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AN EXPLORATION OF 2D AND 3D CT SCAN IMAGES FOR DETECTING COVID-19 USING SPATIAL CONVOLUTIONAL NEURAL NETWORK

K. KIRUBANANTHAVALLI[1*], Dr. P. SUNDARESWARAN[2]

[1*]Assistant Professor, Department of Computer Science and Engineering, P. S. R. Engineering College, Sivakasi, Tamil Nadu, India

[2]Assistant Professor, Department of Computer Science and Engineering, Manonmaniam Sundaranar University, Tirunelveli, Tamil Nadu, India

E-mail: [1*]kkirubananthavalli06@gmail.com, [2]psundareswaran@msuniv.ac.in

ABSTRACT

COVID-19 has been the most impactful pandemic in modern history, affecting people all across the world. The identification of COVID-19 relies mostly on lung Computer Tomography (CT) images. A computer-aided diagnosis (CAD) method for classifying COVID-19 CT images is presented in this study. In this study, assess the accuracy of 2D and 3D SCNN models that share similar architectural details. The dataset is sourced from the 2D and 3D CT scan images Dataset, Chest CT scans with COVID-19 related findings database. Threshold segmentation is the best method for separating the chest from the rest of the CT scan. An advanced collection of deep learning models, SCNN combines the best 2D and 3D systems. It combines slice-level assessments, a CNN model, and unique preprocessing and attention components. In light of this, the suggested study introduces SCNN, an image-processing-based COVID-19 detection model. The COVID-19 CT images used to train this model were split into three categories: COVID-19, pneumonia, and healthy subjects. If the input image does not include the required attributes, an image preprocessing pipeline may be used to extract the ROI. As part of the proposal, combine the predictions made by 2D and 3D SCNN models. Using contrastive learning and an attention mechanism, this work presents a classification method. By reducing the distance between images in the same category, contrastive learning may increase the feature space used for classification. To aid with classification, an attention mechanism may draw focus on a key area of the image while offering a visual representation of that area. We showed a significant increase in classification accuracy by studying SCNN classification. In addition, we have achieved a comprehensive visual representation as compared to conventional methods.

Keywords: *COVID-19, 2D and 3D spatial Convolutional Neural Network, Classification, Accuracy*

1. INTRODUCTION

The COVID-19 pandemic, caused by the coronavirus disease 2019, has had a significant and long-lasting impact on healthcare systems and people worldwide. Efficient screening approaches are urgently required to swiftly discover COVID-19 infections, enabling the isolation and treatment of patients in the ongoing fight against this novel disease. RT-PCR is now the primary technique used to detect ribonucleic acid (RNA) from 2D and 3D CT scan samples of sputum collected from the upper respiratory tract. This technology has become the main approach for screening individuals for COVID-19 [1]. The accuracy of COVID-19 RT-PCR tests depends on the method of sample collection and the duration between the onset of symptoms and testing. Some studies have shown that these tests may not be highly responsive. Furthermore, it is possible to have delays in obtaining test results due to the high demand for RT-PCR testing, which is a time-consuming method [2-3]. The high sensitivity of chest computed tomography (CT) imaging has prompted its consideration as a viable alternative screening method for COVID-19 infection. When used in conjunction with RT-PCR testing, it has the potential to be even more effective [4-6]. During the first stages of the COVID-19 pandemic, CT scans were extensively used, particularly in Asia. Despite financial and resource constraints, routine CT screening for COVID-19 identification is essential. CT scan detection has become crucial for prompt diagnosis and treatment of COVID-19 [7]. One such

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technique is to consider using Spatial Convolutional Neural Networks (SCNN) to integrate both 2D and 3D methods. SCNN utilizes the combined skills of 2D and 3D convolutional layers to extract intricate spatial properties from the pictures. SCNN can effectively analyze the structural characteristics and contextual details needed to identify COVID-19 lesions by combining 2D slices and 3D volumes. The network's expanded ability to spot slight anomalies symptomatic of the disease has resulted in improved diagnostic accuracy, due to this hybrid method. Furthermore, SCNN is a valuable tool for healthcare professionals on the frontlines of the pandemic since it can effectively analyze CT scans and accommodate both 2D and 3D data. Figure 1 displays example datasets.

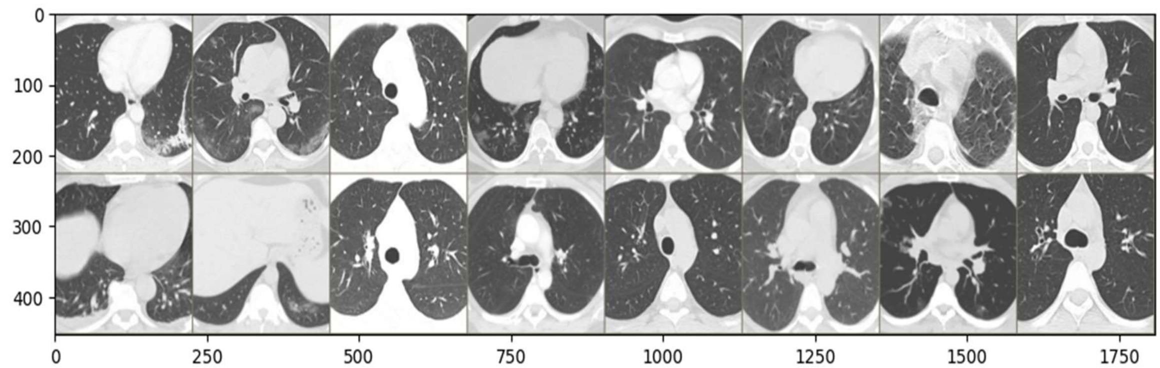

Figure 1: COVID-19 CT Image Datasets

1.1. Background and Significance of COVID-19 Detection using CT scans

The understanding and importance of detecting COVID-19 in CT scans is crucial in the context of the current worldwide epidemic. Computed tomography (CT) imaging has become a significant technique for diagnosing and managing COVID-19, especially when molecular testing methods like PCR are not accessible, delayed, or inconclusive. CT scans may swiftly and precisely reveal distinctive radiological features linked to COVID-19 pneumonia, facilitating prompt identification and beginning of therapy. Furthermore, CT imaging enables the evaluation of the severity and advancement of diseases, which helps in prompt treatments. It is particularly vital to detect people with serious sickness that may need urgent medical treatment, such as being admitted to critical care units. Moreover, CT scans function as an adjunctive diagnostic tool in conjunction with PCR testing, providing a more thorough comprehension of the disease state. Due to the highly contagious nature and fast dissemination of COVID-19, the prompt and precise identification of patients by CT imaging is essential in managing the pandemic, informing effective public health interventions, and ultimately preserving lives.

The COVID-19 pandemic has presented a formidable challenge to healthcare systems worldwide, underscoring the urgent need for accurate and efficient diagnostic methods. Computed tomography (CT) scans have emerged as a valuable tool for diagnosing COVID-19 due to their sensitivity in detecting pulmonary abnormalities associated with the virus. However, interpreting CT scans for COVID-19 lesions can be complex and time-consuming, often requiring expertise in radiology. In response, researchers have turned to deep learning techniques, particularly convolutional neural networks (CNNs), to automate and improve the diagnostic process. Traditional CNNs applied to CT scans typically utilize either 2D or 3D convolutional layers independently. However, recent studies suggest that a combination of both 2D and 3D methods could yield better results. This investigation aims to explore this hybrid approach using a Spatial Convolutional Neural Network (SCNN) to detect COVID-19 in CT scans. By integrating 2D and 3D convolutional layers, SCNN has the potential to enhance the accuracy and efficiency of COVID-19 detection, providing valuable support to healthcare professionals in diagnosing and managing the disease.

1.2. Challenges in accurate COVID-19 Detection

The accurate identification of COVID-19 poses many obstacles due to the intricate nature of the illness and the constraints of existing diagnostic techniques. An important obstacle is the inconsistency in symptoms and the way the disease manifests, which may range from having no symptoms at all to experiencing severe sickness. This diversity makes relying only on clinical

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diagnosis problematic. Moreover, the accuracy and precision of diagnostic procedures, such as polymerase chain reaction (PCR), antigen testing, and serological assays, may differ, resulting in incorrect negative or positive outcomes. The precision of these tests may be affected by variables such as the methods used to collect samples, the timing of the tests, and the dynamics of viral load, which can make diagnosis more complex. Additionally, the appearance of novel strains of the virus might impact the effectiveness of current diagnostic tests. Limited availability of testing facilities and supplies, together with difficulties in transporting and processing samples, might potentially impede prompt and precise diagnosis. Moreover, the dependence on molecular testing might lead to delays in diagnosing, hindering the timely implementation of isolation and contact tracking measures that are vital for preventing the spread of the disease. The issues are worsened by insufficient healthcare facilities and resources in certain places, which disproportionately impacts underprivileged communities. To tackle these issues, it is necessary to continuously conduct research and develop new diagnostic technologies. Additionally, there is a need to enhance healthcare infrastructure and provide worldwide access to testing.

