BRITISH JOURNAL OF
HOSPITAL MEDICINE

ARTICLE

Deep Learning-Based System Combining Chest X-Ray and Computerized Tomography Images for COVID-19 Diagnosis

Hui Ding[1], Lingyan Fan[2], Jingfeng Zhang[1,*], Guosheng Gao[3,*]

[1]Department of Radiology, Ningbo No.2 Hospital, Ningbo, Zhejiang, China
[2]Department of Acute Infectious Diseases, Ningbo No.2 Hospital, Ningbo, Zhejiang, China
[3]Department of Clinical Laboratory, Ningbo No.2 Hospital, Ningbo, Zhejiang, China
*Correspondence: jingfengzhang73@163.com (Jingfeng Zhang); gaoguosheng@ucas.ac.cn (Guosheng Gao)

Abstract

Aims/Background The coronavirus disease 2019 (COVID-19) pandemic has highlighted the need for accurate and efficient diagnostic methods. This study aims to improve COVID-19 detection by integrating chest X-ray (CXR) and computerized tomography (CT) images using deep learning techniques, further improving diagnostic accuracy by using a combined imaging approach.
Methods The study used two publicly accessible databases, COVID-19 Questionnaires for Understanding the Exposure (COVID-QU-Ex) and Integrated Clinical and Translational Cancer Foundation (iCTCF), containing CXR and CT images, respectively. The proposed system employed convolutional neural networks (CNNs) for classification, specifically EfficientNet and ResNet architectures. The data underwent preprocessing steps, including image resizing, Gaussian noise addition, and data augmentation. The dataset was divided into training, validation, and test sets. Gradient-weighted Class Activation Mapping (Grad-CAM) was used for model interpretability.
Results The EfficientNet-based models outperformed the ResNet-based models across all metrics. The highest accuracy achieved was 99.44% for CXR images and 99.81% for CT images with EfficientNetB5. The models also demonstrated high precision, recall, and F1 scores. For statistical significance, the *p*-values were less than 0.05, indicating that the results are significant.
Conclusion Integrating CXR and CT images using deep learning significantly improves the accuracy of COVID-19 diagnosis. The EfficientNet-based models, with their superior feature extraction capabilities, show better performance than ResNet models. Grad-CAM Visualizations provide insights into the model's decision-making process, potentially reducing diagnostic errors and accelerating diagnosis processes. This approach can improve patient care and support healthcare systems in managing the pandemic more effectively.

Key words: COVID-19; diagnosis; deep learning; chest X-ray; computerized tomography

Submitted: 3 May 2024 Revised: 11 June 2024 Accepted: 17 June 2024

How to cite this article:
Ding H, Fan L, Zhang J, Gao G. Deep Learning-Based System Combining Chest X-Ray and Computerized Tomography Images for COVID-19 Diagnosis. Br J Hosp Med. 2024. https://doi.org/10.12968/hmed.2024.0244

Introduction

The coronavirus disease 2019 (COVID-19) pandemic, caused by the coronavirus Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), has inflicted widespread damage worldwide. Proper detection of COVID-19 is integral for ensuring proper care of infected patients and containment of the virus. COVID-19 can be diagnosed by many methods, including polymerase chain reaction (PCR) testing, antigen testing, and antibody testing (Vandenberg et al, 2021; Yuki et al, 2020). With the continuous emergence of new virus variants, rapid, accurate, and low-cost diagnostic methods have become the focus of researchers and clinicians.

In the effort to combat the COVID-19 pandemic, various medical imaging methods, such as chest X-ray (CXR), computerized tomography (CT), and magnetic resonance imaging (MRI), have been used to facilitate the advancement of deep learning methods, enabling accurate diagnosis and segmentation. For instance, Chen et al (2020) presented a novel deep learning approach to automatically divide multiple COVID-19 infected areas with CT scans. Building on this, Liu and colleagues (2020) developed a lesion-attention deep neural network (LA-DNN) model that uses data-driven techniques to classify COVID-19 cases as positive or negative. The model includes an auxiliary multi-label learning module to help it focus on the five key lesions that distinguish the virus. Meanwhile, Additionally, Jaiswal et al (2021) explored the use of pre-trained deep learning architectures as an automated method for detecting and diagnosing COVID-19 using chest CT scans. Furthermore, Ozsahin et al (2020) surveyed the application of chest CT for artificial intelligence (AI)-assisted diagnosis of COVID-19, whereas Attallah et al (2020) suggested an innovative computer-aided detection system for diagnosing COVID-19 by combining multiple convolutional neural networks (CNNs). In another significant development, Chen and colleagues (2021) developed a new deep learning algorithm that can diagnose COVID-19 with a high level of accuracy using only a small number of training samples. Similarly, Saood and Hatem (2021) provided viable alternatives for identifying and labeling COVID-19 affected lung tissues in CT images. Another highly cited COVID-19 CT-based deep learning study is that of Fusco and colleagues (2021). These studies collectively highlight the significant advancements in deep learning methodologies for the effective diagnosis and segmentation of COVID-19 using medical imaging techniques.

In the realm of CXR-based deep learning research, Chowdhury et al (2020) devised a dependable approach for the automated identification of COVID-19 pneumonias from digital CXR images through pre-trained deep learning techniques that enhanced precision. Khobahi et al (2020) identified CXR-based methods as invaluable diagnosis and monitoring tools in the initial and mid periods of the disorder. To further address the dynamic COVID-19 pandemic, Burlacu and colleagues (2020) investigated the formation of a quick, accessible screening entity via image processing of CXR images coupled with innovative machine learning techniques. In another approach, Oh et al (2020) used a small-scale patch-based convolutional neural network approach, whereas Zebin and Rezvy (2021) developed a transfer learning model to classify COVID-19 CXR images from two distinct datasets. Seeking to enhance detection capabilities, Albahli and Yar (2021) attempted to enhance COVID-19 detection speed and accuracy. However, they observed the inability of the CNN-based deep learning technique to capture consistencies because of an image-specific bias. This challenge led Mondal et al (2021) to recommend vision transformers as an alternative approach to recognize COVID-19 from CXR and CT images. Moreover, Jin and colleagues (2021) proposed a novel three-step hybrid ensemble model, including a feature extractor, a feature selector, and a classifier, to diagnose COVID-19. Lastly, Degerli et al (2021) put forward a joint localization, grading, and COVID-19 detection technique from CXR image. Collectively, these studies underscore the diverse and innovative approaches being employed to leverage deep learning for COVID-19 diagnosis using CXR and CT images.

