Vol 6 No 1 (2024) E-ISSN: 2682-860X

International Journal on Robotics, Automation and Sciences

A Cutting-Edge Hybrid Approach for Precise COVID-19 Detection Using Deep Learning

Hamza Younis, Safdar Abbas, Umar Hayat*, Muhammad Hammad Musaddiq, and Adeel Hashmi

***Abstract* - The early detection of COVID-19 is essential for decision-makers to develop effective containment and treatment plans. Traditionally, researchers interpret computer tomography (CT) scans or X-ray images in order to diagnose this disease. This study aims to demonstrate that deep learning models can be applied to three common medical imaging modes: X-rays, ultrasounds, and CT scans. This study employs and enhances four convolutional neural networks for coronavirus detection, including DenseNet121, ResNet101V2, NASNetMobile, and MobileNetV2. In this study, two main experiments were carried out. In the first experiment, a model was developed by combining imagery data to detect this virus. In order to determine which model performed the best, separate models were trained using different datasets in the second experiment. Because there were only so many photos accessible, data augmentation techniques were used to enhance the amount artificially. The results indicate that the proposed models effectively accomplished the task of classifying COVID-19. The accuracyrates achieved by the combined model, utilizing DenseNet121, ResNet101V2, NASNetMobile, and MobileNetV2, were 88.21%, 93.02%, and 88.89% respectively. When using the combined imaging dataset, the CNN model employing ResNet101v2 exhibited superior accuracy compared to NASNetMobile, DenseNet121, and MobileNetV2 models.**

Keywords— X-rays, CT-Scan, Covid19, Deep Learning, NASNetMobile

I. INTRODUCTION

Over 6 million people have died as a result ofthis pandemic virus infection in the past two anda half years, infecting over 561 million people. As coronavirus changes with time, the effects persist even after the immunization process. A crucial method for early disease management [1] is still the early detection, isolation, and care of patients. Symptoms associated with COVID-19 are comparable to those of respiratory syncytial virus (RSV), influenza, and pneumonia, which also cause upper respiratory infections [2].

COVID-19 outbreak is commonly diagnosed using quantitative reverse transcription-polymerase chain reaction (qRT-PCR) [3], [4] and antibody testing [5]. The precisionof the antibody method is doubtable; moreover, it provides faster results than the other method. qRT-PCR gives more accurate results but takes a longer time. Hence, it's not recommended for real-time use [6]. Following the outbreak, different machine learning and computer vision approaches

*Corresponding author, email: uhayat.buic@bahria.edu.pk
Hamza Youns, is with School of Electrical Engineering and Computer Science, National University of Science and Technology, Islamabad, Pakistan. (e-mail: myounis.msit18seecs@seecs.edu.pk).
Safdar Abbas, is with School of Electrical Engineering and Computer science, National University of Science and Technology, Islamabad, Pakistan. (e-mail: safdar.abbas@seecs.nust.edu.pk).
*Umar Hayat was with Computer Science department, Bahria University, Islamabad, Pakistan (e-mail: uhayat.buic@bahria.edu.pk).
Muhammad Hammad Musaddiq is with School of Information and Communication Engineering, University of Electronic Science and Technology of China, Chengdu, China.(e-mail: hammadmusaddiq@gmail.com).
Adeel Hashmi was with Computer Science department, University of Leeds UK, Woodhouse, Leeds LS2 9JT, United Kingdom. (e-mail: adeel.hashmi@gmail.com).

International Journal on Robotics, Automation and Sciences (2024) 6,1:86-93
https://doi.org/10.33093/ijoras.2024.6.1.12
Manuscript received: 23 Jan 2024 | Accepted: 26 Mar 2024 | Published: : 30 Apr 2024
Published by MMU PRESS. URL: http://journals.mmupress.com/ijoras

were investigated for detection of COVID-19 using computed tomography (CT), X-ray, and ultrasound imaging.

The virus detection method based on CT scans is labor-intensive, manual, and requires expertise. However, CT scanners are challenging to use since patients need to be moved to the CT scan room, the scanners need to be meticulously cleaned after each use, and the radiation dangers are increased [7]. In contrast, X-ray imaging is less expensive and frequently used to identify coronavirus and lung infections [8]. On the early COVID-19 X-ray images, no anomalies are evident [1].

