Combining Bioinspired Red Kite Optimization and Deep Learning for Effective COVID-19 Detection in Chest Radiography

Mohammed Altaf Ahmed[1,*], Suleman Alnatheer[1], Sachi Nandan Mohanty[2], Paruchuri Pavan Kumar[3], Bibhuti Bhushan Dash[4], and Qutubuddin Mohammed[5]

[1]Department of Computer Engineering, College of Computer Engineering and Sciences, Prince Sattam bin Abdulaziz University, Al-Kharj, Saudi Arabia
[2]School of Computer Science & Engineering (SCOPE), VIT-AP University, Amaravati, Andhra Pradesh, India
[3]Department of Artificial Intelligence and Data Science, Faculty of Science and Technology (ICFAITECH), ICFAI Foundation for Higher Education, Hyderabad, India
[4]School of Computer Applications, KIIT Deemed to be Univsity, Bhuabneswar, Odisha, India
[5]Department of Electrical Engineering, College of Engineering Wadi Addawasir, Prince Sattam bin Abdulaziz University, Saudi Arabia
Email: m.altaf@psau.edu.sa (M.A.A.); s.alnatheer@psau.edu.sa (S.A.); sachinandan09@gmail.com (S.N.M.); pavanpk@ifheindia.org (P.P.K.); bibhuti.dash@gmail.com (B.B.D.); q.mohammed@psau.edu.sa (Q.M.)
*Corresponding author
Manuscript received June 14, 2025; revised July 24, 2025; accepted November 25, 2025; published March 31, 2026

Abstract*—Deep Learning (DL)-based systems, employing advanced growths, pave the way for bioinspired methods in almost all domains of life. Healthcare organizations can employ DL approaches due to their precision in recognizing and identifying distinct diseases. The coronavirus disease (COVID-19) epidemic has emerged as the most dangerous disease in recent times, posing a significant burden on health organizations worldwide. Medical imaging and PCR testing have the potential to analyze COVID-19. Given the high spreadability of COVID-19, Chest X-Ray (CXR) analysis is considered safe under various conditions. DL systems are capable of enhancing medical imaging tools and supporting radiologists in making medical decisions for the analysis, diagnosis, and monitoring of distinct diseases. With this motivation, this study presents a novel bioinspired red kite optimizer with a DL-based COVID-19 classification (BRKODL-COVIDC) method on CXR images. The BRKODL-COVIDC method intends to recognize and categorize the presence of COVID-19 using DL models. In the presented BRKODL-COVIDC method, the Bilateral Filtering (BF) model can be used for image pre-processing tasks. In addition, the complex patterns and features in the images can be derived from the DenseNet121 model. For optimal hyperparameter selection of the DL techniques, the Random Key Optimizer (RKO) model can be employed in this research. Last, the BRKODL-COVIDC technique makes use of the Dilated Convolutional Auto-Encoder (DCAE) model and is used for identification purposes. Thus, with this research study, we are contributing to the National Priorities for Research, Development, and Innovation (RDI) in health and wellness to provide and maintain a sustainable environment in the health sector. The simulation outputs of the BRKODL-COVIDC technique can be examined on a standard dataset. The simulated outputs demonstrated the enhanced performance of the BRKODL-COVIDC technique in the COVID-19 detection procedure.

***Keywords*—computer-aided diagnosis, bioinspired algorithms, deep learning, intelligent systems, leukaemia cancer, sustainable environment, healthcare**

I. Introduction

COVID-19 is the latest viral epidemic, which began in Wuhan City in China. It spreads to every part of the world within a few months. It is an extremely transmittable disease that spreads through respiring droplets while breathing [1]. For testing COVID-19 cases, imaging models, namely Computed Tomography (CT) and X-ray, play a significant part [2]. As the disease commonly infects the lungs, chest radiography images (CT images or CXR) become broadly measured, and radiologists physically do the analysis of these images to detect pictorial signs of COVID-19 disease [3]. For quick checking for the diseased patient, visual indicators can serve as an alternate technique. The conservative analysis method is comparatively rapid but still creates a higher threat for medicinal staff [4]. There are limited analytical tests since they are expensive. In contrast, medical imaging methods, namely CT and X-ray screening, are faster, safer, and readily available. X-ray imaging has been widely utilized in COVID-19 check-ups, as it involves fewer imaging periods, the charge is also lower, and X-ray scanners are broadly accessible in rural sectors compared to CT imaging [5]. However, the visual assessment of X-ray images by radiologists at a large scale is long and weighty and can result in wrong analysis because of the absence of prior awareness about the infected areas. Therefore, there is a great requirement for designing mechanized approaches to get effective COVID-19 analysis [6, 7].

