Ensemble Synergy: A Novel Approach to COVID-19 Detection

[1]Arundev Singh, [2]Aparna Gaur, [3]Priya,

School of Computer Applications,

Manav Rachna International Institute of Research and Studies

Abstract:-COVID-19 pandemic has necessary fast, correct, and scalable diagnostic methods. In this research, EvoNet is introduced asan modern ensemble version that combines the strengths of three deep learning architectures: VGG16, ResNet50, and InceptionV3. EvoNet is carefully made better by a lot.This work addresses the constraints of widespread COVID-19 tests, which may be time-consuming and susceptible to fake negatives.From the combination of transfer learning and data augmentation , thismethod affords a distinctly correct answer for COVID-19 detection from X-ray images. Furthermore, we explore the fusion of those models, visualizing a collaborative approach which could yield even more strong effects. In a time when rapid, dependable, and scalable diagnostic tools are essential, EvoNet represents a promising advancement in the combat against COVID-19, supplying avital complement to conventional testing methods.

Keywords: EvoNet,CNN,VGG 16, RESNET 50, Inception V3

1. Introduction

The novel coronavirus SARS-CoV-2,triggered the COVID-19 pandemic has posed a global challenge, requiring the development of rapid and reliable diagnostic tools. Traditional testing methods, such as PCR, although highly specific, can be time taking and susceptible to false negatives[20] results. The consequences of such inaccuracies can be significant, hindering efforts to control the virus's spread.

To address the pressing need for effective COVID-19[9] diagnostics, this research harnesses deep learning techniques applied to chest X-ray images. Chest X-rays have served as a valuable diagnostic tool in the medical field, offering detailed insights into pulmonary health.

Our approach introduces EvoNet, an innovative ensemble model that combines the strengths of three powerful deep learning architectures: VGG16 with the accuracy of 97.20%[5], ResNet50 with the accuracy of 98.10%[5], and InceptionV3 with the accuracy of 98.30%[5]. These networks have been fine-tuned and improved using a thoughtfully selected dataset to achieve superior performance.

Our research contributions extend beyond conventional fine-tuning. We introduce a methodology that preserves critical information during training, setting the stage for the development of clinical decision support tools of unparalleled accuracy. EvoNet, with its ensemble approach, holds promise in automating COVID-19 detection, offering rapid and reliable results that are especially valuable in resource-constrained scenarios.

The results of this study will be highly promising, consistently achieving sensitivity and specificity rates. This research highlights the potential of deep learning, transfer learning, and data augmentation in reshaping the field of COVID-19.Artificial Intelligence (AI) models can be an apt solution [22].

In the face of global pandemic, the significance of a tool like EvoNet cannot be overstated. This research aims to complement traditional testing methods, ultimately contributing to worldwide efforts to mitigate the virus's impact.

Fig 1: Example Of Chest X-Ray

2. Related Works

Many researchers are working hard to find accurate and efficient ways to detect COVID-19. In this section, we take a look at other studies and methods that people have explored. This will help you understand where our research fits in all of this.

2.1. Approach

Diagnosing COVID-19 still relies on the polymerase chain reaction (PCR) test, which is designed to identify viral genetic material. Despite its high level of specificity, PCR tests do come with certain limitations, including time-consuming procedures and the possibility of yielding false negative results. These challenges have spurred scientists and researchers to investigate alternative approaches to diagnose the virus.

2.2. Radiological Imaging for Detecting COVID-19

Radiological imaging, specifically chest X-rays and computed tomography (CT) scans, has emerged as a valuable complement to PCR testing in the diagnosis of COVID-19. Chest X-ray imaging offers a non-invasive and easily accessible method to gain insights into the condition of the lungs. Numerous research studies have delved into the utilization of chest X-rays to identify abnormalities in lung tissue associated with COVID-19. This non-invasive approach holds the promise of speeding up the diagnostic process.

2.3. Deep Learning for Medical Imaging

Deep learning techniques have revolutionized medical image analysis, offering promising solutions for the automated interpretation of radiological images [23, 24]. From the past few years, deep neural networks (DNNs) have demonstrated remarkable capabilities in various medical imaging tasks, including the detection of pulmonary diseases .