As a result of its low risk of infection spread and its superior ability to identify virus lung disorders, ultrasound imaging is recommended as a tool for assessing virus lung conditions at the bedside. It costs more than an X-ray, albeit [9]. Convolutional neural networks and deep learning neural networks have shown beneficial for numerous medical picture categorization applications [10], [11].

Most of the existing studies only considered singular or two kinds of data sets for training and predicting COVID-19. This research aims to build a model to detect this disease using any input image, such as an X-ray, CT scan, or ultrasound. The following are the contributions of our study:

- To combine and develop a dataset with X-ray, CT-scan, and ultrasound images.
- Using the above-mentioned combined dataset to check how well transfer learning approachesdeal with it to classify COVID and normal classes.
- We propose a system capable of dealing with any image as an input. Separate systems for different types of image inputs are not necessary.
- Comparing four deep learning models Resnet101v2, NASNetMobile, Mobinetv2, and DenseNet121 for our demonstration.

Following the introduction, we will present a brief history of related scholarly work and a description of the dataset and sources. We will then discuss the proposed methodology and compare the results with and without fine-tuning and pipeline flow. Finally, we will present our models' performance results with a discussion.

II. Related Work

Early detection of anomalies in this global pandemic and tracking its progression is facilitated by computer-aided detection techniques, potentially reducing mortality rates. We assessed several popular deep learning frameworks, such as MobileNet, DenseNet, Xception, ResNet, InceptionV3, InceptionResNetV2, VGGNet, and NASNet, for feature extraction and classification of COVID-19 cases [2]. Chest X-rays and CT scan images were utilized to gauge the effectiveness of our approach. Our findings revealed that employing a DenseNet121 feature extractor along with a Bagging tree classifier yielded the highest classification accuracy of 99 percent, with the hybrid of a ResNet50 feature extractor and LightGBM as the second-best learner.

Furthermore, we illustrate how virus identification using images from prevalent medical imaging modalities—ultrasound, CT scans, and X-rays—can be achieved through transfer learning from deep learning models. Following a comparison of various deep learning architectures, we selected and optimized the VGG19 model for handling COVID-19 datasets. Our experiments demonstrated 100% precision with ultrasound images using a finely tuned VGG19 model on a high-performance computing system, outperforming X-rays (86% accuracy) and CT scans (84% accuracy). Additionally, we developed a computer-aided virus pandemic detection model utilizing chest X-ray images [12]. This model integrates diverse pre-trained models and employs an automatic encoder and a feedforward neural network for dimensionality reduction and disease identification. Trained on 504 COVID images and 542 non-COVID images from publicly accessible datasets, our proposed method combines InceptionResNetV2 and Xception, achieving accuracy rates of 95.78% and 98.21% using sparse autoencoders for dimensionality reduction.The author investigated using CNN for coronavirus disease identification [13]. In three Kaggle datasets and one Mendeley dataset, chest X-rays and CT scans of these disease patients, pneumonia patients, and healthyindividuals were collected for this study. 600 photos are randomly selected from each group and used for both datasets. Out of the 600 images, there are 400, 100, and 100 shots for the training, validation, and test subsets, respectively. The InceptionV3, ResNet50V2, Xception, DenseNet121, MobileNetV2, and EfficientNet-B0 convolutional neural networks have been developed. A lightweight convolutional neural network, LightEfficientNetV2, has been developed as well. Based on the three data sets, the proposed model produced the best accuracy of 98.33 percent and 97.48 percent on chest X-rays and CT scans, respectively. It also took less time to calculate and run than the original model. Compared to the related studies, Light-EfficientNetV2 has fewer model parameters, but it could provide better accuracy. As a result, substantial work in this direction is required to advance.

Currently, relatively few automated models can reliably identify the existence of the 2019 coronavirus disease outbreak using X-ray and CT-scan. Deep transfer learning algorithms are being investigated by the authors for the prediction of virus infection based on chest computed tomography (CT) and X-ray images [14]. In CT scan, a total of 846 images were used for this study, while 657 chest radiograph images were collected from various publicly available sources. An actual set of images was used to pre-train six deep convolutional neural network (CNN) architectures, AlexNet, DenseNet, GoogleNet, NASNet-Mobile, ResNet18, and DarkNet.