Although prior research has illustrated the successful use of deep learning techniques with CXR and CT images for COVID-19 detection, both approaches come with certain limitations. CXR examination is a quick, low-cost, and low-radiation imaging method, but it only provides a 2-dimensional image of the anterior chest and lacks sufficient local details. CT images provide a detailed view of the anatomy, but they require higher doses of radiation and are more expensive.

This paper presents a new deep learning framework that integrates CXR and CT scans for enhanced virus detection accuracy. This system has the potential to assist medical personnel in diagnosing COVID-19 patients with greater efficiency and accuracy, making it an invaluable tool for the fight against the virus.

Methods

Data Collection

The study used two publicly accessible image databases to construct the dataset. One of these databases, COVID-19 Questionnaires for Understanding the Exposure (COVID-QU-Ex), was established through a collaborative effort and can be accessed at https://www.kaggle.com/datasets/anasmohammedtahir/covidqu. This database comprises 25,071 chest X-ray images, including 3616 confirmed COVID-19 cases, 10,192 normal cases, and 11,263 non-COVID infections such as viral or bacterial pneumonia (Rahman et al, 2021). The second database, Integrated Clinical and Translational Cancer Foundation (iCTCF), was created by Ning and colleagues (2020), and it includes 19,685 CT images, with 4001 showing evidence of COVID-19 infection, 9979 normal cases, and 5705 showing no evidence of COVID. This database can be accessed at https://ngdc.cncb.ac.cn/ictcf/. Both databases are regularly updated with new additions.

Architecture of Proposed Deep Learning-Based System

The proposed system used CNNs to build a model from CXR and CT image datasets. As seen in Fig. 1, prior to the training stage, Exploratory Data Analysis (EDA), image resizing, Gaussian noise addition, and data augmentation were performed. During the training phase, the dataset was split into training, validation, and testing subsets, and the model was transferred over the CNNs. Other metrics, such as accuracy and F1 score, were considered for assessing the model's efficacy, and its performance could be further explored through Gradient-weighted Class Activation Mapping (Grad-CAM) Visualization for more graphical understanding.

Preprocessing

Preprocessing is an essential part of any deep learning system, as it helps to prepare, clean, and transform data for modeling. In this study, EDA was the first step of preprocessing. Through EDA, label distributions and pixel value statistics were evaluated to acquire an understanding of the image dataset, as well as to identify any potential issues. This helped to ensure that the data was suitable for modeling.

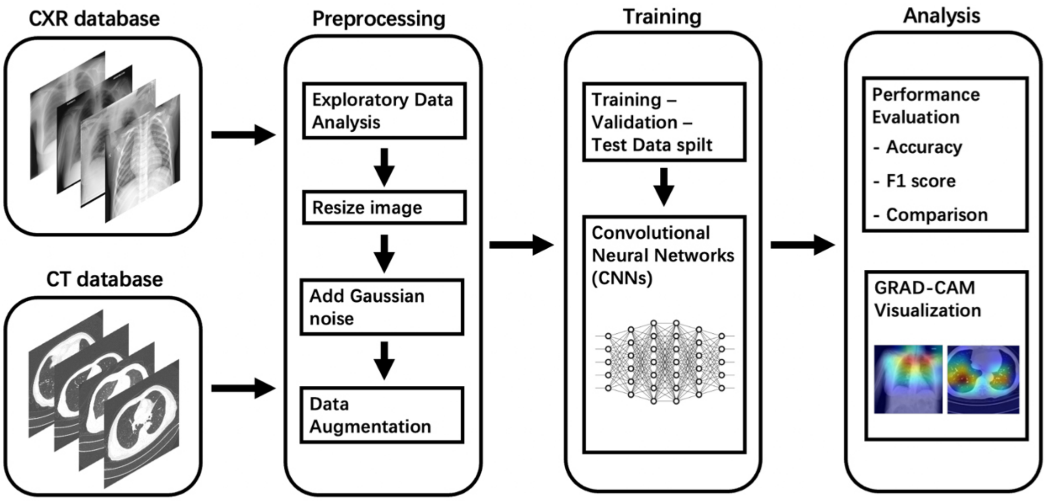

Fig. 1. Workflow of the proposed system integrating CXR and CT images for COVID-19 diagnosis. It includes data collection, preprocessing (EDA, resizing, noise addition, augmentation), training (data split, CNN training), and analysis (performance evaluation, Grad-CAM Visualization). CXR, chest X-ray; COVID-19, coronavirus disease 2019; CT, computerized tomography; EDA, Exploratory Data Analysis; CNNs, convolutional neural networks; Grad-CAM, Gradient-weighted Class Activation Mapping.

Fig. 2 depicts the distribution of positive (COVID) and negative (normal) samples in both the CXR image database and CT image database, respectively. There were 3616 positive (P) and 10,192 negative (N) samples in the CXR image database, respectively, with a ratio of 1:2.8. There were 4001 P and 9979 N samples in the CT image database, respectively, with a ratio of 1:2.5. It is evident that the P and N sample ratios for both databases are unbalanced, and thus, may affect the model's training accuracy. Therefore, further data augmentation procedures were required. Fig. 3 displays the mean image pixel value distribution of the P and N samples of the CXR image database and the CT image database, respectively. Compared to the CT data, it can be observed that the distribution of CXR data pixel values was more centralized.

The following step in preprocessing involved data augmentation, which serves to enlarge the training dataset by generating extra data points. This was done by applying random transformations, such as vertical flipping, contrast and brightness adjustments, cropping, and rotations, as shown in Fig. 4 on CXR and CT. To enhance the effectiveness of deep learning models, data augmentation was employed on both sets of data. The following step resizes the images. This ensures that all the images have the same size, which helps the neural network process data more quickly and efficiently. All sample images were resized to 224 $\times$ 224 pixels. Furthermore, grey masks were added to the original images to form a preprocessed image with 3 channels. Moreover, random Gaussian noise was added to the images to increase the randomness of the data, making it less predictable and preventing overfitting. Fig. 5 shows the images after resizing, as well as adding masks and Gaussian noise.