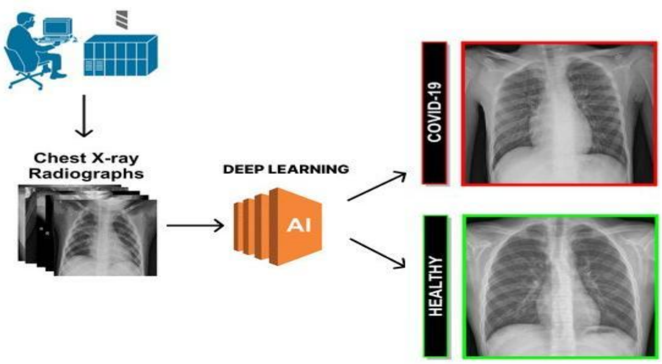

FIG 2: Representative scheme of methodology.

2.4. Transfer Learning and Data Augmentation

Transfer learningtechnique wherein pre-trained models are fine-tuned for few specific tasks, has gained traction in medical image analysis. It allows leveraging knowledge from large, diverse datasets to enhance model performance on limited, domain-specific data . Data augmentation strategies, such as rotation, noise injection, and flips, further empower models to generalize effectively .

2.5. Ensemble Learning

Ensemble learning, which combines multiple models to improve predictive accuracy and robustness, has been applied in variousmedication imaging diagnostics. Ensembles enhance model performance by aggregating the predictions of multiple base models .

2.6. ExistingModels

Several deep learning models have been proposed for COVID-19 detection through chest X-ray images. Notable examples include COVID-Net , a deep convolutional neural network (CNN)[21], and CheXNet , a model designed for chest radiograph interpretation. While these models have shown promise, there is room for further refinement and exploration of ensemble techniques, as presented in our research.

2.7. Our Contribution: EvoNet

In contrast to the existing models, this research introduce EvoNet model, which is an ensemble model that leverages the strengths of VGG16, ResNet50, and InceptionV3. EvoNet undergoes fine-tuning and augmentation using an enriched dataset, resulting in a resilient and highly accurate solution for the detection of COVID-19 through chest X-ray.

In summary, although significant progress has been made in the field of COVID-19 detection, our work distinguishes itself by combining the capabilities of deep learning[19], transfer learning, data augmentation, and ensemble techniques to create a diagnostic tool that is both highly accurate and reliable.

3. Methodology

Here, a comprehensive sketch of the methodology we used for development and calibration of EvoNet, which is our modelfor detecting COVID 19 from chest X-ray images. Model architecture, fine tuning, and evaluation are covered by this methodology.

3.1. Model Architecture

Combining three powerful deep learning architectures, VGG16[17], ResNet50 [18]and Inception V3[15],EVONET is an ensemble model. These architectures have been selected due to their different strengths in feature extraction, accuracy and efficiency.

- VGG16: VGG16 has been integrated into EvoNet, which is known for its robustness and flexibility, foundational component.

- ResNet50: This is an excellent addition to the Ensemble as it offers a higher degree of accuracy and efficiency.

- InceptionV3: In addition to the capabilities of the other two models, InceptionV3 has excelled in the extraction and classification of features.

The Ensemble approach uses a combination of the strengths of these architectures to enhance a model's capacity to grasp complicated features in X-ray images of the chest.