Three prediction tasks: detection of COVID-19 compared to non-COVID-19 CT-scan, detection of this disease in contrast to unedited X-ray images, and detection of coronavirus in contrast to other viral pneumonia in X-ray images, are used toevaluate and test the models. For classifying thevirus against normal versus other images, themodels utilizing raw CT-scan and X-ray dataproduced AUC values of 90.10% and 97.0%, respectively. COVID-19 can be distinguished, however, from non-COVID-19 using chest CT-scans and X-rays with the highest accuracy and AUC at 99.09% and 99.89%, respectively, according to the DarkNet architecture. This pandemic may be better understood with a larger cohort drawn from different regions of the world as well as more substantial clinical data. In addition to the study above, several publications have been made on computer-aided virus identification. Coronavirus-developed modelsusing an ensemble of CNNs for detection [15], [16]. Ten convolutional networks were used to detect the disease [17], [18]. In the proposed research, a new approach for feature selection was created by fusing the filter and wrapper approaches with ensemble learning for classification. A transfer learning method that modifies the previously trained network was developed [19]. Below is a brief comparison of several ways, and the strategy used in this experiment is also included in Table 1.

III. METHODOLOGY

Our study has developed a new method for detecting COVID-19 during pandemics using a step-by-step approach. Figure 1 illustrates the entire process. A dataset with different types of data was chosen to simulate real-world conditions. After verifying the dataset's reliability, we adjusted the scale so all the data was similar. In addition, all unusual data bits were handled properly. To find patterns in data, we used different pre-trained models. Based on the COVID-19 data we collected earlier, we trained these models. Using reliable measurement methods, we thoroughly tested the effectiveness of our model. With this approach, we have a clear and organized way of establishing and checking a method to detect COVID-19 in healthcare systems.

A. Dataset

Our dataset was created by combining different publicly available datasets. The combination of datasets refers to taking an equal number of images from each dataset (X-ray, CT scan, and ultrasound). X-ray dataset was provided in [23] [24] with more than 3600 COVID images and normal images of around 10,000. It's a combination of X-ray datasets available online. This team collected images from different sources and stored them in a single place.

TABLE 1. A Comparative Discussion on Literature Work.

Authors	Approaches	Accuracy	Hybrid Dataset
Horry et al. [1]	VGG19 model	0.86	No
Tahamtan et.al. [3]	CNN	0.91	No
Al Rahhal et al. [6]	Vision Transformers	0.96	No
Chaddad et.al. [14]	CNN	0.90	No
Huang et al. [13]	CNN	0.97	No
Muhammad et.al. [20]	CNN	0.95	No
Baltazar et.al. [21]	InceptionV3	0.91	No
Xuehai He et.al. [22]	Self-Trans Approach	0.93	No
Proposed Solution	Transfer Learning	0.93	Yes

Moving on to the CT scan dataset, it is most difficult to obtain as hospitals don't disclose these scans publicly; hence, very little publicly available data is found. The COVID-19 patient's scans and 397 normal person scans were provided by [25].

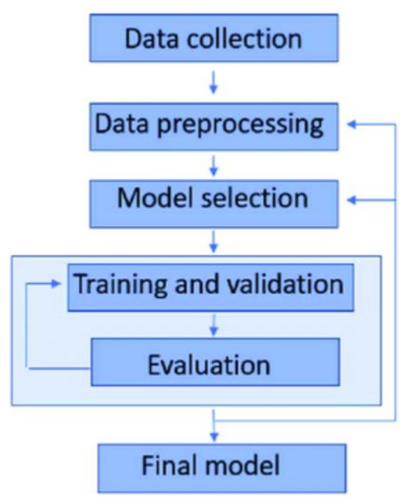

Figure 1. Methodology for Developing COVID-19 Detection System using Deep Learning

The ultrasound dataset has been updated regularly and is available on Git Hub. Due to the abundance of data available there, we were able to extract images from videos. In total, 800 images of COVID-19 were collected, while 1200 images of normal people were collected.

X-ray and ultrasound images are more abundant than CT-scan images, so it is necessary to use balanced images for all three medical data images. We removed bias from each dataset and took 349 images from each dataset containing approximately 1047 Coronavirus disease images and 1047 normal images. Sample images from each type of medical data are shown in Figure 2.

B. *Proposed Methodology*

Multiple steps were performed to detect this disease outbreak after collecting the Ultrasound, X-ray, and CT scan imagery data. In this frame of reference, the first image pre-processing was performed; before processing, dataset images were resized to 224 by 224 pixels, corresponding to the pre-trained model's input size. Two experiments were conducted on these three datasets. As shown in Figure 3, the experiments were conducted according to the proposed methodology.