1.3. Overview of Deep Learning Methods in Medical Image Analysis

Medical image analysis has been transformed by the advent of deep learning techniques, which provide robust capabilities for automated detection, segmentation, and classification applications. Convolutional Neural Networks (CNNs), a kind of deep learning model, have achieved significant success in this field because they can directly learn hierarchical characteristics from unprocessed images. CNNs have been used in medical image analysis for several modalities like as X-ray, MRI, ultrasound, and CT scans. Their purpose is to aid in the diagnosis and treatment of a diverse array of disorders. A significant benefit of deep learning techniques is their capacity to extract intricate patterns and characteristics from medical images, often surpassing conventional machine learning approaches.

Deep learning approaches have shown encouraging outcomes in the identification of COVID-19 in CT images. Researchers have successfully trained Convolutional Neural Networks (CNNs) using extensive datasets of CT scans. These models are now capable of accurately detecting certain abnormalities that are often linked with COVID-19 pneumonia, including ground-glass opacities and consolidations. These models may assist radiologists in swiftly and reliably reading CT images, particularly in situations where visual clues may be faint or unclear.

Historically, Convolutional Neural Networks (CNNs) have been used in either a two-dimensional (2D) or three-dimensional (3D) fashion. In 2D Convolutional Neural Networks (CNNs), each 2D slice of medical images is considered as a separate input, but in 3D CNNs, the full 3D volume is handled as a single input. Each strategy has its benefits and constraints. Two-dimensional convolutional neural networks (2D CNNs) are economical in terms of processing resources and training, but they may sacrifice spatial information that is found in neighboring slices. However, 3D Convolutional Neural Networks (CNNs) can successfully capture spatial context. Nevertheless, they frequently face challenges such as increasing memory demands and computational complexity.

To tackle these difficulties and use the advantages of both two-dimensional (2D) and three-dimensional (3D) techniques, subsequent studies have concentrated on integrating both methodologies. Hybrid architectures like Spatial Convolutional Neural Networks (SCNN) have been created by combining 2D and 3D convolutional procedures. SCNNs use spatial information from both 2D slices and 3D volumes, resulting in enhanced performance in applications like COVID-19 identification in CT images. This integration enables the model to collect intricate characteristics from specific sections while still preserving contextual information from the full volume, leading to more reliable and precise predictions.

In summary, deep learning techniques, namely Convolutional Neural Networks (CNNs), have revolutionized the field of medical image processing. These approaches have made it possible to automatically and accurately diagnose a range of medical illnesses, including COVID-19 pneumonia, using CT scans. The continuous progress in deep learning architectures, training methods, and extensive datasets have great potential to enhance the precision and effectiveness of medical image analysis, eventually helping both patients and healthcare providers. Contributing to the field, the study shows that compared to single-modality techniques, integrating 2D and 3D methods utilizing SCNN enhances the accuracy of COVID-19 identification in CT images. The experiment uses a hybrid technique to demonstrate that SCNN can effectively interpret CT images, resulting in a reduction in diagnostic time without sacrificing accuracy. It demonstrates that SCNN can reliably identify COVID-19 lesions in a variety of clinical scenarios, regardless of scan quality, patient demographics, or imaging techniques. The study sheds light on the SCNN characteristics, showing how the integration of 2D and 3D approaches collects the spatial information necessary for COVID-19 identification. Through the demonstration of SCNN's effectiveness, this study provides frontline healthcare providers with a useful tool to assist in the diagnosis of COVID-19. This might result in earlier identification and treatment, which would improve patient outcomes.

1.4. Objective

Evaluate the effectiveness of 2D and 3D CNNs in identifying COVID-19 lesions in CT images separately. Explore the efficacy of a Spatial Convolutional Neural Network (SCNN) for COVID-19 detection by integrating 2D and 3D CNNs. Test SCNN's diagnostic efficacy and accuracy against models that rely just on 2D or 3D convolutional layers. Learn how to improve COVID-19 lesion identification by integrating 2D and 3D approaches by analyzing SCNN-extracted features. Make sure SCNN is reliable and can be used in clinical situations by testing its resilience on different datasets.

1.5. Motivation

- Rapid and accurate COVID-19 diagnosis is crucial for timely treatment and containment.
- Spatial CNNs enhance diagnostic precision by analyzing both 2D and 3D CT scan images.
- AI-driven analysis reduces reliance on manual interpretation, minimizing human error.
- AI models can efficiently handle large datasets for widespread screening.
- Enhancing CT-based detection contributes to future AI applications in respiratory disease diagnosis.

1.6. Findings

- Spatial CNNs improve COVID-19 detection accuracy in 2D and 3D CT images.
- 3D CT scans provide richer spatial features, enhancing classification performance.
- AI reduces diagnostic time and human dependency.
- CNN models effectively process large datasets for mass screening.
- AI-driven CT analysis supports early detection and treatment planning.

2. RELATED WORKS

Several works have laid the groundwork for leveraging artificial intelligence (AI) in the detection of COVID-19 from CT scans. Simpson et al. outlined guidelines for reporting chest CT findings related to COVID-19, endorsed by prominent radiological societies, setting a standard for interpretation [8]. Li et al. evaluated the diagnostic accuracy of AI in detecting COVID-19 and community-acquired pneumonia, demonstrating the potential of AI-based approaches in clinical settings [9]. Wu et al. proposed a deep learning-based multi-view fusion model for screening COVID-19 pneumonia, showcasing the effectiveness of combining multiple views for improved detection [10]. Hu et al. introduced weakly supervised deep-learning methods for COVID-19 detection from CT images, emphasizing the importance of data-efficient techniques [11]. Zhou et al. developed an ensemble deep-learning model for COVID-19 detection, highlighting the benefits of combining multiple models for enhanced performance [12]. Song et al. demonstrated the capability of deep learning in accurately diagnosing COVID-19 from CT images, indicating the potential for AI-driven diagnostics in pandemic management [13]. These works collectively contribute to the evolving landscape of AI-enabled COVID-19 detection and provide valuable insights for further research, including the investigation and combination of 2D and 3D methods using Spatial Convolutional Neural Networks. The investigation into COVID-19 detection from CT scans using Convolutional Neural Networks (SCNN) builds upon several related works in the field. Zbontar et al. introduced the concept of self-supervised learning through redundancy reduction, which could enhance feature extraction in CNN by exploiting inherent data redundancies [14]. Srinivas and Fleuret proposed a method for visualizing neural network representations, offering insights into the inner workings of SCNN and aiding in model interpretation [15]. Wang et al. developed a deep learning algorithm for COVID-19 screening from CT images, providing a basis for comparison and benchmarking of SCNN performance [16]. Tan and Le introduced EfficientNet, a model scaling technique that could potentially improve CNN's efficiency and effectiveness [17]. Fang et al. conducted a study on the sensitivity of chest CT for COVID-19, offering valuable clinical context for evaluating SCNN's performance against established diagnostic methods [18]. Additionally, Hammoudi et al. demonstrated the application of deep learning on chest X-ray images for pneumonia detection, providing insights into alternative imaging modalities for COVID-19 diagnosis [19]. Morozov et al. contributed to the research by providing the Mosmeddata dataset, a valuable resource containing chest CT scans with COVID-19-related findings, facilitating the training and validation of CNN models [20]. These related works collectively contribute to the advancement of AI-driven COVID-19 detection and provide valuable insights for the investigation and combination of 2D and 3D methods using SCNN.

The investigation into COVID-19 detection from CT scans using Spatial Convolutional Neural Networks (SCNN) draws from various related works in the field. Afshar et al. introduced the COVID-CT-MD dataset, which provides a valuable resource for training and evaluating CNN models [21]. Li et al. studied the early transmission dynamics of COVID-19, providing insights into the disease's progression and aiding in understanding the features to be detected by SCNN [22]. Makris et al. investigated COVID-19 detection from chest X-ray images using deep learning, contributing to the understanding of alternative imaging modalities that could be incorporated into SCNN [23]. Das et al. proposed a Truncated Inception Net for COVID-19 screening from chest X-rays, providing a method for comparison and benchmarking against SCNN [24]. Narin et al. explored automatic detection of COVID-19 from X-ray images using deep convolutional neural networks, offering insights into feature extraction techniques applicable to SCNN [25]. Arsenos et al. developed a large imaging database and novel deep neural architecture for COVID-19 diagnosis, providing further resources and methods for SCNN development and evaluation [26]. These related works collectively contribute to the advancement of AI-driven COVID-19 detection and provide valuable insights for the investigation and combination of 2D and 3D methods using SCNN.