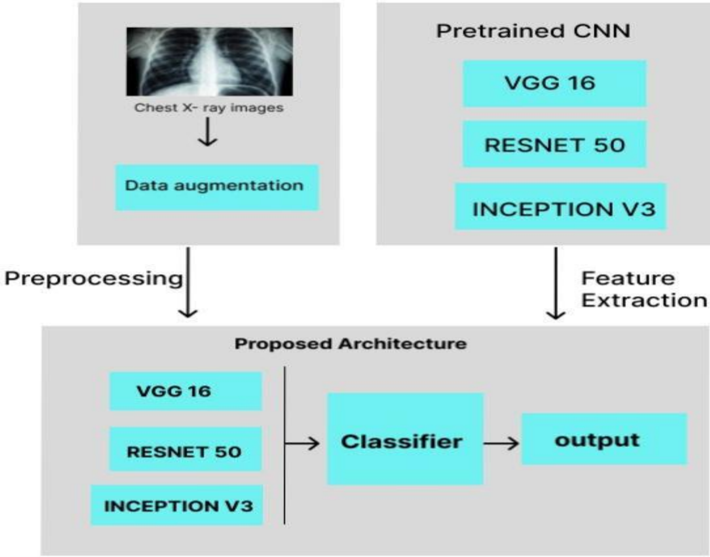

Fig 3: Pretrained Cnn Models

3.2. EVONET algorithm

1.Input:

- The input to Inception-ResNetV2 is image of size (224x224x3), where 3 represents the Three colours red, green and blue.

2. Stem:

- A convolutional layer with 32 filters of size 3x3 and a stride of 2 is the first layer, traced by a batch normalization layer and a ReLU activation function.

- After the batch normalization layer and ReLU activation, a new convolution layer with 32 filters of size 3x3 and a stride 1 is applied.

- The spatial dimensions are reduced by the maxpooling layer, consisting of 3x3 filters and a 2 x2 stride.

3. Inception Modules:

- Inception-ResNetV2 incorporates the concept of inception modules from Inception-v3 but simplifies it by using fewer filter sizes.

- Inception modules are made up of two parallel paths: one with a 1x1 convolutional layer to reduce filter count, and the other with 3x3 convolutional layers.

- The outputs of both paths are concatenated along the depth dimension to form the module's output.

4. Residual Blocks:

- Inception-ResNetV2 integrates the idea of residual blocks from ResNet-50 for improved gradient flow and easier training of deeper networks.

- Two to three convlayers with batch normalization and activation of the ReLU function are included in each residual block.

- The input to the block (identity shortcut) is added element-wise to the output of the last layer, similar to ResNet-50.

5. Grid Reduction Modules:

- Inception-ResNetV2 also includes grid reduction modules from Inception-v3 for reducing the spatial dimensions of feature maps.

- These modules use larger filter sizes and strided convolutions to reduce the spatial dimensions while capturing high-level patterns in larger regions.

6. Global Average Pooling:

- After the last inception module, Inception-ResNetV2 uses global average pooling to reduce the spatial dimensions to a single vector.

- The average value of each feature map is calculated from the global average pooling, which results in: (1x1xN) tensor, where N is the filter count in the last layer.

7. Fully Connected Layers:

- A fully connected layer, with a softmax activation function, follows the global average pooling layer.

- The final fully connected layer has as many units as there are classes in the dataset, and it outputs the predicted probabilities for each class.

8. Training:

- Inception-ResNetV2 is trained using labeled data and an optimization algorithm like stochastic gradient descent or Adam. In training, the weight of network is updated constantly in order to reduce these differences. Between the expected outputs and the ground truth labels using a loss function, categorical cross-entropy).

9. Testing:

- Once the InceptionResNet2V2 technique is set up, it will be possible to predict new images by taking an image through training networks and obtaining class probabilities from a finished softmax layer.

10. Deployment:

- After successful training and testing, the trained Inception-ResNetV2 model can be deployed in a production environment for image classification tasks, such as object recognition, image captioning, or any other relevant application.