In the first experiment, during experiment 1, we trained a combined model based on collecting all three medical data types. All three datasets are separated into two classes (normal and COVID-19), each stored in its folder. The combined dataset has 1047 images in the normal and COVID-19 classes. The integrated model divides each dataset into 20% for testing and 80% for training.

These two experiments used four transfer learning models. These models are MobileNetV2, NASNetMobile, ResNet101V2 and DenseNet. The pre-trained models have been fine-tuned to recognize classes not initially trained. Comparing this approach to feature-based transfer learning can improve accuracy. The output layer of the pre-trained model can be stripped off in several techniques [26], and the remaining network can be used to extract features [27], [28]. All weights are assigned randomly before the model is trained on its dataset, but the pretrained model's architecture is used [29]. New weights are added to the later layers of the model while the starting layers' weights remain the same. There may be a need to make several attempts to find the perfect match between frozen and retrained layers. To reduce the total number of parameters in the model to less than one million, we froze the weights of the first few pre-trained layers and retrained the remaining layers due to the limited dataset and high image similarity.

During the training process, a data augmentation layer was added to increase the number of images. The initial fully connected layer was replaced by a pooling layer with global averages, and a dropout layer was added before the classification layer, as shown in Figure 3. A transfer learning model was then used to preprocess the input layer and the layer for the transfer learning model [30].

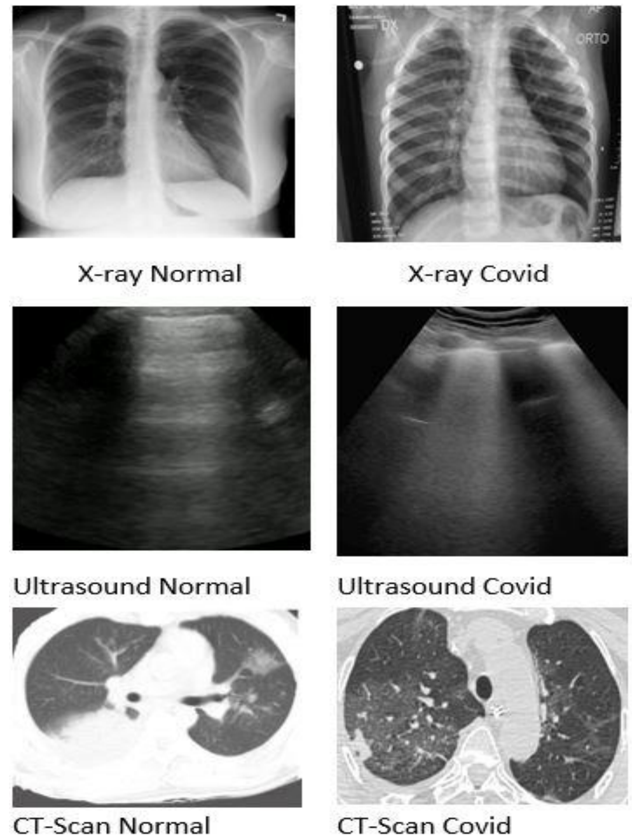

FIGURE 2. Dataset Samples.

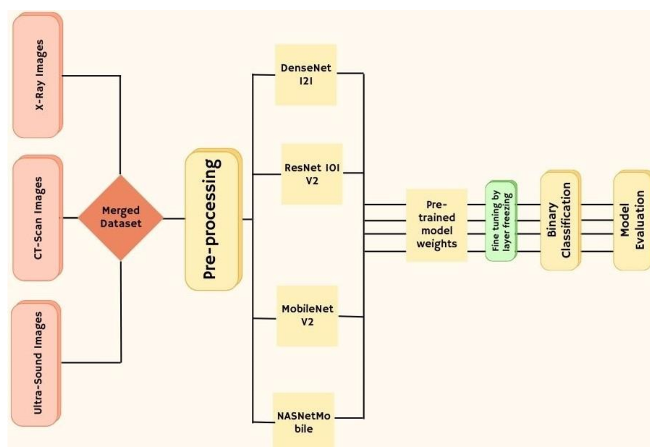

FIGURE 3. Methodology for Developing COVID-19 Detection System using Deep Learning.

This study used an adaptive moment estimation (Adam) optimizer to train the suggested models throughout 50 epochs because of its superior convergence speed. In all trials, learning rates have been set to 0.0001 to ensure the best accuracy and shortest training time. Additionally, a softmax activation function converts the outputs into potential values, enabling the model to choose one of the two classes as its output prediction.