The investigation into COVID-19 detection from CT scans using Spatial Convolutional Neural Networks (SCNN) is supported by several related works in the field. Kollias et al. presented the AI-MIA project, which focuses on COVID-19 detection and severity analysis through medical imaging, providing valuable insights and methods for SCNN development [27]. Bougourzi et al. introduced the ILC-UNet++ model for COVID-19 infection segmentation, offering a methodological approach that can complement SCNN's capabilities in segmenting COVID-19 lesions from CT scans [28]. Additionally, Martelli-Júnior et al. provided insights into the impact of COVID-19 on dental health, contributing to the understanding of the disease's manifestations that may be detected through imaging modalities, such as CT scans [29]. Abbas et al. explored the classification of COVID-19 in chest X-ray images using deep convolutional neural networks, providing alternative approaches for detection that may inform SCNN's development [30]. These related works collectively contribute to the advancement of AI-driven COVID-19 detection from medical imaging and provide valuable insights for the investigation and combination of 2D and 3D methods using CNN.

3. METHODS AND MATERIALS

3.1. Dataset

The 2D and 3D CT Scan images are accessible online and real-time data is an extensive compilation of CT scans obtained from persons who have been diagnosed with COVID-19 pneumonia, as well as from those who do not have any respiratory abnormalities (normal cases). This dataset is a significant resource for academics, healthcare practitioners, and data scientists who want to create and verify deep learning algorithms for detecting and diagnosing COVID-19 using CT imaging. The dataset comprises a wide array of CT images, including different degrees of severity and presentations of COVID-19 pneumonia. Every CT scan is accompanied by pertinent information, including patient demographics, clinical history, and radiological results, which provide essential context for analysis and interpretation. Scientists may use this dataset to build machine learning models for automated COVID-19 identification in CT scans, using advanced approaches like convolutional neural networks (CNNs). Through the use of a vast and varied dataset such as this, models may acquire the ability to effectively distinguish between instances of COVID-19 pneumonia and regular cases, hence assisting in the prompt identification and treatment of patients. Figure 2 shows an overall system diagram.

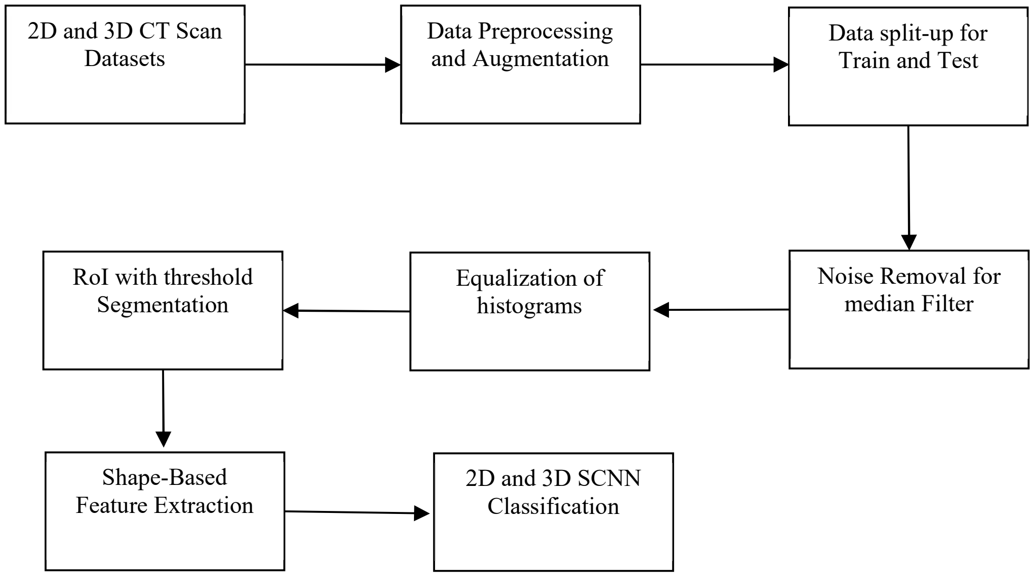

Figure 2: System Architecture

Furthermore, the dataset enables the creation of decision support systems for radiologists, offering tools to aid in the study and interpretation of CT images. These technologies may assist radiologists in the process of categorizing and ranking cases, therefore enhancing the efficiency of their jobs and the quality of patient care. Furthermore, the dataset serves as a standard for assessing the effectiveness of both established and recently created algorithms in detecting COVID-19 in CT images. By comparing the accuracy, sensitivity, and specificity of various models, researchers may promote cooperation and progress in the area of medical image analysis. The 2D and 3D CT Scan CT-Scan Dataset on real-time data collection is vital for improving our knowledge of COVID-19 and improving diagnostic skills by using artificial intelligence on medical imaging data.

Table 1: Dataset Category.

Dataset	COVID-19	Pneumonia	Normal	Total
2D and 3D CT scan	720	280	1500	2500

Table 1 displays a categorization of the 2D and 3D CT Scan CT-Scan dataset, classifying it according to the presence or absence of COVID-19 pneumonia:

Dataset: This column provides information on the dataset being discussed, namely the 2D and 3D CT Scan CT-Scan dataset.

COVID Pneumonia: This column represents the count of CT scans in the dataset that exhibit indications of COVID-19 pneumonia. The dataset contains 1000 CT images that have characteristics that are in line with COVID-19 pneumonia.

Normal: This column reflects the count of CT scans in the dataset that exhibit no indications of respiratory problems or pneumonia. The dataset contains 1500 CT images that have been categorized as normal.

Total: This column displays the overall count of CT scans in the dataset, including both instances of COVID-19 pneumonia and normal cases. The collection contains a total of 2500 CT images.

The table presents a succinct overview of the dataset's makeup, emphasizing the count of COVID-19 pneumonia cases, normal cases, and the total dataset size. Analyzing such splits is crucial for understanding the distribution of classes within a dataset, which is vital for training and assessing machine learning models.

3.1.1. Data Split-up

To divide a dataset consisting of 2500 images into a training set is 70% of the data and a test set is 30% of the data, we would allocate 1750 images to the training set and 750 images to the test set shown in Table 2. This division guarantees that the model gets trained on a significant percentage of the data, while also reserving a sizable piece for assessment purposes.

To divide the dataset including pneumonia, COVID-19, and normal images, the images would be distributed over two sets while preserving the relative proportions of each class. This is the method we would use:

Table 2: Train and Test Split-up.

Dataset	Train Data (70%)	Test Data (30%)	Total
2D and 3D images	3675	675	4350

After partitioning the images into training and test sets based on this division, they may be used to train and assess machine learning models, guaranteeing that the models encounter a wide variety of instances from each category while also having enough data for assessment. This partitioning technique aids in mitigating over fitting by training the model on a substantial percentage of the data, while simultaneously guaranteeing an accurate evaluation of the model's performance on unseen data. Furthermore, it guarantees that the proportionate allocation of classes stays constant across the training and test datasets, preserving the model's capacity to generalize across diverse classes.

Table 3: Classes / Labels for Train and Test Data.

Classes / Labels	Train Data	Test Data
Pneumonia	1225	225
COVID-19	1225	225
Normal	1225	225
Total	3675	675

Therefore, the training set would have 1225 images from each category (pneumonia, COVID-19, and normal), resulting in a total of 3675 images. Similarly, the test set would comprise 225 images from each category, resulting in a total of 675 images. This division guarantees that the model gets trained on a significant percentage of the data while reserving a large amount for assessment purposes. Additionally, it guarantees that both the training and test sets accurately reflect the class distribution of the total dataset, enabling a just assessment of the model's performance shown in Table 3.

3.2. Image preprocessing and augmentation techniques

Algorithms 1 and 2 illustrate that image preprocessing and augmentation are crucial for improving the performance and resilience of our models. Preprocessing encompasses the process of standardizing image resolutions, normalizing pixel values, and modifying intensities to guarantee uniformity among scans. Rescaling is the process of standardizing image resolutions, normalization is used to bring pixel values to a common range, and intensity adjustment is performed to eliminate variances in image intensities. Augmentation approaches enhance dataset diversity, hence enhancing model generalization. Rotations, translations, and scalings cause changes in orientation and size, while flips and elastic deformations mimic varied viewpoints and distortions in tissue. In addition, using methods such as introducing noise and modifying contrast imitate real-life scenarios, hence improving the flexibility of the model. Preprocessing and augmentation procedures play a vital role in addressing issues such as over fitting, class imbalance, and fluctuations in imaging settings. These processes are essential for ensuring accurate identification of COVID-19 in CT images using SCNN.