To save effort and time, it is significant to mechanize the CXR inquiry, which is an extensive and errant method that consumes effort and time [8, 9]. Consequently, fully mechanized and actual radiography images are essential to help physicians precisely identify the COVID-19 virus. Doctors can use Computer Added Design (CAD) methods that rely on DL approaches to help them understand and analyze CXR images better and to overcome the challenges of current imaging techniques. DL approaches are frequently used in medical imaging because they can handle large datasets that surpass human capabilities. Uniting CAD methods with radiologists' medical diagnostics reduces doctors' pressure and develops precision and arithmetical inquiry. The modern mechanized approaches employ modern-day Artificial Intelligence (AI) tools (mostly the DL method) to develop the control of CXR imaging and are meant to diminish the work of radiologists [10, 11]. DL methods, particularly Convolution Neural Network (CNN), have been shown to be more efficient than outdated AI approaches and are broadly utilized for studying numerous medical images [12, 13].

This study presents a novel bioinspired red kite optimizer with a DL-based COVID-19 classification (BRKODL-COVIDC) method on CXR images. The BRKODL-COVIDC method intends to recognize and categorize the presence of COVID-19 using DL models. In the presented BRKODL-COVIDC method, the Bilateral Filtering (BF) model can be used for image pre-processing tasks. In addition, the complex patterns and features in the images can be derived from the DenseNet121 model. For optimal hyperparameter selection of the DL techniques, the RKO model can be employed in this research. Last, the BRKODL-COVIDC technique makes use of the Dilated Convolutional Auto-Encoder (DCAE) model and is used for identification purposes. The simulation outputs of the BRKODL-COVIDC technique can be examined on a standard dataset. This research aims to target study, development, and innovation in health and wellness and contribute to providing a sustainable health environment.

II. Literature Review

Gupta and Bajaj [14] present a model utilizing the DL and chest CT scan-related methods. In this article, an openly available CT-scan image dataset, a couple of pre-trained DL methods (DLMs), viz., MobileNetV2 and DarkNet19, and an innovatively developed frivolous DLM could be used for automated screening of COVID-19. A recurring 10-fold holdout authentication technique is used for the testing, validation, and training of DLMs. Mansour *et al.* [15] presented an innovative unsupervised DL-based Unsupervised Deep Learning based Variational Auto Encoder (UDL VAE) system. The UDL-VAE method elaborates an Adaptive Wiener Filtering (AWF) assisted preprocessing method to improve image excellence. In Refs. [16,17], a feasible and effective DL-based Chest Radiograph Classification (DL-CRC) structure is proposed. This structure controls a Data Augmentation of Radiograph Images (DARI) approach by adaptably using generic data augmentation and Generative Adversarial Network (GAN) approaches. The training information consists of real and artificial CXR images that were served and modified as the CNN method in DL-CRC.

Subhalakshmi *et al.* [18] and Shankar *et al.* [19] proposed a DL-based MultiModal Fusion (DLMMF) method. This method works in three key procedures, viz., WF is dependent upon feature extraction, preprocessing, and identification. The projected method integrates a combination of deep features utilizing the Inception v4 and VGG16 methods. Lastly, the Gaussian Naïve Bayes (GNB) method has been presented for recognizing and classifying CT images into separate classes. Shanthi and Koppu [20] and Dash *et al.* [21] presented effective methods named RNBO_Deep Neuro-Fuzzy Network (RNBO_DNFN) and Remora Namib Beetle Optimizer_Deep Quantum-NN (RNBO_DQNN) method. This method has been aimed at integrating Namib Beetle Optimization (NBO) and the Remora Optimization Algorithm (ROA) to improve performance. In two other studies [22, 23], a new IoT-allowed depthwise separable CNN (DWS-CNN) with the Deep-SVM (DSVM) method is proposed. Primarily, patient information is composed by utilizing IoT devices and directed towards the cloud server. Also, the GF method was used for noise elimination. Then, the DWS-CNN method is used for automatically extracting features. Lastly, the DSVM method could be used to control the multiple and binary classes of COVID-19.