This work used a pre-trained model that included the MobileNetV2, ResNet101V2, NASNetMobile, and DenseNet models to conduct the experiments in three distinct configurations by varying the model's weight. The COVID-19 Ultrasound image dataset, the X-ray image dataset, and the CT-scan image dataset were then used to train and evaluate the suggested models. The upper layers are skilled at this time. The work then tweaks the current models to fine-tune other layers. The specifics of the layers and parameters are displayed in Table 2.

TABLE 2. Models Comparison w.r.t Parameters and Layers.

Model	Number of Layers	Parameters
ResNet 101 v2	377	42,626,560
MobileNet v2	154	2,257,984
DenseNet 121	427	7,037,504
NasNetMobile	769	4,269,716

This work chooses to freeze the top layers and train the remaining layers of each model. The model performance of the four proposed models was then compared to one another. The best pre-trained model for the coronavirus pneumonia imaging dataset will then be determined through analysis.

The ResNet-101 architecture can be represented symbolically as follows:

$$[H]y = F(x, \{W_{i,j}\}) + x \qquad (1)$$

Where:

- x is the input feature map
- F represents the residual function
- $\{W_{i,j}\}$ are the learnable weight parameters for the convolutional layers
- y is the output feature map

Algorithm 1. ResNetV101 Architecture

```
Input: Input image x, Number of classes C
Result: Predicted class probabilities
Initialize convolutional layers;
for layers in 1 to 101, do
    if the layer is a residual block, then
        y = ResidualBlock(x);
    end
    else
        y = ConvolutionLayer(x);
    end
    x = y;
end
Global average pooling;
Fully connected layer with C units;
Softmax activation;
return Predicted class probabilities;
```

The second experiment involved training separate models for all three datasets. Three datasets are organized into folders containing two classes (normal and COVID-19). There are 330 images each in the normal and COVID classes for all datasets. In addition, we divided each dataset into 80/20 training and testing portions. We used a learning rate (lr) of 0.00001 to fine-tune the algorithm, optimization parameters ADAM and epochs 30, and loss function binary cross-entropy. The number of layers for each model is shown in Figure 4.

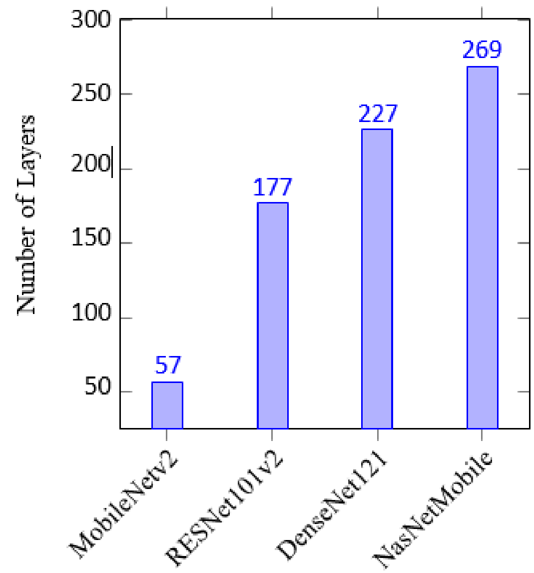

FIGURE 4. Number of Layers in Different Models.

IV. Results

The following section describes and analyzes the results of the experiments used to evaluate the proposed pipeline. Regarding the evaluation measures, we report and discuss the average and detailed results values. The accuracy, precision, and recall performance metrics are used to evaluate the algorithms' performance. Below is the categorization report for each of the four models included in Tables 3, 4, 5, and 6.

TABLE 3. Classification report for MobileNetV2.

Analysis	Precision	Recall	F1-Score	Support
0	0.90	0.88	0.89	297
1	0.88	0.90	0.89	297
Accuracy			0.89	594
Macro Avg	0.89	0.88	0.89	594
Weighted Avg	0.89	0.89	0.89	594

The ResNet model performed best of all four pre-trained models when binary cross-entropy losses were used as losses. We were able to achieve 93.3% accuracy using ResNet. As shown in Figure 5, the accuracy loss graphs of DenseNet121, ResNet101V2, MobileNetV2, and NASNetMobile have improved, both in accuracy and loss reduction, after fine-tuning.