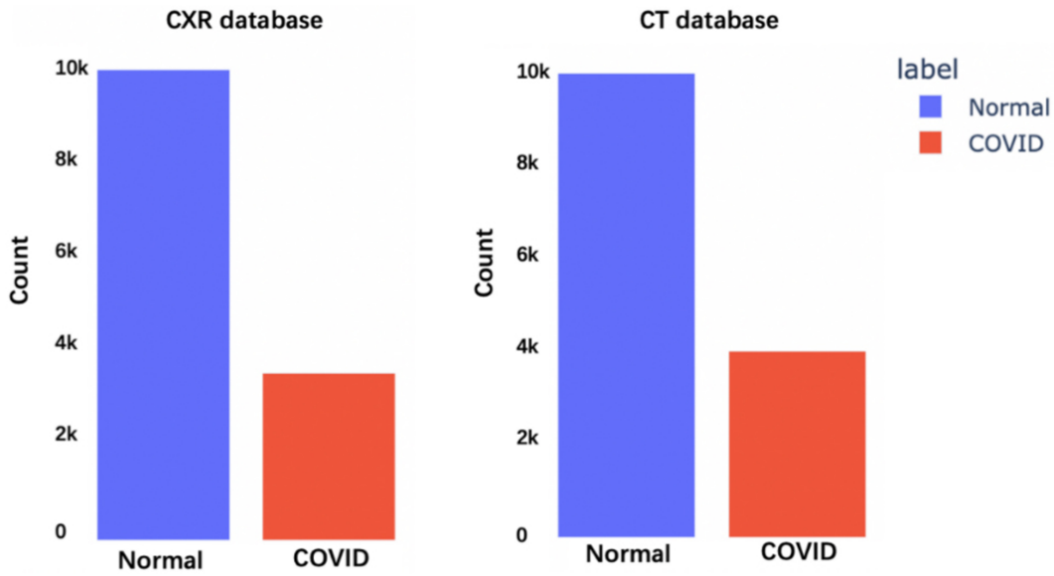

Fig. 2. Distribution of P and N samples of the dataset. Left, CXR database sample distribution; right, CT database sample distribution. P, positive; N, negative.

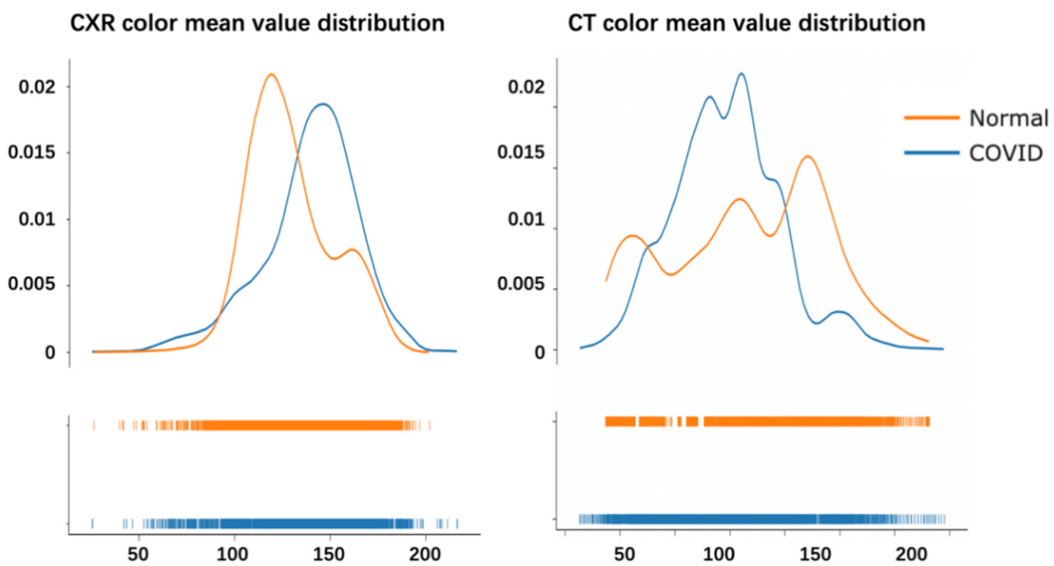

Fig. 3. Mean image pixel value distribution for P and N samples of the dataset. Left, CXR database sample distribution; right, CT database sample distribution.

Training Using Pretrained CNN Models

Pretrained CNN models have demonstrated remarkable efficiency in various tasks, including but not limited to image classification, object detection, and segmentation. Studies have demonstrated that such pre-trained models can generate accurate results quickly for tasks such as CXR and CT imaging (Abraham and Nair, 2020; Rajpurkar et al, 2017; Deng et al, 2020). Moreover, these models are pretrained, meaning that significantly reduced time and resources are spent training new models. In this study, four pre-trained CNN models were used to classify positive and negative cases in CXR and CT datasets, namely EfficientNetB0, EfficientNetB5, ResNet50, and ResNet152. EfficientNetB0 is a lightweight CNN architec-

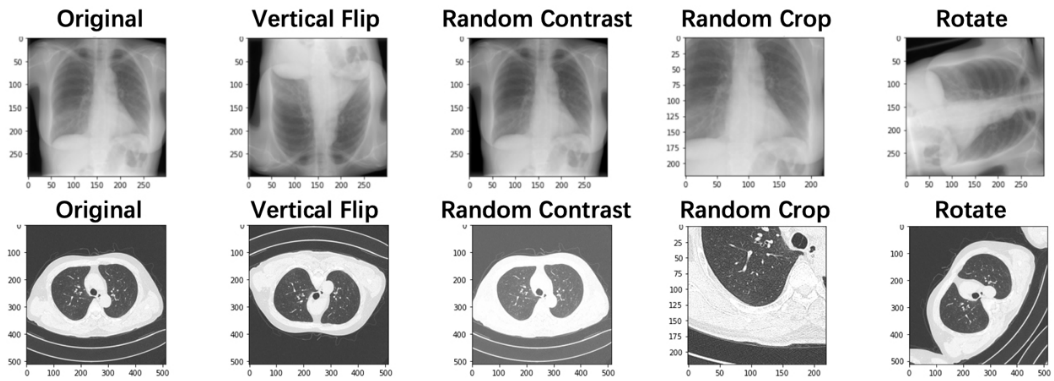

Fig. 4. Data augmentation techniques applied to CXR and CT images: vertical flipping, random contrast adjustment, random cropping, and rotation.