Sharma *et al.* [24] proposed 16 deep learning-based systems for segmentation and identification. They used two segmentation networks (UNet and UNet+) along with eight classification models: VGG19, VGG16, InceptionV3, Xception, NASNetMobile, ResNet50, MobileNet, and DenseNet201. The performance of these systems was evaluated using Jaccard, Dice, Area Under the Curve (AUC), and Receiver Operating Characteristics (ROC) metrics, and explainability was provided through Gradient-weighted Class Activation Mapping (Grad-CAM).

In another study [25], a method called Sine-Cosine Optimization + DL-based Disease Detection and Classification (SCODL-DDC) was introduced, which combines a sine cosine optimizer with deep learning. EfficientNet was used to extract features, and the Sine Cosine Optimizer (SCO) tuned the model parameters. A Quantum Neural Network (QNN) was also applied for accurate COVID-19 detection.

III. Materials and Methods

In this paper, a programmed COVID-19 identification and classification algorithm, named BRKODL-COVIDC technique on CXR images, is proposed. The BRKODL-COVIDC method intends to recognize and categorize the existence of COVID19 employing DL models. In this developed BRKODL-COVIDC approach, four main processes such as BF-based pre-processing, RKO based hyperparameter tuning, DenseNet121 feature extractor, and DCAE based classification. Fig. 1 represents the workflow of BRKODL-COVIDC method.

A. Image Pre-processing Using BF Approach

For noise elimination, the BF approach is utilized. BF is an image processing system utilized to smooth noise reduction while maintaining boundaries from the image [26]. A nonlinear, edge-preserving filter integrates spatial domain and intensity (pixel value) domain data to achieve its effects. BF is mainly effective in conditions, but typical smoothing filters can blur edges and fine details. The basic concept behind BF is to execute a weighted average for the pixel values from the local neighborhood but assuming either spatial closeness or intensity similarity. The weight of all the pixels is defined by the Gaussian function in either the spatial or the intensity domains. The working of BF is provided as follows:

Spatial Domain: A window (kernel) is determined near all the pixels from the image. This window defines the spatial neighborhood for which filtering can be executed.

Intensity Domain: During the spatial window, the pixel values can be related depending on their intensities. A Gaussian kernel can be executed for computing the weighted dependence upon intensity similarity. Pixels with the same intensity values are superior weights, meaning they

performs consistently well across different performance metrics, particularly in recognizing positive and negative cases with high specificity.

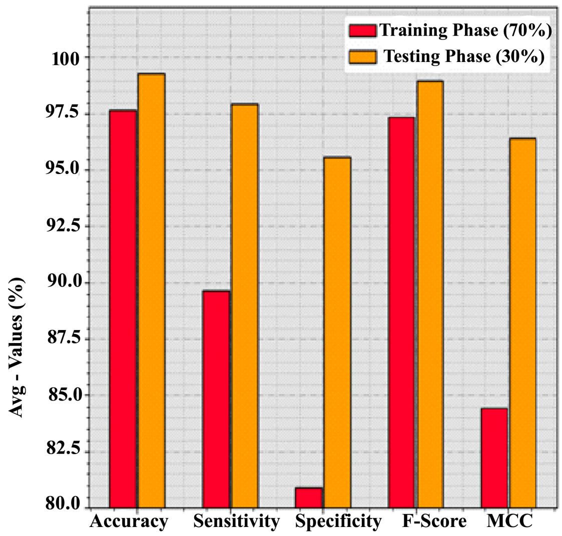

Fig. 5. Average of BRKODL-COVIDC model at 70:30 of TRAP/TESP.