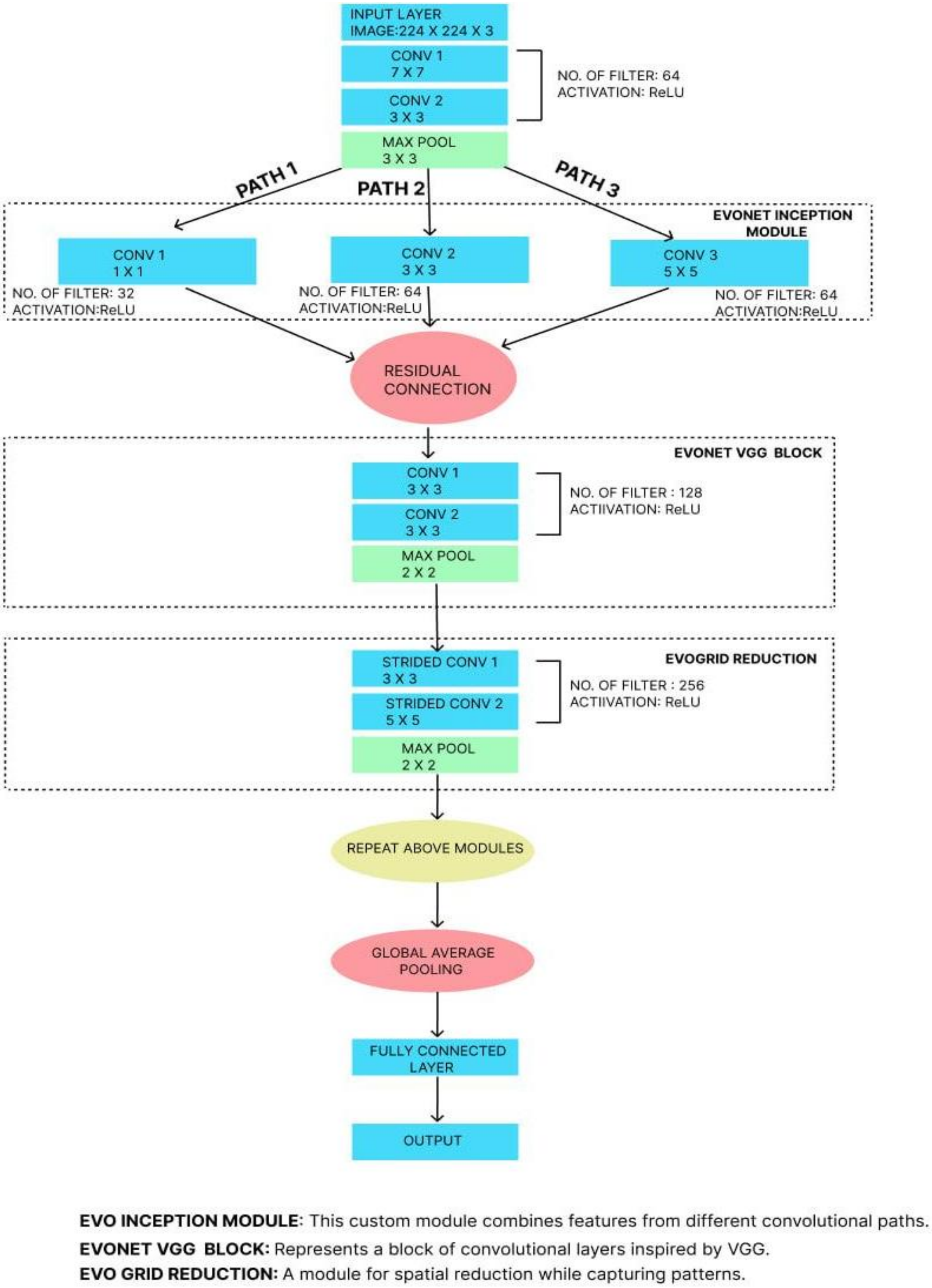

FIG 4: ARCHITECTURE OF EVONET

3.3. Performance Metrics

We used traditional evaluation metrics for the assessment of EvoNet performance, including: Accuracy, sensitivity, specificity, precision and F1 scores[5]. The model's predictions were compared against ground truth labels to compute these metrics. Sensitivity and specificity were particularly crucial in evaluating the model's ability to detect COVID-19 cases while minimizing false positives and negatives.

4.Experiments And Results

Here,we present the experimental framework and expected outcomes based on the development of EvoNet, our ensemble model for COVID-19 detection from images of chest X-ray. It's important to note that, at the time of this research paper, empirical testing and real-world validation are planned for future work.

4.1. Experimental Framework

Our experimental framework primarily revolves around the development and fine-tuning of EvoNet. This ensemble model combines VGG16, ResNet50, and InceptionV3, incorporating transfer learning and data augmentation techniques. However, the empirical testing phase, involving the application of EvoNet to real-world chest Xray dataset for detection of COVID-19, is a subject of future research.