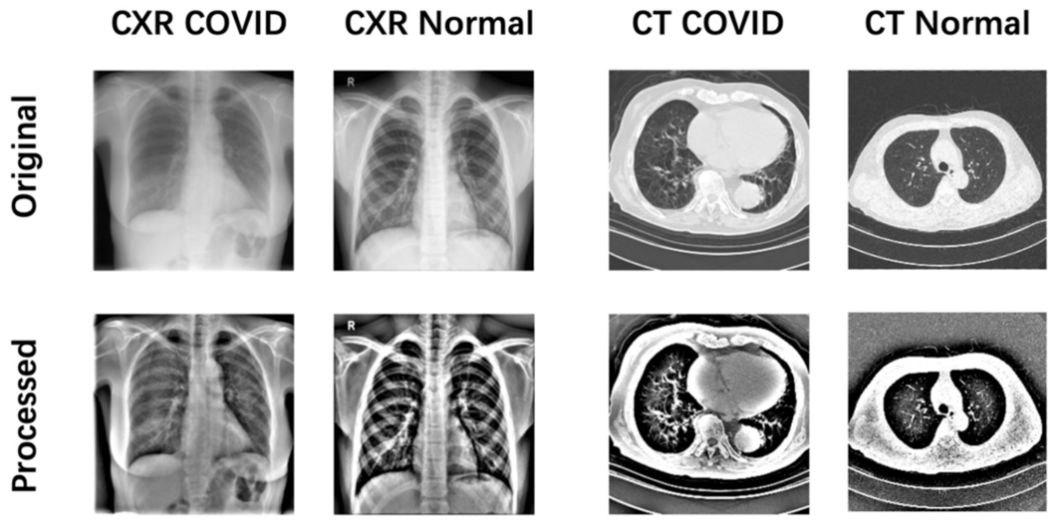

Fig. 5. Samples of the images after resizing, as well as adding masks and Gaussian noise.

ture created in 2019 by Google as part of their EfficientNet family, which minimizes parameters while preserving accuracy through depth-wise separable convolutions and global average pooling (Tan and Le, 2019). EfficientNetB5 is a larger, more powerful descendant of EfficientNetB0 and was developed to optimize accuracy with fewer parameters through the use of depth-wise separable convolutions, residual connections, and squeeze-and-excitation modules. ResNet50 and ResNet152 are two deep learning architectures developed by Microsoft Research in 2015 (He et al, 2016). Both ResNet50 and ResNet152 are powerful deep residual neural networks, pre-trained on the ImageNet dataset, used for various challenging computer vision tasks. Both comprise multiple convolutional layers to extract features from an image, pooling layers that reduce the feature map's size while combining features and fully connected layers to produce a set of probabilities representing the likelihood of the input image to each class. Furthermore, ResNet152 has an additional 102 layers, making it more robust and suited for more intricate vision-related tasks such as object detection, segmentation, and image captioning.

For model training, 60% of CXR and CT imaging datasets were used, 20% to assess model proficiency on the validation set and the rest for testing its adaptability on new data. The dropout rate of the CNN model was set at 0.5 and the nonlinear sigmoid function was selected as the activation mechanism. Optimization was conducted with the Adam algorithm to minimize errors by adjusting learning rate.

Performance Evaluation

In this work, we employed two interactive metrics, accuracy and F1 score, to evaluate the performance of CNN models for image classification. The accuracy was computed from the total number of correctly classified images (True Positive (TP), True Negative (TN)) and total number of images (TP, TN, False Positive (FP), False Negative (FN)) (Eqn. 1). Meanwhile, the F1 score was defined as the harmonic mean of precision and recall (Eqns. 2,3,4), where precision is the rate of correctly predicted positive results while recall is the proportion of correctly predicted actual positives. The accuracy and F1 score of the model were calculated by Tensorflow-Keras Model Evaluation API with 10-fold cross-validation. Finally, the average accuracy and F1 score of the CNN model were calculated.

$$Model\ Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Model\ Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Model\ Recall = \frac{TP}{TP + FN} \tag{3}$$

$$Model\ F1\ score = \frac{2 \times\ Precision\ \times\ Recall}{Precision\ +\ Recall} \tag{4}$$

The Grad-CAM Visualization was the next step of model analysis. With this approach, the gradient of the targeted class was calculated with respect to the feature maps of the last convolutional layer, allowing the creation of a heatmap that displays the important regions of the image for classification. This heatmap was then superimposed onto the input image, giving us the ability to identify the areas that are influential for classifying the image. This technique is employed in several different research areas for understanding the decision-making process of deep learning models and can explain why a model classifies an image in a certain way (Moujahid et al, 2022; Zhang et al, 2021).

Results

Training Results

The trainable parameters for EfficientNetB0, EfficientNetB5, ResNet50, and ResNet152 are 4,010,110, 28,344,882, 23,538,690, and 58,223,618, respectively. All models run on a 16 GB Random Access Memory-Graphics Processing Unit (RAM-GPU), and pre-trained models are provided by TensorFlow. The batch size and epochs are both set to 32 and 20, respectively.

The results of training two sets of CNN models based on EfficientNet (EfficientNetB0, EfficientNetB5) and ResNet (ResNet50, ResNet152) on CXR and CT

Table 1. Precision, recall and F1 score of CXR training and CT training.

	CXR training				CT training			
	EfficientNet B0	EfficientNet B5	ResNet 50	ResNet 152	EfficientNet B0	EfficientNet B5	ResNet 50	ResNet 152
Precision	0.992	0.993	0.991	0.988	0.999	1	0.998	0.998
Recall	0.997	0.998	0.992	0.992	0.999	1	0.998	0.998
F1 score	0.994	0.995	0.991	0.990	0.999	1	0.998	0.998

image data are shown in Figs. 6,7, with the accuracy in Fig. 6 and the loss curve in Fig. 7. The precision, recall and F1 score are listed in Table 1. The results show that the CNN models gradually converge with training time over 20 epochs on the CXR and CT datasets. The EfficientNet-based models achieved a maximum accuracy of 99.44% on the CXR dataset and 99.81% on the CT dataset, which is 0.37% and 0.18% higher than the ResNet-based models, respectively. Fig. 7 shows that the loss curves of the two sets of models on the two data sets are relatively similar, with the final training loss of the EfficientNet-based model being slightly lower than that of the ResNet-based model. Table 1 reveals that the EfficientNet-based model achieved maximum F1 scores of 0.995 and 1.000 for the CXR and CT datasets, respectively, while the ResNet-based models had slightly worse F1 scores of 0.991 and 0.998, respectively. These results demonstrate that EfficientNet-based models outperform ResNet-based models on CT and CXR datasets in terms of training accuracy and F1 score likely due to the different architectures of the two models.