Furthermore, when evaluated on the remaining 30% of the data (TESP), the BRKODL-COVIDC model delivered even better performance, achieving an average accuracy of 99.28%, precision of 97.92%, recall of 95.60%, specificity of 98.97%, and F1-score of 96.41%. These results demonstrate the robustness and generalization capability of the model, confirming its suitability for reliable COVID-19 classification in practical scenarios.

To evaluate the accomplishment of the BRKODL-COVIDC technique with 80:20 of TRAP/TESP, Training and Testing accuracy curves are determined, as portrayed in Fig. 6. The TRA and TES accuracy curves display the performance of BRKODL-COVIDC technique over several epochs. The figure exhibits the capability of the learning tasks and generalized abilities of the BRKODL-COVIDC technique. As the epoch rises, it is perceived that the TRA and TES accuracy curves attain improvement. It is detected that the BRKODL-COVIDC technique obtains amended testing accuracy for identifying the patterns in the TRA and TES data.

Fig. 6. $Accu_y$ curve of BRKODL-COVIDC model at 80:20 of TRAP/TESP.

Fig. 7 demonstrated the complete loss values of the TRA and TES of the BRKODL-COVIDC approach with 80:20 of TRAP/TESP over epochs. The TRA loss signified the loss reduces over epochs. Chiefly, the loss decreases as the model alters the weight to decline the forecast error on the TRA and /TES data. The loss curves exhibit the level to which the model is fitting the TRA data. It is seen that the TRA and TES losses are slowly minimized, and it is defined that the modified BRKODL-COVIDC method effectively learns the patterns shown in the TR and TS data. The BRKODL-COVIDC method modified the parameters to reduce the discrepancies between the forecast and the actual TRA label.

Fig. 7. Loss curve of BRKODL-COVIDC method at 80:20 of TRAP/TESP.

The Plotting accuracy alongside recall illustrates the Precision-Recall (PR) accomplishment of the BRKODL-COVIDC method with an 80:20 TRAP/TESP ratio, as presented in Fig. 8. The investigational outputs showed that the BRKODL-COVIDC method acquires enhanced PR with each 6 classes. The figure indicates that the technique learns to identify five discrete classes. The BRKODL-COVIDC method attains augmented outputs in the detection of positive instances with decreased false positives.

Fig. 8. PR curve of BRKODL-COVIDC method at 80:20 of TRAP/TESP.

The ROC study shown by the BRKODL-COVIDC system, which uses an 80:20 ratio of TRAP/TESP, is displayed in Fig. 9 and can tell apart the 5 classes. The figure provided valuable details about the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR) across various classification thresholds and different epoch counts. It precisely portrays the anticipated accomplishment of the BRKODL-COVIDC system through the identification of six diverse classes.

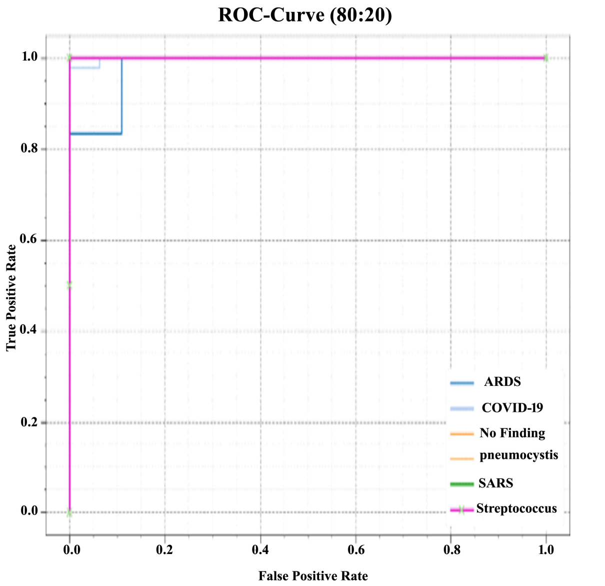

Fig. 9. ROC curve of BRKODL-COVIDC method at 80:20 of TRAP/TESP.