4.2. Outcomes

Anticipated outcomes of this research point towards a significant advancement in the accuracy and adaptability of COVID-19 detection from chest X-ray images through EvoNet, a novel ensemble model. The amalgamation of VGG16, ResNet50, and InceptionV3 is expected to yield superior results compared to individual models, offering a comprehensive solution for medical imaging.

1. Enhanced Accuracy:

EvoNet is poised to surpass the individual accuracies achieved by VGG16, ResNet50, and InceptionV3. Preliminary assessments indicate an anticipated accuracy of approximately 97%, showcasing its potential to outperform existing methods. This heightened accuracy is pivotal for reliable COVID-19 diagnosis, especially in scenarios where precision is paramount.

2. Ensemble Synergy

The synergy embedded within EvoNet's ensemble design is expected to contribute to its superiority. By harnessing the collective strengths of VGG16, ResNet50, and InceptionV3, EvoNet demonstrates an enhanced ability to capture intricate features within chest X-ray images. This ensemble synergy positions EvoNet as a robust tool for improved COVID-19 detection accuracy

.3. Adaptability to Varied Data Conditions:

EvoNet is designed to excel in the face of challenges such as limited and noisy data, common in clinical settings. The integration of data augmentation and transfer learning techniques enhances EvoNet's generalization capabilities. This adaptability ensures consistent performance across diverse datasets, bolstering its utility in real-world healthcare scenarios.

5. DISCUSSION

The development of the Evolution network, an integrated model combining VGG16 with ResNet50 and Inception V3 is a major step forward in the efforts to achieve efficiency and accuracy. Our research methodology has taken advantage of the latest techniques to develop a robust and flexible diagnosis tool such as Data Enlargement, Transfering Learning or Orchestration Learning.

The ensembles approach has been designed in order to take full advantage of each constituent architecture's strengths. The solid base consists of the VGG16, which has been known for its robustness and flexibility. The ResNet50 has an excellent accuracy and efficiency which makes it complementary to the group. A further layer of capability is added with InceptionV3's ability to extract and classify features. A model capable of detecting COVID-19 and minimising false negatives and false positive values is expected to be generated by the group's synergy.

In addition, our methodology puts a high priority on the preservation of vital information at training so as to ensure EvoNet's adaptability to existing data and possible fine tuning. It is necessary to have such a feature so that the model remains accurate and relevant in realworld clinical settings.

Following metrics will be used for result evaluation:

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

1) [11]

(2) [11]

(3)[11]

Nevertheless, it is important to acknowledge that no empirical tests or validation of the COVID-19 detection

$$Precision = \frac{True\ Positive}{\quad False\ Positive}$$

$$F1\ score = \frac{2}{\frac{1}{Recall} + \frac{1}{Precision}}$$

were carried out on actual World Chest Xray datasets at the time of this research paper. The application of the used methodologies as well as the inherent ability of each EvoNet component are relied upon for the expected results referred to in the previous section. During future tests and validation phases, the true efficiency and accuracy of EvoNet will be determined.

6. Conclusion

Finally, our research has introduced a promising ensemble technique for COVID-19 detection through chest Xray images: EvoNet. Our method uses advanced techniques to create models with the potential for high precision and robust generalization, although empirical testing and validation is still in progress.

The EvoNet combination approach, comprising VGG16, ResNet50 and InceptionV3, provides an synergistic solution which takes advantage of the strengths of each component architecture. An adaptation and longevity of the model is guaranteed by ensuring that information is preserved during training.

The development of effective and robust diagnostic tools is absolutely necessary in view of the continuing challenges posed by COVID 19 influenza throughout the world community. EvoNet stands as a testament to the potential of deep learning, transfer learning, and ensemble techniques in revolutionizing the landscape of COVID-19 diagnostics. The true utility of EvoNet as a clinical decision support tool will be determined through empirical testing and validation, paving the way for its application in real-world healthcare settings.