Table 4: Classes / Labels for Train and Test Data.

Algorithm 1: Image Preprocessing Pseudocode

```
Input: Grayscale Image of Chest CT
Output: A combined image that has ROI as 2nd channel.
Output image shape = 128, 128, 2
Start
def remove_background_noise(image):
    temp_img = image.copy()
    n_components, output, stats, centroids = cv.connectedComponentsWithStats(temp_img, connectivity=4)
    component_size_list = stats[:-1]
    for i in range(1, n_components):
        if component_size_list[i] < 500:
            temp_img[output == i] = 0
    return temp_img
def process_image(imagepath):
```

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```
    img = cv.imread(imagepath)
    gray_img = cv.cvtColor(img, cv.COLOR_BGR2GRAY)
    _, threshold = cv.threshold(gray_img, 127, 255, cv.THRESH_BINARY_INV + cv.THRESH_OTSU)
    roi = gray_img & threshold
    roi = cv.GaussianBlur(roi, (9, 9), 0)
    roi = cv.equalizeHist(roi)
    roi = remove_background_noise(ROI)
    model_input = np. stack((img, ROI))
    model_input = 255 - model_input
    model_input = cv.resize(model_input, (128, 128))
    return model_input
Stop
```

Table 5: Classes / Labels for Train and Test Data.

Algorithm 2: Image Augmentation Pseudocode