The COVID-19 classification results using the proposed BRKODL-COVIDC method, along with other recent deep learning models, are shown in Table 4 and Fig. 10. The experimental results show that the DLS-SCD method performs poorly. In comparison, methods like InceptionV3, ResNet-50, VGG16, and AD-TLCNN perform slightly better. The SCODL-DDC method achieves relatively good results. However, the BRKODL-COVIDC method outperforms all others, achieving an accuracy of 99.59%, precision of 96.53%, recall of 99.28%, and F1-score of 97.99%. These results clearly demonstrate that BRKODL-COVIDC delivers superior performance in COVID-19 classification.

Table 4. Relative output of BRKODL-COVIDC approach with recent DL models

Methods	$Accu_y$/%	$Sens_y$/%	$Spec_y$/%	F_{score}/%
BRKODL-COVIDC	99.59	96.53	99.28	97.99
SCODL-DDC	99.45	95.65	99.11	97.27
InceptionV3	97.65	94.26	97.68	90.43
ResNet50	97.08	88.17	97.85	84.07
VGG16	96.59	86.57	97.80	83.26
DLS-SCD	86.44	86.21	86.66	86.01
AD-TLCNN	95.07	95.46	97.18	92.33

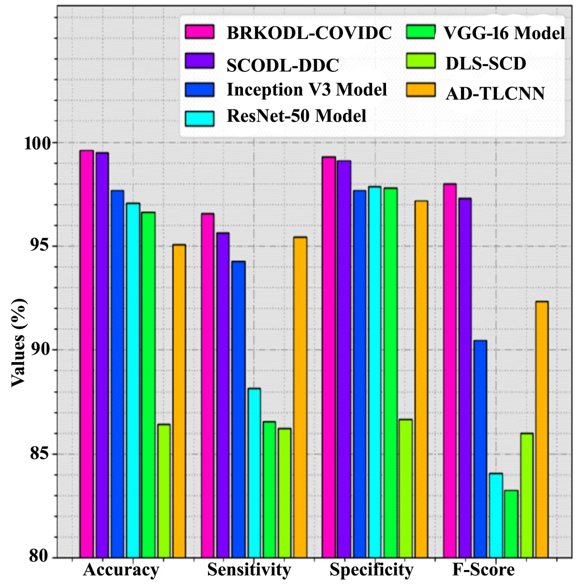

Fig. 10. Comparative outcome of BRKODL-COVIDC method with current DL methods.

V. Conclusion

This study paper proposes the BRKODL-COVIDC approach, an automated model for COVID-19 recognition and classification on CXR images. The aim of the BRKODL-COVIDC approach is to detect and identify the models. The presented BRKODL-COVIDC technique utilizes four main functions: BF-based pre-processing, DenseNet121 feature extractor, RKO-based hyperparameter tuning, and DCAE-based classification. In this work, the complex patterns and features in the images can be derived from the DenseNet121 model. For optimal hyperparameter selection of the DL methods, the RKO model can be applied in this study. Finally, the BRKODL-COVIDC technique employs the DCAE model and is utilized for classification purposes. The simulation outcomes of the BRKODL-COVIDC model are experimented on with a standard dataset. The simulation outputs described the improved accomplishment of the BRKODL-COVIDC model for the COVID-19 detection process. Thus, the study offers solutions for sustainable health care that aim to maintain a sustainable health environment for public health challenges and contribute to the national priorities of RDI.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, M.A.A., S.A., S.N.M., P.K., B.B.D.; methodology, M.A.A. S.A., S.N.M., P.K., B.B.D.; software, M.A.A. S.A., S.N.M., P.K., B.B.D.; validation, M.A.A. S.A., S.N.M., P.K., B.B.D., Q.M.,; formal analysis, S.A., S.N.M., P.K., B.B.D.; investigation, M.A.A. S.A., S.N.M., P.K., B.B.D., Q.M.; resources, S.A., S.N.M., P.K., B.B.D.; data curation, M.A.A.; writing original draft preparation, M.A.A.; writing review and editing, M.A.A. S.A., S.N.M., P.K., B.B.D.; visualization, M.A.A. S.A., S.N.M., P.K., B.B.D., Q.M.; supervision, S.A., S.N.M., P.K., B.B.D.; project administration, M.A.A., S.A., S.N.M., P.K., B.B.D.; funding acquisition, S.A. All authors have read and agreed to the published version of the manuscript.