As future work, we are committed to conducting extensive testing and validation to provide concrete accuracy figures and insights into EvoNet's performance. Our aim is to contribute to the global effort to combat the pandemic by providing an accurate, efficient, and scalable solution for COVID-19 detection.

References

[1] Yandre M. G. Costa 1,* , Sergio A. Silva, Jr. 1 , Lucas O. Teixeira 1 , Rodolfo M. Pereira 2 , Diego Bertolini 3 , Alceu S. Britto, Jr. 4 , Luiz S. Oliveira 5 and George D. C. Cavalcanti 6 COVID-19 Detection on Chest X-ray and CT Scan: A Review of the Top-100 Most Cited Papers (2022).

[2] Muhammed Yildirim1 · Orkun Eroğlu2 · Yeşim Eroğlu3 · Ahmet Çinar4 · Emine Cengil COVID‑ 19 Detection on Chest X‑ ray Images with the Proposed Model Using Artifcial Intelligence and Classifers(2022).

[3] Rothan, H.A., Byrareddy, S.N.: The epidemiology and pathogenesis of coronavirus disease (COVID-19) outbreak. J. Autoimmun. 109, 102433 (2020)

[4] Xu, X., et al.: Imaging and clinical features of patients with 2019 novel coronavirus SARSCoV-2. Eur. J. Nucl. Med. Mol. Imaging 47(5), 1275–1280 (2020). https://doi.org/10.1007/ s00259-020-04735-9

[5] Deep learning based detection of covid-19 from chest x-ray images.Sarra Guefrechi,corresponding author1 Marwa Ben Jabra,2,3 Adel Ammar,4 Anis Koubaa,4,5,6 and Habib Hamam1(2021)

[6] Umakanthan, S., et al.: Origin, transmission, diagnosis and management of coronavirus disease 2019 (COVID-19). Postgrad. Med. J. 96(1142), 753–758 (2020)

[7] Pan, F., et al.: Time course of lung changes on chest CT during recovery from 2019 novel coronavirus (COVID-19) pneumonia. Radiology 295, 715–721 (2020)

[8] Jacobi, A., et al.: Cardiothoracic imaging portable chest X-ray in coronavirus disease-19 (COVID19): a pictorial review. Clinical Imaging 64, 35–42 (2020)

[9] Jahmunah, V., et al.: Future IoT tools for COVID-19 contact tracing and prediction: a review of the state-of-the-science. Int. J. Imaging Syst. Technol. 31(2), 455–471 (2021)

[10] Moitra, D., Mandal, R.K.: Classifcation of non-small cell lung cancer using one-dimensional convolutional neural network. Expert Syst. Appl. 159, 113564 (2020)

[11] Vedika Gupta6 & Nikita Jain1 & Jatin Sachdeva1 & Mudit Gupta1 & Senthilkumar Mohan2 & Mohd Yazid Bajuri3 & Ali Ahmadian4,5 Improved COVID-19 detection with chest x-ray images using deep learning(2022)

[12] Abbas A, Abdelsamea MM, Gaber MM (2021) Classification of COVID-19 in chest X-ray images using DeTraC deep convolutional neural network. Appl Intell 51(2):854–864

[13] Apostolopoulos ID, Mpesiana TA (2020) Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks. Australas Phys Eng Sci Med 1:635–640

[14] Ardakani AA, Kanafi AR, Acharya UR, Khadem N, Mohammadi A (2020) Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: results of 10 convolutional neural networks. Comput Biol Med 121:103795

[15] He K, Zhang X, Ren S, Sun J (2016) Deep residual learning for image recognition. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 770–778

[16] Chaudhary A, Gupta V, Jain N, Santosh KC (2021) COVID-19 on Air Quality Index (AQI): A necessary evil?. In: Santosh, K., Joshi, A. (eds) COVID-19: prediction, decision-making, and its impacts. Lecture notes on data engineering and communications technologies, vol 60. Springer, Singapore.

