten Dense1 Dense2 Dense3	4*4*1024 16384 1024 512 256
Concatenate Layer Drop out Dense	768 0.5 3

Table III. HYPER PARAMETERS USED FOR ALL MODEL

Parameters	**Values**
Activation function (Hidden)	ReLU
Activation function (Output)	Softmax
Optimizers	RMSprop
Epochs	25
Zoom Range	0-360
Dropout	0.5
Learning Rate	0.0001
Re-scaling	1/255
Loss function	Categorical cross-entropy

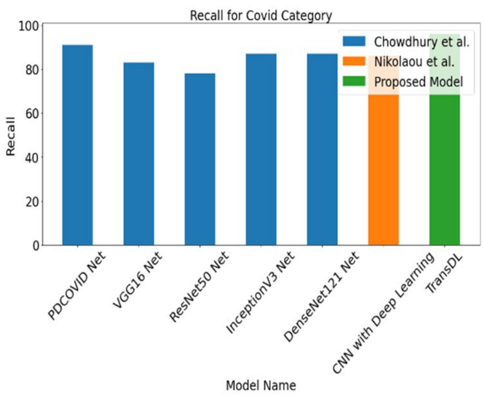

Figure 6: Recall vs. model name comparison

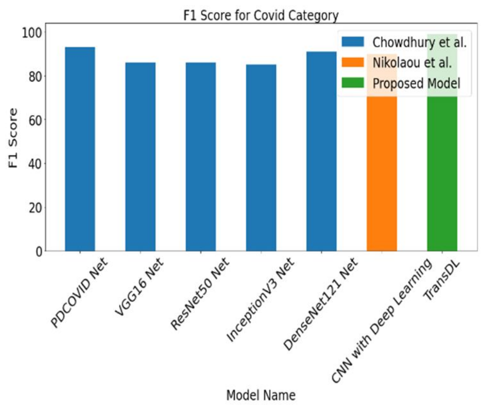

Figure 7: F1 Score vs. model name comparison

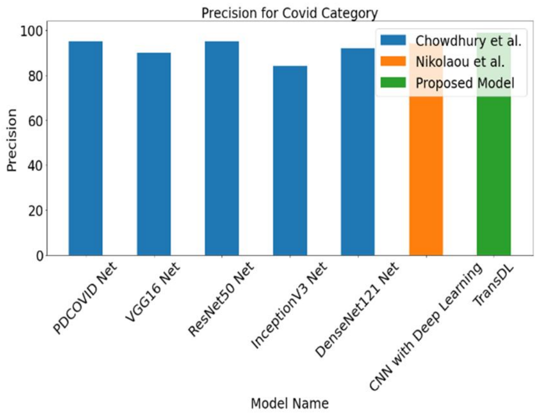

Figure 8: Precision vs. model name comparison

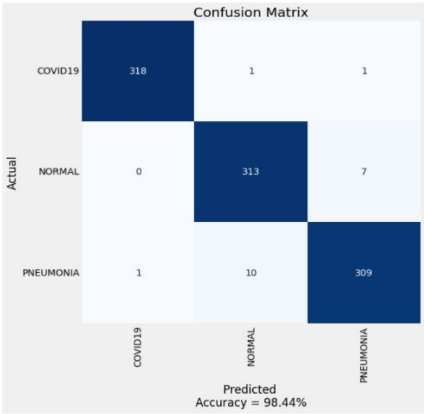

Figure 9: Confusion matrix on test data

Acknowledgment

Funding. No funding was received for conducting this study.

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