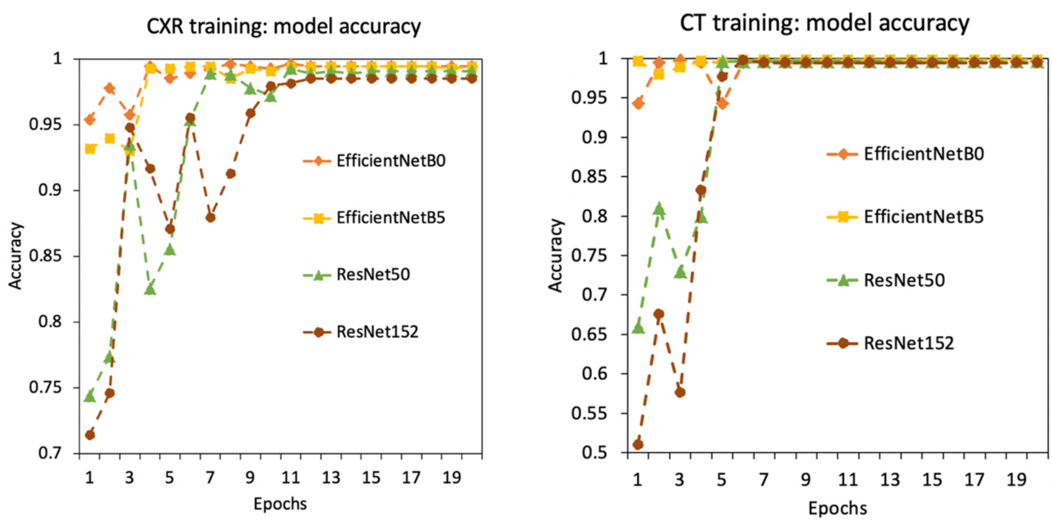

Fig. 6. Training accuracy of EfficientNetB0, EfficientNetB5, ResNet50, and ResNet152 models on CXR and CT datasets over epochs.

Grad-CAM Visualization

The results obtained by the Grad-CAM method are shown in Fig. 8. One COVID-positive CXR picture and one COVID-positive CT picture were selected.

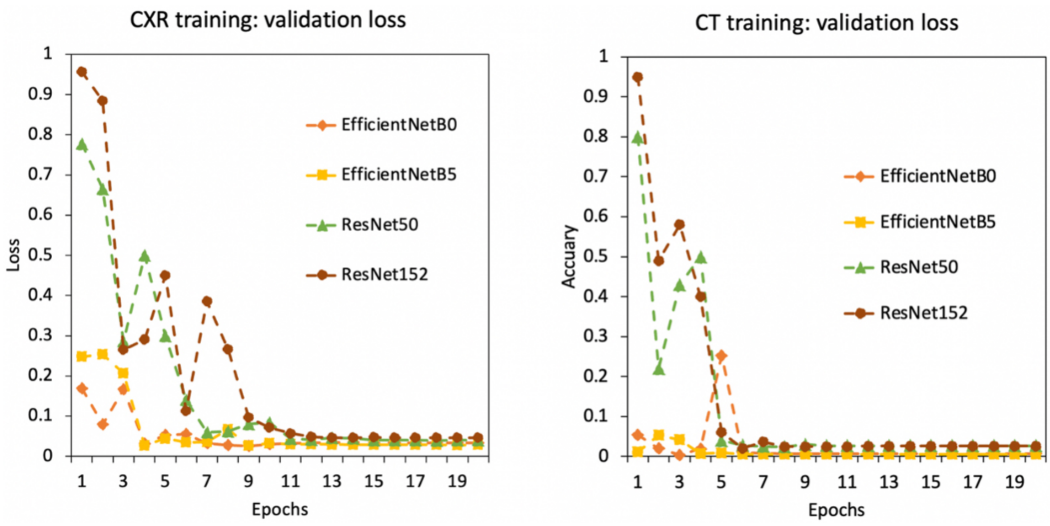

Fig. 7. Validation loss of EfficientNetB0, EfficientNetB5, ResNet50, and ResNet152 models on CXR and CT datasets over epochs.

Grad-CAM results showed that hotspots in images of COVID-positive CXR samples included right and left upper lobes. In the COVID-positive CT sample images, hot spots were found in the middle area of the left and right lungs. These areas have been identified by Grad-CAM as areas of high COVID-19 activity. We performed visual inspection of the COVID-positive CXR and CT images, and noted nodular opacities showing hot spots in the lung identified by Grad-CAM, as expected for a COVID-19 patient.

Discussion

COVID-19 is a highly contagious respiratory illness caused by the SARS-CoV-2 virus. The disease manifests in a wide spectrum of symptoms, which can range from mild to severe. Mild symptoms include fever, cough, and loss of taste or smell, while severe symptoms can involve difficulty breathing, chest pain, and confusion. In some cases, patients may develop acute respiratory distress syndrome, requiring hospitalization and intensive care. The disease can affect multiple organ systems beyond the respiratory tract. It has been associated with complications such as myocarditis, thromboembolic events, and acute kidney injury. The variability in clinical presentation and the potential for rapid deterioration make early and accurate diagnosis critical. COVID-19 primarily spreads through respiratory droplets when an infected person coughs, sneezes, or talks. It can also be transmitted by touching surfaces contaminated with the virus and then touching the face. Preventive measures include wearing masks, maintaining physical distance, hand hygiene, and vaccination. Early detection is crucial in reducing virus-related hospitalizations, deaths, and long-term complications. It also helps ease the burden on healthcare systems and informs public health strategies and policies (Xu et al, 2020).