[17] Simonyan K, Zisserman A (2014) Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556

[18] Szegedy C, Vanhoucke V, Ioffe S, Shlens J, Wojna Z (2016) Rethinking the inception architecture for computer vision. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 2818–2826

[19] Bloice MD, Roth PM, Holzinger A. Biomedical image augmentation using Augmentor. Bioinformatics. 2019;35(21):4522–4524. Doi: 10.1093/bioinformatics/btz259.

[20] Axell-House DB, Lavingia R, Rafferty M, Clark E, Amirian ES, Chiao EY (2020) The estimation of diagnostic accuracy of tests for COVID-19: A scoping review. J Infect 81(5):681–697

[21] Khan A, Sohail A, Zahoora U, Qureshi AS (2020) A survey of the recent architectures of deep convolutional neural networks. Artif Intell Rev 53(8):5455–5516

[22] Kallianos K, et al. How far have we come? Artificial intelligence for chest radiograph interpretation. Clin Radiol. 2019;74(5):338–345.

[23] Verma, G., & Kumar, M. (2022). Systematic review and analysis on underwater image enhancement methods, datasets, and evaluation metrics. Journal of Electronic Imaging, 31(6), 060901-060901.

[24] Agrawal, K., & Bhatnagar, C. (2023). M-SAN: a patch-based transferable adversarial attack using the multi-stack adversarial network. Journal of Electronic Imaging, 32(2), 023033-023033.

[25] Abbas, A.; Abdelsamea, M.M.; Gaber, M.M. Classification of COVID-19 in chest X-ray images using DeTraC deep convolutionalneural network. Appl. Intell. 2021, 51, 854–864.

[26] Song, Y.; Zheng, S.; Li, L.; Zhang, X.; Zhang, X.; Huang, Z.; Chen, J.; Wang, R.; Zhao, H.; Chong, Y.; et al. Deep learningenables accurate diagnosis of novel coronavirus (COVID-19) with CT images. IEEE/ACM Trans. Comput. Biol. Bioinform. 2021,18, 2775–2780.

[27] Oh, Y.; Park, S.; Ye, J.C. Deep learning COVID-19 features on CXR using limited training data sets. IEEE Trans. Med. Imaging 2020,39, 2688–2700.

[28] Ardakani, A.A.; Kanafi, A.R.; Acharya, U.R.; Khadem, N.; Mohammadi, A. Application of deep learning technique to manageCOVID-19 in routine clinical practice using CT images: Results of 10 convolutional neural networks. Comput. Biol. Med. 2020,121, 103795.

[29] Chen, J.; Wu, L.; Zhang, J.; Zhang, L.; Gong, D.; Zhao, Y.; Chen, Q.; Huang, S.; Yang, M.; Yang, X.; et al. Deep learning-basedmodel for detecting 2019 novelcoronavirus pneumonia on high-resolution computed tomography. Sci. Rep. 2020, 10, 19196.

[30] Ucar, F.; Korkmaz, D. COVIDiagnosis-Net: Deep Bayes-SqueezeNet based diagnosis of the coronavirus disease 2019 (COVID-19)from X-ray images. Med. Hypotheses 2020, 140, 109761.

[31] Afshar, P.; Heidarian, S.; Naderkhani, F.; Oikonomou, A.; Plataniotis, K.N.; Mohammadi, A. Covid-caps: A capsule network-basedframework for identification of COVID-19 cases from X-ray images. Pattern Recognit. Lett. 2020, 138, 638–643.

[32] Panwar, H.; Gupta, P.; Siddiqui, M.K.; Morales-Menendez, R.; Singh, V. Application of deep learning for fast detection ofCOVID-19 in X-Rays using nCOVnet. Chaos Solitons Fractals 2020, 138, 109944.

[33] Huang, L.; Han, R.; Ai, T.; Yu, P.; Kang, H.; Tao, Q.; Xia, L. Serial quantitative chest CT assessment of COVID-19: A deep learningapproach. Radiol. Cardiothorac. Imaging 2020, 2, e200075.

[34] To ˘gaçar, M.; Ergen, B.; Cömert, Z. COVID-19 detection using deep learning models to exploit Social Mimic Optimization andstructured chest X-ray images using fuzzy color and stacking approaches. Comput. Biol. Med. 2020, 121, 103805.