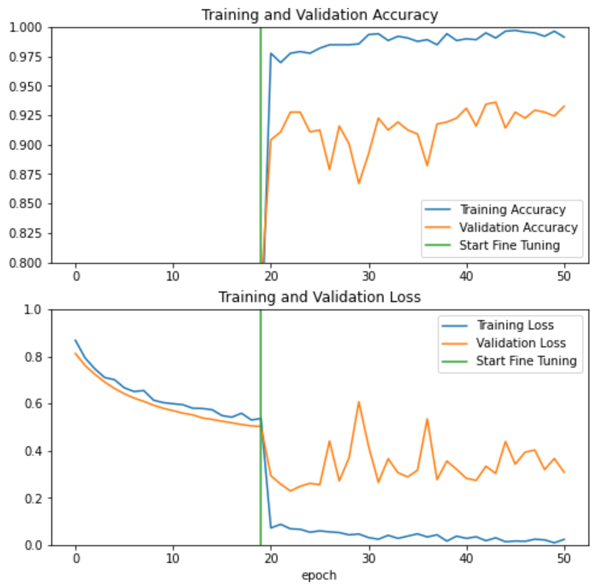

FIGURE 5. Accuracy and loss curve of ResNet101v2.

The four models used gave quite effective results when used separately with X-ray, CT-scan, and Ultrasound images and with the merged dataset. Table 7 depicts a detailed comparison of the models based on the evaluation metrics. The table describes the results of the performance measures combined with X-ray, CT-scan, and Ultrasound images that were later implemented on the CNN models.

TABLE 4. Classification report for ResNet101V2.

Analysis	Precision	Recall	F1-Score	Support
0	0.92	0.94	0.93	297
1	0.94	0.92	0.93	297
Accuracy			0.93	594
Macro Avg	0.93	0.93	0.93	594
Weighted Avg	0.93	0.93	0.93	594

TABLE 5. Classification report for DenseNet121.

Analysis	Precision	Recall	F1-Score	Support
0	0.86	0.94	0.90	198
1	0.94	0.84	0.89	198
Accuracy			0.89	396
Macro Avg	0.90	0.89	0.89	396
Weighted Avg	0.90	0.89	0.89	396

TABLE 6. Classification report for NASNetMobile.

Analysis	Precision	Recall	F1-Score	Support
0	0.83	0.96	0.89	297
1	0.96	0.80	0.87	297
Accuracy			0.88	594
Macro Avg	0.89	0.88	0.88	594
Weighted Avg	0.89	0.88	0.88	594

Table 7 shows the results with X-ray, CT-scan, and Ultrasound images separately implemented on the ResNet101V2 model. Since the results produced by ResNet101V2 were more reliable and outperformed every other model, we applied every data separately to test the outcomes.

TABLE 7. Results of ResNet 101 V2 on Separate Images Dataset for COVID-19.

Analysis	Accuracy	Precision	Recall	F1-Score
ResNet 101 V2 with CT-scan	0.84	0.86	0.85	0.85
ResNet 101 V2 with X-ray	0.94	0.93	0.92	0.92
ResNet 101 V2 with Ultrasound	0.99	0.99	0.99	0.99

The ResNet101V2 model with the merged dataset of X-ray, CT-scan, and Ultrasounds gave an accuracy of 93.3%, much higher than the rest of the models. ResNet 101V2 was picked to run with the same images separately, such that each time, the model deals with a single type of image, such as an X-ray, CT scan, or ultrasound. When applied separately, the model gave the best outcome with ultrasound images, an accuracy of approximately 99.24%, nearly 100. It gave good results with X-ray, too, with an accuracy of 94.42%. Hence, it is quite reliable if it deals with more combined data.

V. Conclusion

This research has been developed with the capability to predict COVID-19 using diverse image inputs. Through comparative analysis of pre-trained models, ResNet101v2 has been identified as the optimal choice, achieving an accuracy of 93.26%, surpassing alternative models. This endeavor introduces an innovative approach, establishing a precedent for subsequent investigations in this domain. It is noteworthy that the devised approach adopts a hybrid methodology. Ultrasound images have demonstrated exceptional promise, yielding an impressive accuracy of 99% in an independent model evaluation. Consequently, prioritizing ultrasound images is advisable, given their considerable positive influence on model performance. Following this, X-ray images exhibit a 94.42% accuracy, while CT-scan attains 84.84%. These modalities are valuable substitutes when ultrasound imaging facilities are not readily accessible. The findings advance COVID-19 diagnosis through image analysis and suggest a promising avenue for future research and innovation within this emerging field.