In addressing the critical need for efficient and rapid COVID-19 detection, this study introduces a novel diagnostic system that integrates CXR and CT imaging,

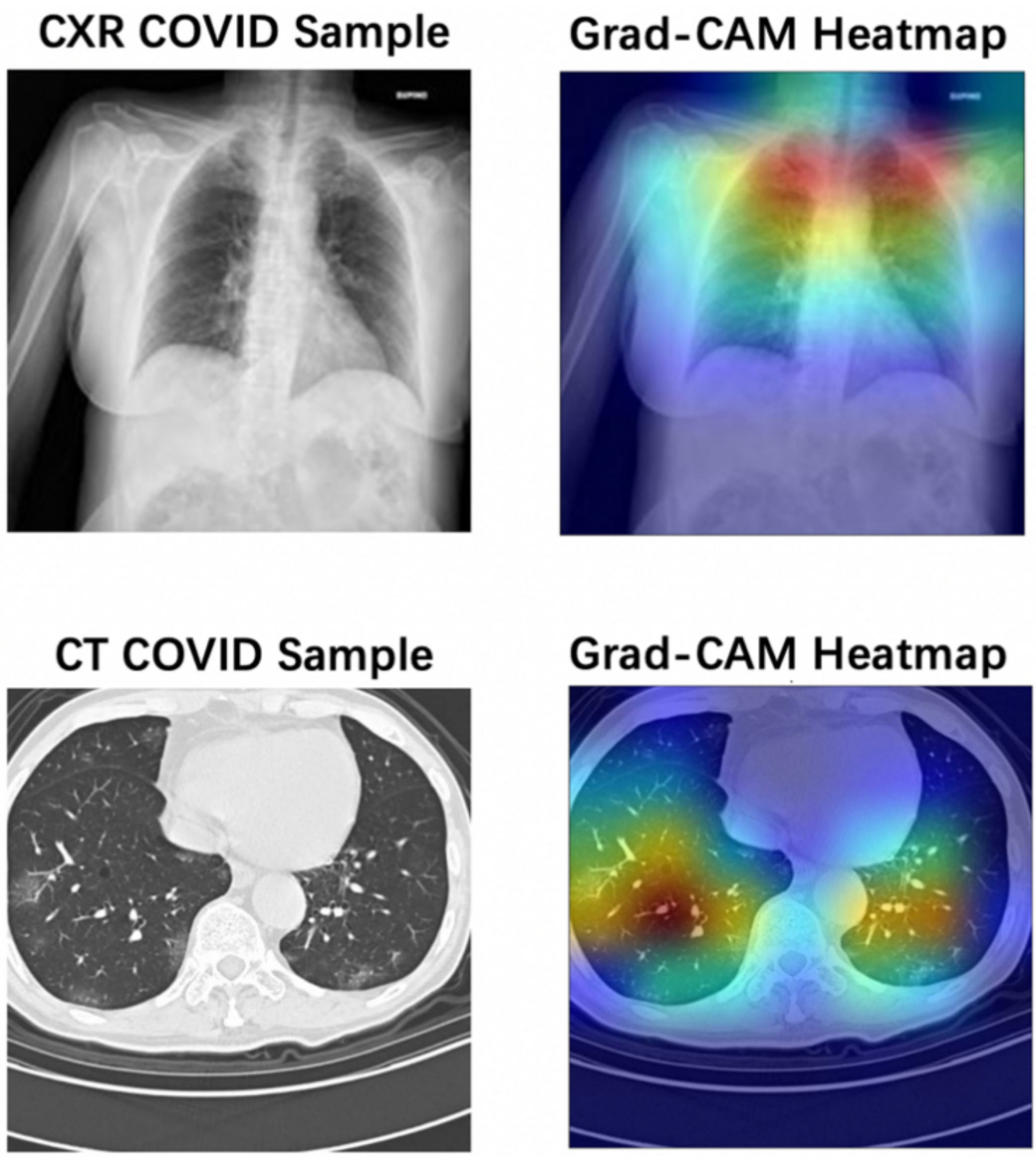

Fig. 8. Grad-CAM heatmaps for CXR and CT images of COVID-19 positive cases, highlighting important regions used by the CNN models for classification.

leveraging the strengths of deep learning. Although PCR testing remains the gold standard for COVID-19 diagnosis, it has limitations in terms of processing time and logistical constraints, particularly during peak periods of the pandemic (Cheng et al, 2020). Similarly, antigen tests, though faster, typically have lower sensitivity and are more effective during the initial stages of infection (Abduljalil, 2020). Antibody tests, which help identify past infections, do not facilitate the immediate detection of active cases (Watson et al, 2020). Our approach, by contrast, provides a rapid, real-time analysis of imaging data, essential for immediate clinical decisions and patient management. The effectiveness of integrating CXR and CT scans, as demonstrated in our results, shows a higher diagnostic accuracy and faster processing capability compared to these traditional methods, thus addressing significant gaps in the current diagnostic landscape.

The results of the study showed that the CNN-based deep learning model had a high accuracy rate in correctly classifying both new crown positive and negative CXR and CT images. This is in line with previous study where Siddiqi (2019) obtained an accuracy of 94.39%. Additionally, Guo et al (2020) obtained an accuracy rate of 98%. Pham (2020) investigated pretrained convolutional neural networks (CNNs) for classifying COVID-19 on CT scans using a large public database. When training the networks without data augmentation, CNN-based models had the average accuracy of 96–99%.

Combining CXR and CT images for diagnosis is important because they provide complementary information. CXR can detect abnormalities in the lungs, while CT images can provide a more detailed view of the anatomy and detect abnormalities in other organs. By integrating these two imaging modalities, a more detailed assessment of COVID-19 infection can be achieved, enhancing diagnostic accuracy and patient outcomes. Moreover, EfficientNet-based model was found to perform slightly better than the ResNet-based model in all aspects, suggesting that the larger convolutional layers of EfficientNet-based models enable them to better capture features from the data, leading to higher accuracy. With its excellent performance, the EfficientNet-based model is a potential candidate to build a system for diagnosing COVID-19 with hybrid chest X-ray and CT scans. Further research is needed to examine how to better tune the models to achieve higher accuracy in diagnosing the disease.

The results of the Grad-CAM analysis further demonstrate the utility of the Grad-CAM method in medical imaging, which may help reduce diagnostic errors and accelerate the diagnosis of COVID-19. By evaluating regions with high COVID-19 incidence, additional knowledge of the disease's origin may be acquired, thus aiding in the production of new therapies to combat the virus.