Funding

This research was funded by Prince Sattam bin Abdulaziz University, Al-Kharj, Saudi Arabia, through project grant number (PSAU-2024/01/31379).

Acknowledgement

The authors extend their appreciation to Prince Sattam bin Abdulaziz University for funding this research work through the project number (PSAU-2024/01/31379).

References

[1] M. E. Sahin, H. Ulutas, E. Yuce *et al.*, "Detection and classification of COVID-19 by using faster R-CNN and mask R-CNN on CT images," *Neural Computing and Applications*, vol. 35, no. 18, pp. 13597–13611, 2023.

[2] Ç. Oğuz and M. Yağanoğlu, "Detection of COVID-19 using deep learning techniques and classification methods," *Information Processing & Management*, vol. 59, no. 5, 103025, 2022.

[3] E. Hussain, M. Hasan, M. A. Rahman *et al.*, "CoroDet: A deep learning-based classification for COVID-19 detection using chest X-ray images," *Chaos, Solitons & Fractals*, vol. 142, 110495, 2021.

[4] H. Zhu, Z. Zhu, S. Wang *et al.*, "CovC-ReDRNet: A deep learning model for COVID-19 classification," *Machine Learning and Knowledge Extraction*, vol. 5, no. 3, pp. 684–712, 2023.

[5] W. A. Shehri, J. Almalki, R. Mehmood *et al.*, "A novel COVID-19 detection technique using deep learning based approaches," *Sustainability*, vol. 14, no. 19, 12222, 2022.

[6] A. I. Khan, J. L. Shah, and M. M. Bhat, "CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest X-ray images," *Computer Methods and Programs in Biomedicine*, vol. 196, 105581, 2020.

[7] N. Agarwal, S. N. Mohanty, S. Sankhwar *et al.*, "A novel model to predict the effects of enhanced students' computer interaction on their health in COVID-19 pandemics," *New Generation Computing*, vol. 41, no. 3, pp. 635–668, 2023. https://doi.org/10.1007/s00354-023-00224-3

[8] V. Rastogi and A. K. Jain, "Detection and classification of COVID-19 disease using SWHO-based deep neural network classifier," *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*, vol. 11, no. 6, pp. 2183–2195, 2023.

[9] S. K. Satapathy, S. Saravanan, S. Mishra *et al.*, "A comparative analysis of multidiemnsional COVID-19 poverty determinants: An observational machine learning approach," *New Generation Computing*, vol. 41, no. 1, pp. 155–184, 2023. https://doi.org/10.1007/s00354-023-00203-8

[10] M. A. Khan, M. Azhar, K. Ibrar *et al.*, "COVID-19 classification from chest X-ray images: A framework of deep explainable artificial intelligence," *Computational Intelligence and Neuroscience*, vol. no. 1, 2022.

[11] G. S. Chakraborty, S. Batra, A. Singh *et al.*, "A novel deep learning-based classification framework for COVID-19 assisted with weighted average ensemble modeling," *Diagnostics*, vol. 13, no. 10, 1806, 2023.

[12] S. Kumar, S. K. Gupta, V. Kumar *et al.*, "Ensemble multimodal deep learning for early diagnosis and accurate classification of COVID-19," *Computers and Electrical Engineering*, vol. 103, 108396, 2022.

[13] S. Sah, B. Surendiran, R. Dhanalakshmi *et al.*, "Forecasting COVID-19 pandemic using prophet, ARIMA, and hybrid stacked LSTM-GRU models in India," *Computational and Mathematical Methods in Medicine*, vol. 2022, no. 1, 2022. doi:10.1155/2022/1556025

[14] K. Gupta and V. Bajaj, "Deep learning models-based CT-scan image classification for automated screening of COVID-19," *Biomedical Signal Processing and Control*, vol. 80, 104268, 2023.