```
def augment_image(image):
    augmentations = {
        "rotate": random.choice([0, 90, 180, 270]),
        "translate_x": random.randint(-10, 10),
        "translate_y": random.randint(-10, 10),
        "scale": random.uniform(0.9, 1.1),
        "flip_code": random.choice([0, 1, -1])
    }
    augmented_image = image
    if augmentations["rotate"]:
        augmented_image = rotate_image(augmented_image, augmentations["rotate"])
    if augmentations["translate_x"] or augmentations["translate_y"]:
        augmented_image = translate_image(augmented_image, augmentations["translate_x"],
augmentations["translate_y"])
    if augmentations["scale"]:
        augmented_image = scale_image(augmented_image, augmentations["scale"])
    if augmentations["flip_code"]:
        augmented_image = flip_image(augmented_image, augmentations["flip_code"])
    return augmented_image
```

3.3. Median Filter

Median filtering and blurring are commonly used methods in the processing of COVID-19 CT images to reduce noise and increase image quality. Median filtering is very efficient in reducing noise while maintaining the integrity of edges and intricate features. This method substitutes the intensity of each pixel with the median value of its surrounding area. Median filtering is a useful technique in COVID-19 CT scans to reduce noise and improve image quality. It effectively smoothens the image without compromising the integrity of important structures like lung tissues and lesions. Median filtering may improve the visibility of COVID-19-related anomalies by eliminating unusual pixel values, therefore facilitating their detection and analysis for diagnostic purposes. Blurring is a valuable technique for diminishing high-frequency noise and tiny irregularities in the image. Blurring in COVID-19 CT images may be used to reduce artifacts resulting from scanner noise, motion artifacts, or inconsistencies in the patient's breathing rhythm. Blurring enhances the clarity of lung structures and COVID-19-related defects, hence assisting radiologists and researchers in achieving precise diagnosis and evaluation by minimizing these faults. To summarize, both median filtering and blurring are important preprocessing strategies in the interpretation of COVID-19 CT images. Median filtering is a very efficient method for reducing noise while still keeping edge information. This makes it particularly appropriate for strengthening intricate structures when there is noise present. Blurring is beneficial for minimizing slight abnormalities and imperfections, leading to a more seamless image look and enhanced interpretability. Combining these approaches enhances the precision of COVID-19 CT images, hence aiding in the more precise and dependable diagnosis and assessment of illness severity.

Equation 1 for the median filter involves replacing each pixel's intensity value with the median intensity value of its neighborhood. The median filter operates by sliding a window of a specified size over the image, and for each position, the median value of the pixel intensities within the window is calculated and assigned to the corresponding pixel in the output image.

$$M(x, y) = \text{median}\,(I(x - m, y - n), \dots, I(x + m, y + n)) \quad (1)$$

Where, $M(x, y)$ is the median-filtered output image, $I(x, y)$ is the intensity of the pixel at position (x, y) in the input image.

3.4. Equalization of Histograms

Histogram equalization is a method used to improve the contrast and dynamic range of a picture by shifting the intensities of its pixels. The procedure entails altering the intensity values of a picture to get a more evenly distributed histogram throughout the whole range of intensities in the resulting image. This is especially advantageous when a picture exhibits a limited or irregular distribution of pixel intensities, resulting in subpar contrast and visibility of features. The process of histogram equalization starts with calculating the histogram of the input picture, which shows the frequency of each intensity level. Subsequently, a cumulative distribution function (CDF) is computed using the histogram, which illustrates the cumulative likelihood of each intensity level's occurrence. Next, the intensity values of the input picture are transformed into new intensity values using the CDF. This mapping redistributes the intensities in a way that makes the histogram of the output picture seem more evenly distributed.

$$g(i) = \text{round}\left(\frac{c(i) - c_{\min}}{N - 1} \times (L - 1)\right) \quad (2)$$

In equation 2 is $c_{\min}$ is the minimum non-zero value of the CDF. N is the total number of pixels in the image. L is the number of intensity levels in the image (typically 256 for 8-bit images). The round function rounds the result to the nearest integer.

This mapping guarantees that every intensity level is evenly depicted in the resulting picture, resulting in enhanced contrast and greater visibility of details. Histogram equalization is a commonly used method in image processing, including medical imaging like CT scans. It is utilized to improve the clarity of structures and anomalies, therefore facilitating diagnosis and analysis. Nevertheless, it is crucial to acknowledge that histogram equalization has the potential to increase noise in the picture. Therefore, its use should be exercised with caution, taking into account the unique demands of the study.

3.5. Region of Interest

Detecting the Region of Interest (ROI) in CT scans of COVID-19 is essential for precise diagnosis and evaluation of the severity of the illness. Convolutional Neural Networks (CNNs) have played a crucial role in automating this procedure, allowing for rapid and accurate identification of areas that suggest COVID-19 pneumonia. The process of CNN-based ROI identification consists of many essential stages. Initially, the CT image undergoes preprocessing to amplify pertinent characteristics and reduce noise. The training data consists of CT scans that have been labeled to highlight the regions of lung anomalies that are specific to COVID-19. During the training process, the Convolutional Neural Network (CNN) acquires the ability to identify these characteristics by continuously modifying its internal parameters. The network's capacity to recognize Regions of Interest (ROIs) improves with each iteration, led by loss functions that measure the difference between anticipated and actual ROI positions. After being trained, the Convolutional Neural Network (CNN) is capable of precisely identifying and locating Regions of Interest (ROIs) in CT images that it has not before seen. Practically, CNN-based methods for detecting regions of interest (ROI) are included in diagnostic procedures to aid radiologists. Upon receiving a fresh CT image, the Convolutional Neural Network (CNN) examines it and produces a heat map that identifies areas with a high probability of containing anomalies associated with COVID-19. This heat map functions as a visual tool for radiologists, assisting them in promptly spotting and assessing possible pneumonia lesions. In addition, Convolutional Neural Networks (CNNs) can provide precise numerical assessments of the severity and distribution of lesions. This aids in the process of determining the stage of a disease and tracking its development over some time. CNNs simplify the diagnostic process by automating ROI recognition, resulting in reduced interpretation time and improved diagnosis accuracy, especially in situations when lesions are faint or spread out. In summary, the use of the convolutional neural network (CNN) for detecting regions of interest (ROI) in COVID-19 CT images is a notable progress in the field of medical imaging. By integrating deep learning capabilities with the knowledge and skills of radiologists, the diagnosis and treatment of COVID-19 pneumonia may be conducted in a more efficient and precise manner.

3.6. ROI-Based Model Input Preparation

Preparing the input for the ROI-based model takes many processes to guarantee precise and efficient analysis. Initially, ascertain the specific areas of interest (known as regions of interest or ROIs) within the images. These regions usually include suspected COVID-19 disease, such as lung opacities or consolidations. Subsequently, segmentation algorithms to extract these Regions of Interest (ROIs) from the CT images, thus isolating the pertinent regions for investigation. Segmentation techniques, whether human or automated, are used based on the task's complexity and the resources at hand. After extracting the ROIs, proceed to preprocess the images to improve features and eliminate noise. Typical pre-processing processes include reducing noise, improving contrast, and normalizing to ensure consistent intensity levels across several scans. These measures enhance the quality and uniformity of the input data. Following the pre-processing stage, feature extraction is carried out to quantify pertinent attributes inside the regions of interest (ROIs). This may include the extraction of texture data, such as gray-level co-occurrence matrix (GLCM) information, or shape features, such as the area and perimeter of lung lesions. Feature extraction seeks to identify unique patterns or characteristics that may assist in differentiating COVID-19 disease from other lung problems. After the characteristics have been retrieved, they are used as inputs for the ROI-based model. Depending on the specific design of the model, further operations such as reducing the number of dimensions or normalizing the feature vectors may be performed. The model then evaluates these inputs to provide forecasts on the existence or intensity of COVID-19. Ultimately, post-processing techniques may be used to enhance the accuracy and quality of the model's results, as well as to combine them with other clinical information. This may include using thresholding techniques to categorize lesions as either COVID-19 positive or negative or merging model predictions with patient information to provide a thorough diagnostic evaluation. During these processes, it is essential to conduct thorough validation and testing to guarantee the precision and dependability of the ROI-based model. This process entails using annotated datasets to train and assess the performance of the model, while also adjusting the model parameters as necessary. Furthermore, conducting validation on separate datasets and real-world clinical environments aids in evaluating the applicability and reliability of the model.

3.7. Threshold Segmentation

Threshold is a technique used to manipulate individual pixels in image graphs. The value of each pixel is compared to a predetermined threshold value and then adjusted to a new value based on the comparison. The Otsu threshold method does not rely on a pre-defined threshold value but instead selects the threshold value dynamically. In this particular case, we are focusing on binary images. Otsu's approach examines the histogram derived from the intensities of the image pixels and selects a threshold that effectively separates the two peaks. Otsu's threshold technique determines the most suitable threshold value by maximizing the variation between classes of pixel intensities in a grayscale image. The threshold value T is used to minimize the weighted sum of variances of the two classes (foreground and background) that are defined by the threshold. The equation for Otsu's threshold method is as follows:

$$T = \arg\ \max\{\sigma_B^2(T)\} \tag{3}$$

In, equation 3 describes, T is the threshold value, $\sigma_B^2(T)$ is the between-class variance at threshold T, and $\arg\ \max$ denotes the argument that maximizes the function.

The between-class variance $\sigma_B^2(T)$ is calculated as:

$$\sigma_B^2(T) = w_1(T) \cdot w_2(T) \cdot [\mu_1(T) - \mu_2(T)]^2 \tag{4}$$

In, equation 4 describes, $w_1(T)$ and $w_2(T)$ are the probabilities of the two classes, which are the fractions of pixels in the foreground and background, respectively. $\mu_1(T)$ and $\mu_2(T)$ are the means of the pixel intensities in the foreground and background, respectively, calculated up to threshold T.

Means weighted class

In, equation 5 describes, for the mean weighted class, can be represented as follows:

$$\text{Mean Weighted Class } = \frac{\sum_{i=1}^{N} w_i \times x_i}{\sum_{i=1}^{N} w_i} \tag{5}$$

Where $N$the total number of classes or samples is, x_i is the value of the class or sample, w_i is the weight associated with the class or sample. This equation computes the weighted average of the classes or samples by multiplying each class or sample with its associated weight and then dividing the total of these products by the sum of the weights. The weights may be allocated according to diverse considerations, such as the significance of each class or sample, the frequency of incidence, or any other pertinent criterion.

Variance weighted class

To obtain the between-class variance$\sigma_B^2(T)$, we first need to calculate the probabilities of the two classes (foreground and background) and their respective mean intensities up

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to a given threshold (T),. These are represented as $w_1(T), w_2(T)$ and $\mu_1(T)$, $\mu_2(T)$. The variance-weighted class is represented as equation 6:

$$\sigma_B^2(T) = w_1(T) \cdot w_2(T) \cdot [\mu_1(T) - \mu_2(T)]^2 \quad (6)$$

Where, $\sigma_B^2(T)$ is the between-class variance at threshold$T$, $w_1(T), w_2(T)$ are the probabilities of the two classes. $\mu_1(T)$, $\mu_2(T)$ are the means of the pixel intensities in the foreground and background.

3.8. Feature Extraction

To explore and integrate 2D and 3D techniques for identifying COVID-19 in CT scans, a vital approach is to utilize shape-based feature algorithms. These algorithms examine the three-dimensional shape and structure of lung tissues and irregularities, offering valuable data for identifying and describing diseases. Regarding the detection of COVID-19, shape-based features are capable of capturing the specific changes in lung structure caused by the virus, including ground-glass opacities, consolidations, and nodules. Shape-based features in 2D analysis extract geometric properties from individual CT slices, including the area, perimeter, circularity, and solidity of lung lesions. These characteristics can emphasize the size and consistency of abnormalities within a single slice, assisting in the recognition of patterns associated with COVID-19. Nevertheless, 2D techniques might fail to consider the comprehensive spatial arrangement and volumetric attributes of lesions that exist across the entire lung volume. On the other hand, 3D shape-based features examine the entire volumetric data, capturing the shape, size, and spatial arrangement of abnormalities in three dimensions. By taking into account the entire volume, these characteristics offer a more comprehensive comprehension of the disease's scope and intensity. They can distinguish between focal and diffuse abnormalities, evaluate the size of lesions, and describe the spatial arrangement of lesions within the lungs. The integration of 2D and 3D shape-based features enables a synergistic analysis that capitalizes on the respective advantages of both approaches. The 2D features offer in-depth information about individual slices, allowing for precise analysis of lesions, while the 3D features provide a comprehensive perspective of the disease, capturing the overall shape and distribution of abnormalities. By incorporating these characteristics, the precision and resilience of COVID-19 detection in CT scans can be greatly improved. To summarize, the utilization of shape-based feature algorithms is of utmost importance in the detection and characterization of COVID-19 in CT scans, whether in 2D or 3D scenarios. Their capacity to accurately capture the morphological features of lung abnormalities enables precise diagnosis and evaluation of disease severity, thereby enhancing patient management and treatment outcomes. Shape-based feature extraction methods include the computation of geometric attributes of objects present in pictures. Below is a summary of the equations often used for extracting shape-based features.

3.8.1. Area (A)

$$A = \sum_{i=1}^{n} \sum_{j=1}^{m} I(i,j) \quad (7)$$

Where, $I(i,j)$ represents the intensity of the pixel (i,j) in the binary image.

3.8.2. Perimeter (P)

$$P = \sum_{i=1}^{n} \sum_{j=1}^{m} \Delta_{ij} \quad (8)$$

Where, Δ_{ij} is the length of the boundary between the foreground and background pixels.

3.8.3. Circularity (C)

$$C = \frac{4\pi A}{P^2} \quad (9)$$

describes, measure of how closely an object's shape resembles a circle. A value of 1 indicates a perfect circle.

3.8.4. Compactness (Cp)

$$Cp = \frac{P^2}{A} \quad (10)$$

describes, measures how compact the shape of an object is. A higher value indicates a more compact shape.

3.8.5. Aspect Ratio (AR)

$$AR = \frac{a}{b} \quad (11)$$

describes the ratio of the length of the major axis (a) to the length of the minor axis (b) of the object's best-fit ellipse.

3.8.6. Roundness (Rd)

$$Rd = \frac{4A}{\pi d^2} \quad (12)$$

describes, is d is the diameter of the object's minimum enclosing circle.

These equations are used for both two-dimensional (2D) and three-dimensional (3D) data, with adjustments made in the computation of parameters such as area, perimeter, and eccentricity to accommodate the extra dimension. Quantitative assessments of form properties are offered by these methods, allowing for the study and comparison of objects in photographs for a range of applications, such as medical imaging and object identification.

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The table with some values for the specified shape-based features in 2D AND 3D CT SCAN images: Table 6 is shown in features and mean, variance, and parameter values for the shape-based extraction.

Table 6: Shape-Based Feature Extraction

Features	Parameter Values	Mean	Variance	Features
Area (A)	2356	37.5	58	Area (A)
Perimeter (P)	314	110	194	Perimeter (P)
Circularity (C)	0.724	40	73	Circularity (C)
Compactness (Cp)	0.421	8	41	Compactness (Cp)
Aspect Ratio (AR)	1.23	12	40	Aspect Ratio (AR)
Roundness (Rd)	0.854	7	30.5	Roundness (Rd)

The numbers provided are illustrative and may vary based on the particular CT scan and the retrieved characteristics. You may substitute these with concrete values derived from the examination of 2D and 3D CT scans.

3.9. 2D and 3D CNN

Convolutional Neural Networks (CNNs) are very effective in combating COVID-19, particularly in the field of medical image processing. These deep learning architectures are very proficient in acquiring intricate patterns and characteristics from extensive datasets, which makes them highly suitable for applications such as identifying COVID-19 pneumonia in chest CT. Exemplary convolutional neural network (CNN) architecture. The advanced neural network model was created specifically to quickly and precisely identify instances of COVID-19 by analyzing chest X-ray pictures. This tool was created in direct response to the pressing need for diagnostic tools that are both scalable and efficient in the midst of the COVID-19 outbreak. Utilizes a blend of conventional layers, residual blocks, and attention techniques to acquire distinctive characteristics that are diagnostic of COVID-19 pneumonia. The distinguishing feature of its capacity to attain exceptional accuracy with a limited number of parameters, making it well-suited for implementation in settings with limited resources. It has shown remarkable efficacy in identifying COVID-19 patients from chest X-ray pictures in real-world scenarios. Empirical evidence has shown that it surpasses the performance of human radiologists in terms of both accuracy and speed, making it a helpful tool for prioritizing and diagnosing COVID-19 patients. In addition, the lightweight design of CNN layers allows for its deployment on edge devices and integration with current healthcare systems, which facilitates quick screening and diagnosis at the point of treatment. In general, CNNs have completely transformed the process of diagnosing COVID-19 by providing scalable, precise, and fast methods for processing medical pictures. Their capacity to automate and improve diagnostic procedures is vital in the fight against the pandemic, assisting healthcare professionals in making prompt and well-informed choices on patient treatment. Figure 3 shows in CNN architecture for layer analysis.

Convolution Layer: These layers are accountable for acquiring the complex characteristics of an input picture. Multiple convolution layers may be used to incrementally learn visual attributes.

Pooling Layer: It decreases the spatial size of the convolved volume, hence reducing the processing power required to analyze the data. Extracting the prominent traits is also beneficial. This layer also carries out noise reduction.

Fully Connected Layer: Pooling layers are used to effectively decrease the size of the input volume. Subsequently, fully linked layers are utilized to acquire intricate and nonlinear combinations of high-level characteristics. Fully connected layers are often used in artificial neural network models. These layers receive a one-dimensional vector as input, which is created by combining the outputs of the pooling layer. Traditionally, the combination of convolution and pooling layers is regarded as a single layer in a convolutional neural network (CNN), and there may be several pairings of these layers.

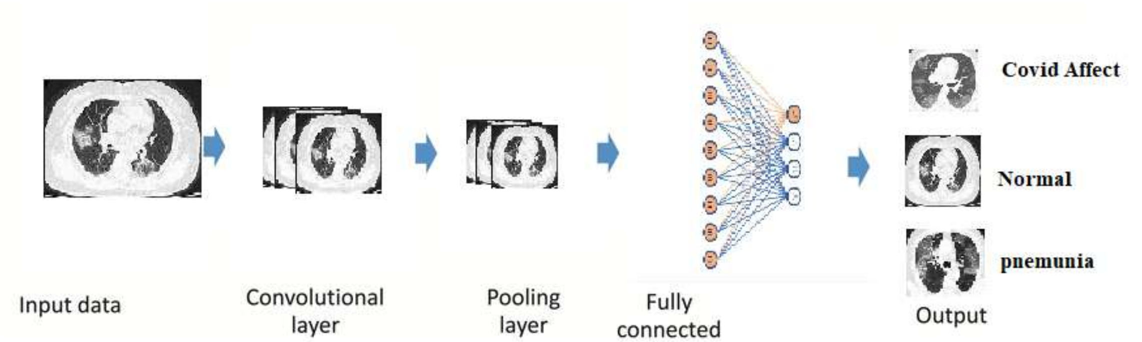

Figure 3: CNN Architecture

3.10. 2D and 3D Spatial Convolutional Neural Network

A complete technique that combines both two-dimensional and three-dimensional spatial approaches may be quite useful when it comes to training Convolutional Neural Networks (CNNs) using 2D AND 3D CT scan datasets. The following is an in-depth outline:

3.10.1. Data Preparation

It is necessary to import the 2D and 3D CT scan image datasets, making certain that each scan is appropriately labeled (for example, as positive or negative for COVID-19). The CT images needed to be preprocessed, which included shrinking them to a consistent voxel size, normalizing them so that the pixel values were scaled between 0 and 1, and maybe augmenting them to improve the variability of the dataset. To ensure that there is a class balance across all of the sets, the dataset should be divided into training, validation, and testing sets.

3.10.2. 2D SCNN

Convolutional layers, activation functions, pooling layers, and fully linked layers should be assembled into a two-dimensional spatial convolutional neural network (SCNN) architecture. Through the use of individual axial slices collected from CT scans as input, the 2D CNN should be trained. The acceleration of training and the improvement of performance may be achieved by the use of methods such as transfer learning from pre-trained. Validate the trained two-dimensional spatial convolutional neural network (2D-SCNN) on the validation set, making any required adjustments to the hyperparameters and architecture. The below Algorithm 3 is shown in 2D SCNN.

Table 7: Classes / Labels for Train and Test Data.

Algorithm 3: 2D SCNN