This research has certain limitations, most notably the difficulty of tackling the imbalance in the sampling data. The lack of COVID-positive samples leads to a disproportionate ratio of healthy to diseased samples, hindering the development of a balanced training model and posing issues with data versatility. Furthermore, to improve the effectiveness and precision of ResNet-based and EfficientNet-based models, considerable tuning of their hyper-parameters, that is, learning rate and batch size is needed. Current hyperparameter settings could be a potential limitation on model accuracy. In addition, models should be tested with data from relevant and diverse sources. Given that the mutation of the COVID virus has certain temporal and regional characteristics, the same model with different data sets may produce different results. Therefore, it is necessary to compare the results of the model with closely related datasets and compare them with the benchmark results.

Conclusion

The study proposes an effective method for diagnosing COVID-19 by combining CXR and CT images using deep learning techniques. The EfficientNet-based models demonstrate superior performance over ResNet-based models, achieving higher accuracy in classifying COVID-19 positive and negative cases. Integrating Grad-CAM technology enhances the interpretability of the models, aiding in reducing diagnostic errors and accelerating the diagnostic process. This approach has significant potential to improve patient care and support healthcare systems in managing the COVID-19 pandemic.

Key Points

- This study innovatively integrates CXR and CT imaging modalities using deep learning techniques. This integration allows for a more comprehensive analysis of lung pathology than could be achieved by either modality alone, enhancing diagnostic precision for COVID-19.
- The implementation of Grad-CAM technology represents a significant innovation. It provides visual explanations for the decisions made by the deep learning model, highlighting areas in the images that significantly influence the diagnosis, thus making the artificial intelligence's (AI's) decision-making process more transparent and interpretable.
- The finding that EfficientNet-based models outperform ResNet models because of their larger convolutional layers offer critical insights into the architectural factors that enhance feature extraction and accuracy in medical imaging.
- The study reports a notably high level of accuracy in utilizing deep learning for categorizing CXR and CT images as COVID-19 positive or negative.

Availability of Data and Materials

All data included in this study are available upon request by contact with the corresponding authors.

Author Contributions

HD, LYF, and JFZ designed the research study. HD and LYF performed the research. GSG provided help and advice on the methodology and data collection. LYF analyzed the data. HD drafted the manuscript. GSG supervised the research. All authors contributed to important editorial changes of important content in the manuscript. All authors contributed to the formal analysis and visualization. All authors read and approved the final manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

Ethics Approval and Consent to Participate

Not applicable.

Acknowledgement

Not applicable.

Funding

This study was supported by Zhejiang Provincial Natural Science Foundation of China (Grant No. LGF21H010005); Ningbo Clinical Research Center for Medical Imaging (Grant No. 2021L003); Ningbo Leading Medical & Health Discipline (Grant No. 2022-S02); Ningbo Public Welfare Science and Technology Plan Project (Major Project of Social Development Grant No. 2021S107); Ningbo "Science and Technology Innovation 2025" Major Project (Grant No. 2021Z021); Ningbo Municipal Emergency Science and Technology Major Project (Grant No. 2022Z034); Zhejiang Province and Ningbo City Co-constructed Project of Leading Medical & Health Discipline (Grant No. 2016-S04).

Conflict of Interest

The authors declare no conflict of interest.

References

Abduljalil JM. Laboratory diagnosis of SARS-CoV-2: available approaches and limitations. New Microbes and New Infections. 2020; 36: 100713. https://doi.org/10.1016/j.nmni.2020.100713

Abraham B, Nair MS. Computer-aided detection of COVID-19 from X-ray images using multi-CNN and Bayesnet classifier. Biocybernetics and Biomedical Engineering. 2020; 40: 1436–1445. https://doi.org/10.1016/j.bbe.2020.08.005

Albahli S, Yar GNAH. Fast and Accurate Detection of COVID-19 Along With 14 Other Chest Pathologies Using a Multi-Level Classification: Algorithm Development and Validation Study. Journal of Medical Internet Research. 2021; 23: e23693. https://doi.org/10.2196/23693

Attallah O, Ragab DA, Sharkas M. MULTI-DEEP: A novel CAD system for coronavirus (COVID-19) diagnosis from CT images using multiple convolution neural networks. PeerJ. 2020; 8: e10086. https://doi.org/10.7717/peerj.10086

Burlacu A, Crisan-Dabija R, Popa IV, Artene B, Birzu V, Pricop M, et al. Curbing the AI-induced enthusiasm in diagnosing COVID-19 on chest X-rays: the present and the near-future. medRxiv. 2020. (preprint). https://doi.org/10.1101/2020.04.28.20082776

Cheng MP, Papenburg J, Desjardins M, Kanjilal S, Quach C, Libman M, et al. Diagnostic Testing for Severe Acute Respiratory Syndrome-Related Coronavirus 2: A Narrative Review. Annals of Internal Medicine. 2020; 172: 726–734. https://doi.org/10.7326/M20-1301

Chen X, Yao L, Zhou T, Dong J, Zhang Y. Momentum contrastive learning for few-shot COVID-19 diagnosis from chest CT images. Pattern Recognition. 2021; 113: 107826. https://doi.org/10.1016/j.patcog.2021.107826

Chen XC, Yao LN, Zhang Y. Residual attention U-Net for automated multi-class segmentation of COVID-19 chest CT images. arXiv. 2020; 2004.05645. https://doi.org/10.48550/arXiv.2004.05645

Chowdhury MEH, Rahman F, Khandakar A, Mazhar R, Kadir MA, Mahbub ZB, et al. Can AI help in screening viral and COVID-19 pneumonia? IEEE Access. 2020; 8: 132665–132676. https://doi.org/10.1109/ACCESS.2020.3010287

Degerli A, Ahishali M, Yamac M, Kiranyaz S, Chowdhury MEH, Hameed K, et al. COVID-19 infection map generation and detection from chest X-ray images. Health Information Science and Systems. 2021; 9: 15. https://doi.org/10.1007/s13755-021-00146-8

Deng X, Shao HJ, Shi L, Wang X, Xie T. A classification–detection approach of COVID-19 based on chest X-ray and CT by using keras pre-trained deep learning models. Computer Modeling in Engineering & Sciences. 2020; 125: 579–596. https://doi.org/10.32604/cmes.2020.011920