[15] R. F. Mansour, J. Escorcia-Gutierrez, M. Gamarra *et al.*, "Unsupervised deep learning-based variational autoencoder model for COVID-19 diagnosis and classification," *Pattern Recognition Letters*, vol. 151, pp. 267–274, 2021.

[16] S. Sakib, T. Tazrin, M. M. Fouda *et al.*, "DL-CRC: Deep learning-based chest radiograph classification for COVID-19 detection: A novel approach," *IEEE Access*, vol. 8, pp.171575–171589, 2020.

[17] D. Shome, T. Kar, S. N. Mohanty *et al.*, "COVID-Transformer: Interpretable COVID-19 detection using vision transformer for healthcare," *International Journal of Environmental Research and Public Health*, vol. 18, no. 21, 11086, 2021. https://doi.org/10.3390/ijerph182111086

[18] R. T. Subhalakshmi, S. A. A. Balamurugan, and S. Sasikala, "Deep learning-based fusion model for COVID-19 diagnosis and classification using computed tomography images," *Concurrent Engineering*, vol. 30, no. 1, pp. 116–127, 2022.

[19] K. Shankar, S. N. Mohanty, K. Yadav *et al.*, "Automated COVID-19 diagnosis and classification using convolutional neural network with fusion based feature extraction model," *Cognitive Neurodynamics*, vol. 17, pp. 1–14, 2023. doi:10.1007/s11571-021-09712-y

[20] A. Shanthi and S. Koppu, "Remora namib beetle optimization enabled deep learning for severity of COVID-19 lung infection identification and classification using CT images," *Sensors*, vol. 23, no. 11, 5316, 2023.

[21] S. Dash, S. Chakravati, S. N. Mohanty *et al.*, "A deep learning method to forecast COVID-19 outbreak," *New Generation Computing*, vol. 39, pp. 515–539, 2021. doi: 10.1007/s00354-021-00129-z

[22] D. N. Le, V. S. Parvathy, D. Gupta *et al.*, "IoT-enabled depthwise separable convolution neural network with deep support vector machine for COVID-19 diagnosis and classification," *International Journal of Machine Learning and Cybernetics*, vol. 12, no. 11, pp. 3235–3248, 2021.

[23] S. Satpathy, M. Mangala, N. Sharma *et al.*, "Predicting mortality rate and associated risks in COVID-19 patients," *Spatial Information Research*, vol. 29, pp. 455–464, 2021. doi: 10.1007/s41324-021-00379-5

[24] N. Sharma, L. Saba, N. N. Khanna *et al.*, "Segmentation-based classification deep learning model embedded with explainable AI for COVID-19 detection in chest X-ray scans," *Diagnostics*, vol. 12, no. 9, 2132, 2022.

[25] T. Althaqafi, A. S. A. M. Al-Ghamdi and M. Ragab, "Artificial intelligence based COVID-19 detection and classification model on chest X-ray images," *Healthcare*, vol. 11, no. 9, 1204, 2023.

[26] J. Ai, R. Liu, B. Tang *et al.*, "A refined bilateral filtering algorithm based on adaptively-trimmed statistics for speckle reduction in SAR imagery," *IEEE Access*, vol. 7, pp. 103443–103455, 2019.

[27] T. Chauhan, H. Palivela, and S. Tiwari, "Optimization and fine-tuning of DenseNet model for classification of COVID-19 cases in medical imaging," *International Journal of Information Management Data Insights*, vol. 1, no. 2, 100020, 2021. doi: 10.1016/j.jjimei.2021.100020

[28] S. M. Alshareef and A. Fathy, "Efficient red kite optimization algorithm for integrating the renewable sources and electric vehicle fast charging stations in radial distribution networks," *Mathematics*, vol. 11, no. 15, 3305, 2023.

[29] G. Hu, F. Zhao, and B. Liu, "Estimation of the two-dimensional direction of arrival for low-elevation and non-low-elevation targets based on dilated convolutional networks," *Remote Sensing*, vol. 15, no. 12, 3117, 2023.

[30] COVID-19 dataset. *GitHub.* [Online]. Available: https://github.com/ieee8023/covid-chestxray-dataset