VI. Future work

In the future, results can be improved by tuning the hyperparameters of pre-trained models, which require a lot of time, effort, and hardware dependencies. We can also compile a bigger dataset and use that to evaluate the models. In addition, GPU-based models can improve accuracy since this experiment used only CPU-based pre-trained models.

Acknowledgement

It is with sincere gratitude that we express our sincere appreciation to the dedicated members of the National University of Science and Technology, Pakistan, for their steadfast support, and insightful discussions on emerging technologies. Further, we are grateful to our families, friends, and colleagues for their unwavering guidance and invaluable contributions.

References

[1] M.J. Horry, S. Chakraborty, M. Paul, A. Ulhaq, B. Pradhan, M. Saha, N. Shukla, "COVID-19 detection through transfer learning using multimodal imaging data," IEEE Access, vol. 8, pp. 149808-149824, 2020. doi: 10.1109/ACCESS.2020.3016780.

[2] S.H. Kassania, P.H. Kassanib, M.J. Wesolowskic, K.A. Schneidera, R. Detersa, "Automatic detection of coronavirus disease (COVID-19) in X-ray and CT images: a machine learning based approach," Biocybernetics and Biomedical Engineering, vol. 41, no. 3, pp. 867-879, 2021.

[3] A. Tahamtan, A. Ardebili, "Real-time RT-PCR in COVID-19 detection: issues affecting the results," Expert Review of Molecular Diagnostics, vol. 20, no. 5, pp. 453-454, 2020.

[4] L. Lan, D. Xu, G. Ye, C. Xia, S. Wang, Y. Li, H. Xu, "Positive RT-PCR test results in patients recovered from COVID-19," Jama, vol. 323, no. 15, pp. 1502-1503, 2020.

[5] D. Jacofsky, E.M. Jacofsky, M. Jacofsky, "Understanding antibody testing for COVID-19," The Journal of Arthroplasty, vol. 35, no. 7, pp. S74-S81, 2020.

[6] M.M. Al Rahhal, Y. Bazi, R.M. Jomaa, A. AlShibli, N. Alajlan, M.L. Mekhalfi, F. Melgani, "Covid-19 detection in ct/x-ray imagery using vision transformers," Journal of Personalized Medicine, vol. 12, no. 2, 310, 2022.

[7] D. Bell, R. Sharma, H. Knipe et al., "COVID-19," Radiopaedia.org. Accessed on 27 Mar 2024. https://doi.org/10.53347/rID-73913.

[8] H.Y.F. Wong, H.Y.S. Lam, A.H.T. Fong, S.T. Leung, T.W.Y. Chin, C.S.Y. Lo, M.M.S. Lui, J.C.Y. Lee, K.W.H. Chiu, T.W.H. Chung, E.Y.P. Lee, "Frequency and distribution of chest radiographic findings in patients positive for COVID-19," Radiology, vol. 296, no. 2, pp. E72-E78, 2020.

[9] D. Buonsenso, D. Pata, A. Chiaretti, "COVID-19 outbreak: less stethoscope, more ultrasound," The Lancet Respiratory Medicine, vol. 8, no. 5, e27, 2020.

[10] R. Yamashita, M. Nishio, R.K.G. Do, K. Togashi, "Convolutional neural networks: an overview and application in radiology," Insights into Imaging, vol. 9, pp. 611-629, 2018.

[11] M.A. Mazurowski, M. Buda, A. Saha, M.R. Bashir, "Deep learning in radiology: An overview of the concepts and a survey of the state of the art with focus on MRI," Journal of Magnetic Resonance Imaging, vol. 49, no. 4, pp. 939-954, 2019.

[12] J.L. Gayathri, B. Abraham, M.S. Sujarani, M.S. Nair, "A computer-aided diagnosis system for the classification of COVID-19 and non-COVID-19 pneumonia on chest X-ray images by integrating CNN with sparse autoencoder and feed forward neural network," Computers in Biology and Medicine, vol. 141, 105134, 2022.

[13] M.L. Huang, Y.C. Liao, "A lightweight CNN-based network on COVID-19 detection using X-ray and CT images," Computers in Biology and Medicine, vol. 146, 105604, 2022.