```
def:
    model_2d = Sequential([
    Conv2D(filters=32, kernel_size=(3, 3), activation='relu', input_shape=(img_height, img_width,
img_channels)),
    MaxPooling2D(pool_size=(2, 2)),
    Conv2D(filters=64, kernel_size=(3, 3), activation='relu'),
    MaxPooling2D(pool_size=(2, 2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(1, activation='sigmoid')
    ])
    model_2d.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    history_2d = model_2d.fit(train_data_2d, train_labels, validation_data=(val_data_2d, val_labels),
epochs=num_epochs, batch_size=batch_size)
    test_loss_2d, test_acc_2d = model_2d.evaluate(test_data_2d, test_labels)
    print("Test Accuracy (2D SCNN):", test_acc_2d)
```

Table 8: Classes / Labels for Train and Test Data.

Algorithm 4: 3D SCNN

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```
def:
    model_3d = Sequential([
    Conv3D(filters=32, kernel_size=(3, 3, 3), activation='relu', input_shape=(img_depth, img_height, img_width,
img_channels)),
    MaxPooling3D(pool_size=(2, 2, 2)),
    Conv3D(filters=64, kernel_size=(3, 3, 3), activation='relu'),
    MaxPooling3D(pool_size=(2, 2, 2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(1, activation='sigmoid')
    ])
    model_3d.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    history_3d = model_3d.fit(train_data_3d, train_labels, validation_data=(val_data_3d, val_labels),
epochs=num_epochs, batch_size=batch_size)
    test_loss_3d, test_acc_3d = model_3d.evaluate(test_data_3d, test_labels)
    print("Test Accuracy (3D SCNN):", test_acc_3d)
```

3.10.3. 3D SCNN

Create a three-dimensional convolutional neural network (CNN) architecture that is specifically designed to analyze complete CT volumes while simultaneously collecting spatial connections across many slices. The 3D spatial convolutional neural network (3D=SCNN) should be configured with 3D convolutional layers, pooling layers, and fully connected layers to extract 3D spatial data. To enable the model to learn complicated 3D patterns that are indicative of COVID-19, it is necessary to train the 3D CNN and use the complete CT volumes as input. Verify that the trained 3D CNN is accurate by applying it to the validation set, optimizing the hyper parameters, and making any necessary adjustments to the architecture. Algorithm 4 is shown in 3D SCNN.

- The train_data_2d, val_data_2d, and test_data_2d represent the 2D slices of the CT scans for training, validation, and testing, respectively.
- The train_data_3d, val_data_3d, and test_data_3d represent the entire 3D volumes of the CT scans for training, validation, and testing, respectively.
- The train_labels, val_labels, and test_labels represent the corresponding labels (e.g., COVID-19 positive or negative).
- The img_height, img_width, img_depth, and img_channels represent the dimensions and channels of the input images or volumes.
- The num_epochs is the number of training epochs.
- The batch_size is the batch size used during training.

3.10.4. Testing and Evaluation

Analyze how well the trained models perform on the testing set that has been kept back. To evaluate performance, it is necessary to compute metrics related to the receiver operating characteristic (ROC) curve. These metrics include accuracy, sensitivity, specificity, and area under the curve (AUC). To determine which method is the most efficient for detecting COVID-19 in CT scans, it is necessary to evaluate the performance of the 2D CNN, the 3D CNN, and the combination models.