Fusco R, Grassi R, Granata V, Setola SV, Grassi F, Cozzi D, et al. Artificial Intelligence and COVID-19 Using Chest CT Scan and Chest X-ray Images: Machine Learning and Deep Learning Approaches for Diagnosis and Treatment. Journal of Personalized Medicine. 2021; 11: 993. https://doi.org/10.3390/jpm11100993

Guo R, Passi K, Jain CK. Tuberculosis Diagnostics and Localization in Chest X-Rays via Deep Learning Models. Frontiers in Artificial Intelligence. 2020; 3: 583427. https://doi.org/10.3389/frai.2020.583427

He KM, Zhang XY, Ren SQ, Sun J. Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 770–778). 2016. https://doi.org/10.1109/CVPR.2016.90

Jaiswal A, Gianchandani N, Singh D, Kumar V, Kaur M. Classification of the COVID-19 infected patients using DenseNet201 based deep transfer learning. Journal of Biomolecular Structure & Dynamics. 2021; 39: 5682–5689. https://doi.org/10.1080/07391102.2020.1788642

Jin W, Dong S, Dong C, Ye X. Hybrid ensemble model for differential diagnosis between COVID-19 and common viral pneumonia by chest X-ray radiograph. Computers in Biology and Medicine. 2021; 131: 104252. https://doi.org/10.1016/j.compbiomed.2021.104252

Khobahi S, Agarwal C, Soltanalian M. Coronet: A deep network architecture for semi-supervised task-based identification of COVID-19 from chest X-ray images. medRxiv. 2020. (preprint) https://doi.org/10.1101/2020.04.14.20065722

Liu B, Gao X, He MS, Lv F, Yin G. Online COVID-19 diagnosis with chest CT images: Lesion-attention deep neural networks. medRxiv. 2020. (preprint) https://doi.org/10.1101/2020.05.11.20097907

Mondal AK, Bhattacharjee A, Singla P, Prathosh AP. xViTCOS: Explainable Vision Transformer Based COVID-19 Screening Using Radiography. IEEE Journal of Translational Engineering in Health and Medicine. 2021; 10: 1100110. https://doi.org/10.1109/JTEHM.2021.3134096

Moujahid H, Cherradi B, AI-Sarem M, Bahatti L, Eljialy ABAMY, Alsaeedi A, et al. Combining CNN and Grad-CAM for COVID-19 disease prediction and visual explanation. Intelligent Automation & Soft Computing. 2022; 32: 723–745. https://doi.org/10.32604/iasc.2022.022179

Ning W, Lei S, Yang J, Cao Y, Jiang P, Yang Q, et al. iCTCF: an integrative resource of chest computed tomography images and clinical features of patients with COVID-19 pneumonia. Research Square. 2020. (preprint) https://doi.org/10.21203/rs.3.rs-21834/v1

Oh Y, Park S, Ye JC. Deep Learning COVID-19 Features on CXR Using Limited Training Data Sets. IEEE Transactions on Medical Imaging. 2020; 39: 2688–2700. https://doi.org/10.1109/TMI.2020.2993291

Ozsahin I, Sekeroglu B, Musa MS, Mustapha MT, Uzun Ozsahin D. Review on Diagnosis of COVID-19 from Chest CT Images Using Artificial Intelligence. Computational and Mathematical Methods in Medicine. 2020; 2020: 9756518. https://doi.org/10.1155/2020/9756518

Pham TD. A comprehensive study on classification of COVID-19 on computed tomography with pretrained convolutional neural networks. Scientific Reports. 2020; 10: 16942. https://doi.org/10.1038/s41598-020-74164-z

Rahman T, Khandakar A, Qiblawey Y, Tahir A, Kiranyaz S, Abul Kashem SB, et al. Exploring the effect of image enhancement techniques on COVID-19 detection using chest X-ray images. Computers in Biology and Medicine. 2021; 132: 104319. https://doi.org/10.1016/j.compbiomed.2021.104319

Rajpurkar P, Irvin J, Zhu K, Yang B, Mehta H, Duan T, et al. Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning. arXiv. 2017; arXiv:1711.05225v3. (preprint) https://doi.org/10.48550/arXiv.1711.05225

Saood A, Hatem I. COVID-19 lung CT image segmentation using deep learning methods: U-Net versus SegNet. BMC Medical Imaging. 2021; 21: 19. https://doi.org/10.1186/s12880-020-00529-5

Siddiqi R. Automated pneumonia diagnosis using a customized sequential convolutional neural network. In Proceedings of the 2019 3rd International Conference on Deep Learning Technologies (pp. 64–70). 2019. https://doi.org/10.1145/3342999.3343001

Tan MX, Le Q. EfficientNet: Rethinking model scaling for convolutional neural networks. In International Conference on Machine Learning (pp. 6105–6114). PMLR. 2019.

Vandenberg O, Martiny D, Rochas O, van Belkum A, Kozlakidis Z. Considerations for diagnostic COVID-19 tests. Nature Reviews. Microbiology. 2021; 19: 171–183. https://doi.org/10.1038/s41579-020-00461-z

Watson J, Richter A, Deeks J. Testing for SARS-CoV-2 antibodies. BMJ (Clinical Research Ed.). 2020; 370: m3325. https://doi.org/10.1136/bmj.m3325

Xu G, Yang Y, Du Y, Peng F, Hu P, Wang R, et al. Clinical Pathway for Early Diagnosis of COVID-19: Updates from Experience to Evidence-Based Practice. Clinical Reviews in Allergy & Immunology. 2020; 59: 89–100. https://doi.org/10.1007/s12016-020-08792-8

Yuki K, Fujiogi M, Koutsogiannaki S. COVID-19 pathophysiology: A review. Clinical Immunology. 2020; 215: 108427. https://doi.org/10.1016/j.clim.2020.108427

Zebin T, Rezvy S. COVID-19 detection and disease progression visualization: Deep learning on chest X-rays for classification and coarse localization. Applied Intelligence. 2021; 51: 1010–1021. https://doi.org/10.1007/s10489-020-01867-1

Zhang Y, Hong D, McClement D, Oladosu O, Pridham G, Slaney G. Grad-CAM helps interpret the deep learning models trained to classify multiple sclerosis types using clinical brain magnetic resonance imaging. Journal of Neuroscience Methods. 2021; 353: 109098. https://doi.org/10.1016/j.jneumeth.2021.109098