[14] A. Chaddad, L. Hassan, C. Desrosiers, "Deep CNN models for predicting COVID-19 in CT and x-ray images," Journal of Medical Imaging, vol. 8, S1, 014502, 2021.

[15] B. Abraham, M.S. Nair, "Computer-aided detection of COVID-19 from X-ray images using multi-CNN and Bayesnet classifier," Biocybernetics and Biomedical Engineering, vol. 40, no. 4, pp. 1436-1445, 2020.

[16] B. Abraham, M.S. Nair, "Computer-aided detection of COVID-19 from CT scans using an ensemble of CNNs and KSVM classifier," Signal, Image and Video Processing, vol. 16, no. 3, pp. 587-594, 2022.

[17] A.A. Ardakani, A.R. Kanafi, U.R. Acharya, N. Khadem, A. Mohammadi, "Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: Results of 10 convolutional neural networks," Computers in Biology and Medicine, vol. 121, 103795, 2020.

[18] W.M. Shaban, A.H. Rabie, A.I. Saleh, M.A. Abo-Elsoud, "A new COVID-19 Patients Detection Strategy (CPDS) based on hybrid feature selection and enhanced KNN classifier," Knowledge-Based Systems, vol. 205, 106270, 2020.

[19] M. Phankokkruad, "COVID-19 pneumonia detection in chest X-ray images using transfer learning of convolutional neural networks," in Proceedings of the 3rd International Conference on Data Science and Information Technology, pp. 147-152, 2020.

[20] G. Muhammad, M.S. Hossain, "COVID-19 and non-COVID-19 classification using multi-layers fusion from lung ultrasound images," Information Fusion, vol. 72, pp. 80-88, 2021.

[21] L.R. Baltazar, M.G. Manzanillo, J. Gaudillo, E.D. Viray, M. Domingo, B. Tiangco, J. Albia, "Artificial intelligence on COVID-19 pneumonia detection using chest xray images," Plos One, vol. 16, no. 10, e0257884, 2021.

[22] X. He, X. Yang, S. Zhang, J. Zhao, Y. Zhang, E. Xing, P. Xie, "Sample-efficient deep learning for COVID-19 diagnosis based on CT scans," medRxiv, 2020. pp. 2020-04.

[23] M.E. Chowdhury, T. Rahman, A. Khandakar, R. Mazhar, M.A. Kadir, Z.B. Mahbub, K.R. Islam, M.S. Khan, A. Iqbal, N. Al Emadi, M.B.I. Reaz, "Can AI help in screening viral and COVID-19 pneumonia?," IEEE Access, vol. 8, pp. 132665-132676, 2020.

[24] T. Rahman, A. Khandakar, Y. Qiblawey, A. Tahir, S. Kiranyaz, S.B.A. Kashem, M.T. Islam, S. Al Maadeed, S.M. Zughaier, M.S. Khan, M.E. Chowdhury, "Exploring the effect of image enhancement techniques on COVID-19 detection using chest X-ray images," Computers in Biology and Medicine, vol. 132, 104319, 2021.

[25] X. Yang, X. He, J. Zhao, Y. Zhang, S. Zhang, P. Xie, "COVID-CT-dataset: a CT scan dataset about COVID-19," arXiv preprint arXiv:2003.13865.

[26] K.H. Shibly, S.K. Dey, M.T.U. Islam, M.M. Rahman, "COVID faster R–CNN: A novel framework to Diagnose Novel Coronavirus Disease (COVID-19) in X-Ray images,"

Informatics in Medicine Unlocked, vol. 20, 100405, 2020.
[27] M.F. Aslan, M.F. Unlersen, K. Sabanci, A. Durdu, "CNN-based transfer learning–BiLSTM network: A novel approach for COVID-19 infection detection," Applied Soft Computing, vol. 98, 106912, 2021.
[28] U. Hayat, M. Yasir, A.U. Rehman, "Transfer Learning for the Medical Diagnosis of Acute Leukemia Cancer," in International Conference on Computational Sciences and Technologies, 2021.
[29] H. Liu, L. Wang, Y. Nan, F. Jin, Q. Wang, J. Pu, "SDFN: Segmentation-based deep fusion network for thoracic disease classification in chest X-ray images," Computerized Medical Imaging and Graphics, vol. 75, pp. 66-73, 2019.
[30] D.P. Kingma, J. Ba, "Adam: A method for stochastic optimization," arXiv preprint arXiv:1412.6980, 2014.