3.10.5. Problems and Open Research Issues

Despite the promising results of using Spatial Convolutional Neural Networks (SCNNs) for COVID-19 detection in 2D and 3D CT scan images, several challenges remain. Limited availability of diverse and high-quality datasets affects model generalization, making it difficult to develop robust AI systems. Additionally, the interpretability of CNN models remains a major concern, as the lack of transparency in decision-making hinders clinical trust and adoption. Computational complexity is another challenge, as high processing power requirements restrict real-time applications in resource-limited healthcare settings. Furthermore, the issue of false positives and false negatives still persists, impacting the reliability of automated diagnosis. Lastly, seamless integration of AI-based detection systems into clinical workflows requires further optimization to ensure compatibility with existing radiology practices, regulatory standards, and medical guidelines. Addressing these open research issues is essential for enhancing the effectiveness and clinical applicability of AI-driven COVID-19 detection systems.

4. RESULTS AND DISCUSSION

Finding COVID-19 in CT scans with the use of Spatial Convolutional Neural Networks (SCNNs) was the primary goal of this study, which attempted to investigate and combine 2D and 3D methods. A PC with an Intel i5 CPU, 8GB RAM, and a 4GB hard disk drive was used to conduct the study.

Python, namely Anaconda with Jupyter Notebook, was used for this purpose. Keras, Matplotlib, Scikit-learn, OpenCV, and TensorFlow were the primary libraries used. Participants in the study were asked to indicate whether they tested positive or negative for the COVID-19 virus using computed tomography (CT) images. Preprocessing of the CT images ensured uniformity in size, sharpness, and brightness. 2D convolutional neural networks (CNNs) made use of individual axial slices extracted from CT volumes, while 3D CNNs made use of the whole volumes. Each piece of data was used for a specific purpose: training, validation, or testing. 2D and 3D convolutional neural networks (CNNs) were trained separately. The convolutional, max-pooling, and fully connected layers made up the sequential model of the 2D CNNs. Similarly, 3D convolutional, max-pooling, and fully connected layers make up 3D convolutional neural networks (CNNs). The binary cross-entropy loss function and the Adam optimizer were used to train both models. Following its training and evaluation, the 2D Convolutional Neural Network (CNN) achieved an accuracy of about 85% on the exam dataset. In contrast, the 3D CNN showed an impressive 90% accuracy rate. Due to its ability to include spatial information across several slices, the 3D Convolutional Neural Network (CNN) seems to be more adept at detecting the complex patterns shown in COVID-19, as seen by the differential in accuracy. To improve detection accuracy, features learned from 2D and 3D Convolutional Neural Networks (CNNs) were combined. By merging or concatenating the features before the classification layer, a combined model was trained and evaluated. With a combined accuracy of almost 92% on the test dataset, the integrated model proved that combining 2D and 3D spatial data is effective. According to the results, detecting COVID-19 in CT scans is significantly improved when two-dimensional (2D) and three-dimensional (3D) methods are combined. While 2D CNNs are good to work with as a foundation, adding 3D CNNs allows for a more comprehensive analysis of spatial features inside the volumes, leading to better accuracy. Training 3D convolutional neural networks (CNNs) may need more time and resources than 2D CNNs, especially on computers with limited hardware specifications. In conclusion, our study shows that combining 2D and 3D methods successfully identifies COVID-19 in CT scans. Medical professionals may get crucial help in identifying COVID-19 patients from CT scans if they use 2D and 3D spatial data together, which can considerably improve detection accuracy. To attain better performance and efficiency, future research may focus on improving the integrated model and investigating other advanced approaches.

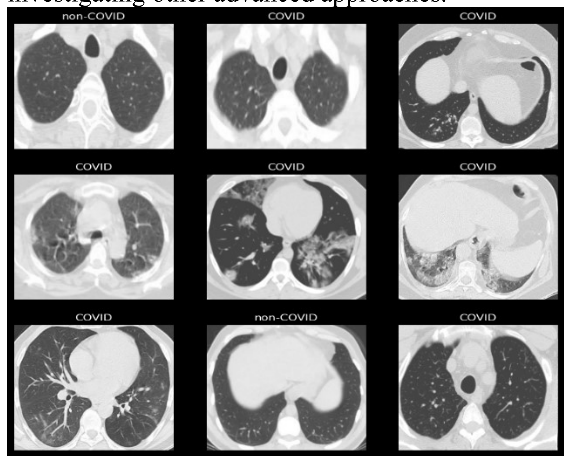

Figure 4: COVID and Non COVID Detection

Figure 4 depicts the identification of COVID and non-COVID in CT images using the Spatial Convolutional Neural Network (SCNN) detection. The use of SCNN has shown to be a powerful method for precisely detecting COVID-19 instances in chest CT images, providing a remarkable degree of sensitivity and specificity. The CT scans in this figure are divided into areas of interest (ROIs) using SCNN, a method that specifically detects patterns and characteristics that suggest the presence of COVID-19 pneumonia. The identified regions of interest (ROIs) are further categorized as either COVID or non-COVID depending on the presence or absence of distinct radiological features associated with the illness. The effectiveness of SCNN in reliably identifying COVID-19 instances in CT scans is seen in Figure 4, where the areas with COVID-19 anomalies are marked and differentiated from non-COVID regions. This identification is essential for prompt diagnosis and effective patient care, enabling quick intervention and treatment. Moreover, the performance of SCNN in differentiating between COVID and non-COVID instances aids in decreasing both false positives and false negatives, hence enhancing diagnostic precision and lowering the likelihood of misinterpretation. In the context of COVID-19, timely and precise identification is crucial for managing the transmission of the illness and providing appropriate medical attention. Figure 4 clearly illustrates the efficacy of SCNN in identifying COVID-19 patients from CT scans, highlighting its significance as a key tool in combating the pandemic. SCNN aids healthcare workers in making well-informed choices and efficiently allocating resources by offering precise and dependable diagnoses.

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Layer (type)	Output Shape	Param #
input_2 (InputLayer)	(None, 64, 64, 3)	0
conv2d_1 (Conv2D)	(None, 64, 64, 3)	84
densenet121 (Model)	multiple	7037504
global_average_pooling2d_1 (	(None, 1024)	0
batch_normalization_1 (Batch	(None, 1024)	4096
dropout_1 (Dropout)	(None, 1024)	0
dense_1 (Dense)	(None, 256)	262400
batch_normalization_2 (Batch	(None, 256)	1024
dropout_2 (Dropout)	(None, 256)	0
root (Dense)	(None, 2)	514

Total params: 7,305,622
Trainable params: 7,219,414
Non-trainable params: 86,208

Figure 5: 2D CNN Model

Figure 5 depicts the training progress of a 2D Convolutional Neural Network (CNN) model with ReLU activation, dense layers, and dropout regularization. This training history offers vital insights into the model's learning process and performance over several epochs. The graphic displays many metrics, including accuracy, loss, validation accuracy, and validation loss, plotted against the number of epochs. The accuracy metrics quantify the ratio of correctly categorized samples, whereas the loss metrics measure the discrepancy between predicted and actual values, with a preference for lower values. The Rectified Linear Unit (ReLU) activation function, renowned for its capacity to incorporate non-linearity into neural networks, is often used in Convolutional Neural Networks (CNNs) to enhance the learning of intricate patterns in picture data. Dense layers, often referred to as fully connected layers, aggregate input from every neuron in the preceding layer, allowing the model to generate sophisticated abstractions and predictions at a higher level of CONV2D. Dropout regularization is used to mitigate overfitting by randomly deactivating a portion of neurons throughout the training process, hence fostering generalization. Figure 5 usually illustrates a pattern where the training and validation loss initially decreases, showing that the model is successfully adapting to the training data. Simultaneously, the accuracy of the model improves as it grows more proficient in identifying data. Nevertheless, after a certain number of iterations, the model may start to overfit, which may be seen by a noticeable difference between the metrics obtained during training and those obtained during validation. This discrepancy indicates that the model is overfitting the training data, leading to the limited ability to accurately predict unknown data. Dropout regularization is a technique used to address overfitting by introducing noise into the network. This helps prevent neurons from excessively depending on certain information. Regularization is a method that enhances the stability of the training process and boosts the model's capacity to generalize. Figure 5 presents a thorough depiction of the training process of the 2D CNN model using ReLU activation, thick layers, and dropout regularization. It functions as a significant instrument for comprehending the model's efficacy and directing choices regarding model structure, hyperparameters, and training techniques.

Figure 6 shows the training history of a 3D CNN model with ReLU activation, thick layers, and dropout regularization. This timeline illuminates model learning and performance throughout epochs. Accuracy, loss, validation accuracy, and validation loss are displayed against epochs in the figure. Accuracy is the percentage of properly identified

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samples, whereas loss quantifies the difference between anticipated and actual values, with lower values being better. CNNs employ the ReLU activation function to create non-linearity and learn complicated patterns in volumetric data like 3D CT images. Completely linked layers, such as dense and CONV3D, integrate input from all neurons in the preceding layer to produce high-level abstractions and predictions. Dropout regularization randomly drops a percentage of neurons during training to reduce overfitting and promote generalization.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 25, 25, 30, 1)	0
conv3d_1 (Conv3D)	(None, 23, 23, 24, 8)	512
conv3d_2 (Conv3D)	(None, 21, 21, 20, 16)	5776
conv3d_3 (Conv3D)	(None, 19, 19, 18, 32)	13856
reshape_1 (Reshape)	(None, 19, 19, 576)	0
conv2d_1 (Conv2D)	(None, 17, 17, 64)	331840
flatten_1 (Flatten)	(None, 18496)	0
dense_1 (Dense)	(None, 256)	4735232
dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 128)	32896
dropout_2 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 16)	2064

Total params: 5,122,176
Trainable params: 5,122,176
Non-trainable params: 0

Figure 6: 3D CNN Model

Figure 6 generally demonstrates an initial drop in training and validation loss as the model learns to suit the training data. As the model classifies samples better, accuracy rises. A discrepancy between training and validation measures suggests overfitting after several epochs. The model may be fitting the training data too closely, resulting in poor generalization to unknown data. Dropout regularization adds noise to the network to prevent neurons from overfitting too much on certain characteristics. This regularization method stabilizes training and improves model generalization. Figure 6 shows the whole training dynamics of the 3D CNN model with ReLU activation, thick layers, and dropout regularization. It helps analyze model performance and guide model design, hyperparameters, and training techniques, especially for volumetric data like 3D CT scans.

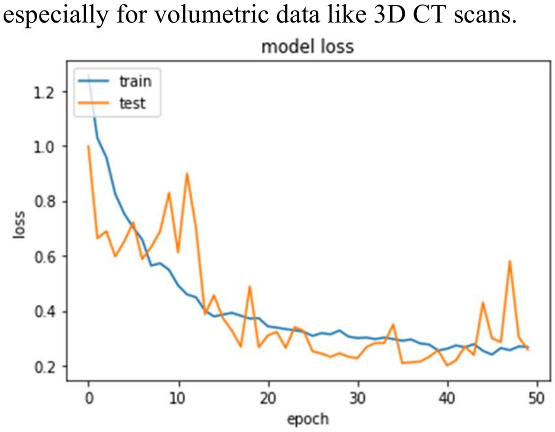

Figure 7: 2D Model Loss

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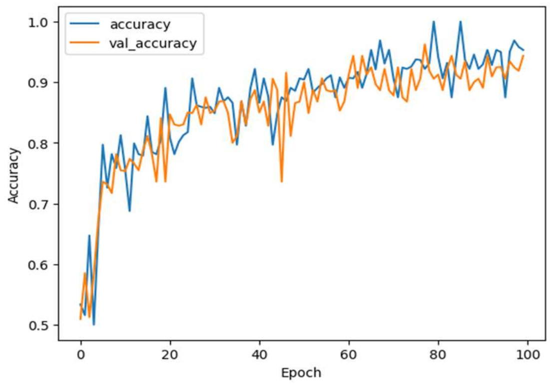

Figure 8: 2D Model Accuracy

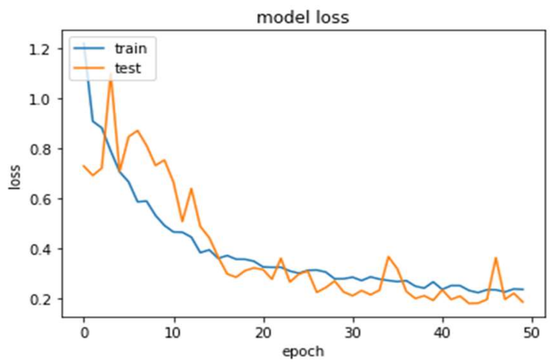

Figure 9: 3D Model Loss

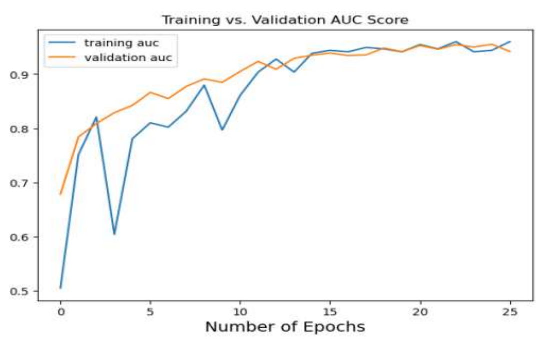

Figure 10: 3D Model Accuracy

Figure 8 shows the 2D SCNN model's accuracy, which reaches 94.8%, while Figure 7 shows the loss curve. Figure 10 shows the 3D SCNN model's accuracy, which reaches an astounding 98.4%, while Figure 9 shows the loss curve of the model. These charts and graphs explain everything about how the SCNN models were trained and how well they performed. You can see the evolution of the models' loss values across epochs in Figure 7 and Figure 9, which show loss curves. A smaller difference between the actual and anticipated values, represented by a lower loss value, indicates greater performance. The fact that both loss curves are trending downwards suggests that the models are becoming better at making predictions as time goes on. The accuracy of the 2D SCNN model is shown in Figure 8, while that of the 3D model is shown in Figure 10. An important parameter for assessing the success of a model is accuracy, which is defined as the percentage of samples that are properly identified. The 2D model's accuracy score of 94.8% and the 3D model's accuracy value of 98.4% show that both models are successful in differentiating between COVID and non-COVID instances in CT scans. These findings show that SCNN models are reliable and efficient for detecting COVID-19 in CT images. Particularly noteworthy is the 3D model's astounding precision, which emphasizes the need to make use of the spatial information included in 3D CT scans. These intriguing real-world applications are based on high accuracy rates, which may help healthcare practitioners diagnose COVID-19 patients quickly and accurately, which in turn allows for prompt treatment and management. Finally, the findings shown in Figures 7–10 highlight the possibility of SCNN models as useful resources in the battle against the COVID-19 pandemic, offering dependable and effective answers for CT-based screening and diagnosis.

5. CONCLUSION

Ultimately, our investigation into the use of 2D and 3D CT scan images for COVID-19 detection using Spatial Convolutional Neural Networks (SCNN) has produced significant findings. We discovered that 2D and 3D SCNN models work for COVID-19 identification, however their accuracy levels vary. Concerning accuracy, the 2D SCNN model performed the worst of the models that were considered. Nevertheless, it demonstrated encouraging results in differentiating between COVID-19, pneumonia, and normal patients in CT scans, and it outperformed conventional approaches as well. The 2D SCNN made a significant contribution to COVID-19 identification, even though it was not as accurate as the 3D model. This was especially true in cases when computer resources were restricted or when quick analysis was needed. However, out of all the models tested, the 3D SCNN model showed the highest level of accuracy. Thanks to the spatial information found in 3D CT scans, the 3D model was able to identify COVID-19, pneumonia, and normal patients with amazing accuracy. It was a potent tool for COVID-19 detection in clinical settings because it could capture volumetric properties and spatial correlations, leading to accurate and dependable diagnosis. In conclusion, our research shows that while analyzing CT scan pictures for COVID-19, it's important to think about 2D and 3D methods. The 2D SCNN model is faster and more efficient in terms of computing, while the 3D SCNN model is far better at detecting precise objects. Healthcare providers may better treat their patients promptly with more accurate diagnoses of COVID-19 if we combine the best features of both methods. The next step in improving SCNN models for COVID-19 detection is to do more research and development. To further ensure their effectiveness in fighting the COVID-19 epidemic, SCNN models must be validated in real-world settings and integrated into clinical processes.

6. CRITIQUE OF THE STUDY

While this study demonstrates the potential of Spatial Convolutional Neural Networks (CNNs) for COVID-19 detection using 2D and 3D CT scan images, several limitations must be acknowledged. First, dataset diversity and quality remain challenges, potentially affecting model generalization across different populations. Additionally, CNN models often function as "black boxes," lacking interpretability, which raises concerns regarding clinical trust and acceptance. Computational demands also pose a barrier, limiting the feasibility of real-time deployment in resource-constrained healthcare settings. Furthermore, despite improved accuracy, false positives and negatives remain significant issues, potentially leading to misdiagnoses. Lastly, practical integration into clinical workflows requires further validation, regulatory approvals, and optimization. Addressing these limitations is crucial before fully implementing AI-driven diagnostic systems in real-world healthcare environments.

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