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Enhancing Covid-19 Detection Accuracy Using R-CNN and Deep Learning Techniques

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ABSTRACT: Deep learning paradigms are commonly used to investigate radiological pictures, particularly thoracic imaging, which include a wealth of information such as patterns and structural groupings. These traits are critical for the consistency and identification of outbreaks like Covid-19. The coronavirus disease (COVID-19) pandemic has had a severe effect on global well-being and public health, with over 27 million confirmed cases globally. Given the growing number of confirmed cases and the problems posed by COVID-19 variations, accurately identifying healthy and infected persons is crucial for successful management and treatment. AI approaches, notably region-based convolutional neural networks (CNNs), have shown effective in evaluating and categorizing medical pictures.In this paper, propose a deep mask R-CNN architecture based on chest image classification for diagnosing COVID-19. However, the lack of chest image datasets of sufficient size and high quality poses challenges in achieving effective and accurate masked R-CNN classification. To address these complexities, we use masked region-based convolutional neural network (RCNN) regions as a framework for detecting COVID-19 patients from chest images using available open source datasets. will be introduced. First, the model was tested using his 100 images from the original processing dataset and achieved high accuracy. The model was then evaluated using an independent COVID-19 X-ray image dataset, and the model outperformed all other models, particularly when tested using an independent test set has been proven.

KEYWORDS: COVID-19, CNN, Mask RCNN, X-ray images, Deep learning

I. INTRODUCTION

The first reported case of COVID-19 occurred on December 1, 2019, when the virus was derived from a novel coronavirus, likely evolving from an animal source and then mutating to cause disease in humans. It is believed that he did. Historically, outbreaks of various infectious diseases have been associated with viruses originating from birds, pigs, bats, and other animals that mutate and pose a threat to human health. Ongoing research aims to elucidate the evolutionary mechanisms behind the coronavirus's transformation into a pandemic-causing pathogen. COVID-19, an infectious disease caused by the virus, typically manifests as mild to moderate respiratory illness in most individuals, with recovery without specialized treatment being common. However, some people can develop serious illnesses that require medical intervention, and older adults and people with underlying health conditions such as cardiovascular disease, diabetes, chronic respiratory disease, and cancer are more likely to develop complications. The risk of It's important to remember that anyone, regardless of age, can become infected with COVID-19 and experience serious illness or death.

Effective prevention and mitigation of infections depends on a comprehensive understanding of the disease and its transmission routes. Individuals protect themselves and others by staying at least one meter away from others, wearing a well-fitting mask, and practicing frequent hand hygiene using soap and water or alcohol-based sanitizers. can be protected. Vaccination is also important and individuals should follow local guidance regarding vaccination eligibility and scheduling. The virus spreads through droplets or aerosols expelled from the mouth or nose when an infected person coughs, sneezes, talks, sings, or breathes.

Deep learning paradigms are commonly used to evaluate radiology X-ray pictures, including chest X-rays (CXRs) and CT scan X-ray images. These photos show intricate patterns and structures that are useful for spotting epidemics such as COVID-19. Deep learning has a wide range of applications, including natural language processing, computer vision, life sciences, and epidemiology. The availability of large data and the design of learning challenges both have an impact on the success of any application. This analysis evaluates the present status of deep learning, identifies

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important limits of deep learning applications in COVID-19 control, and emphasizes the significance of ongoing research and innovation to tackle pandemic problems.

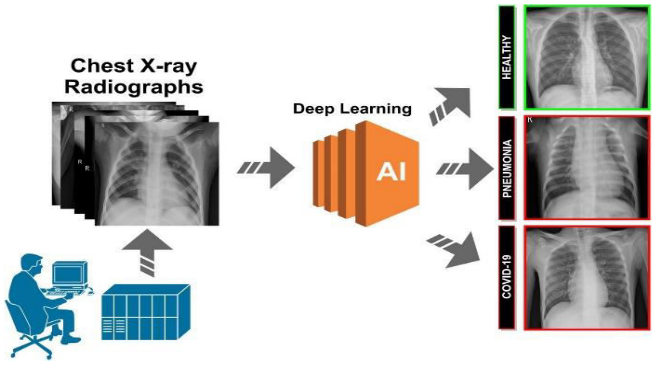

Fig 1: Image processing X-Ray Image

There are several methods for testing COVID-19 positive individuals, frequently relying on respiratory samples, and radiological imaging, particularly X-ray images, play a crucial role in diagnosis. Recent research has demonstrated that X-ray pictures include useful information about the SARS-CoV-2 infection. Deep neural network (DNN) technology used with radiological pictures improves illness detection and tackles the issue of physician shortages in distant places. This research introduces a Faster Regional Convolutional Neural Network (Faster R-CNN) based on the VGG-16 network (also known as OxfordNet) to identify COVID-19 from chest X-ray images utilizing open source technology framework.Mask R-CNN has been effectively used to a variety of tasks, including cell nucleus segmentation, lung nodule identification, and liver segmentation, however its application to COVID-19 detection in chest X-ray images is currently being investigated. There is room. A radiologist generally performs COVID-19 imaging and delivers a diagnostic report based on the visual interpretation of the pictures. Because chest radiography is commonly utilized in medical institutions and hospitals, our suggested approach may be useful for wider practical adoption.

II. LITERATURE REVIEW

The COVID-19 virus has spread globally, including to Indonesia, escalating into a lethal pandemic without a vaccine to curtail transmission. The existing lab facilities for COVID-19[1] testing are nearing capacity, prompting a search for alternative diagnostic methods. Traditionally, swab tests have been employed for detection, but recent research from Stanford University has introduced the CheXNet algorithm [2] [3], initially designed for pneumonia detection from chest X-rays, which has since been adapted to diagnose 14 pathological conditions with superior performance compared to experienced radiologists. In our pursuit of enhanced diagnostic accuracy, we integrated the Firefly algorithm (FA) [18] with a convolutional neural network (CNN) model to refine the performance and efficiency of the proposed model.

To increase the accuracy of computer-aided diagnostic tools, a recent research utilized artificial intelligence to chest X-ray pictures to discern between COVID-19 and non-COVID-19 pneumonia capacity has been assessed [4][17]. As the new coronavirus illness (COVID-19) continues to cause devastation throughout the world, medical experts worldwide [5] acknowledge the need of combating this epidemic. The dataset utilized in this work represents people's real behavior during the COVID-19 epidemic and contains 760 photos and over 4,500 tagged items, including persons, groups, the audience is separated into three groups: training, validation [6], and testing.

Another study proposed [7] a Transfer Learning strategy using CNNs to detect COVID-19 infection from CT images, leveraging a multilayer CNN architecture with the Inception V3 Transfer learning model[8]. Although pre-trained CNN models have shown promising results, this paper endeavors to optimize model size and validate performance on additional datasets, considering various image sizes[10]. COVID-19 has emerged as a rampant epidemic affecting millions worldwide, with dire consequences including fatalities and widespread health implications[14]. As the need for large-scale screening intensifies[11] [12], computer vision researchers have developed deep learning systems capable of predicting COVID-19 using Chest-CT scans, albeit with limitations owing to the immense data requirements of CNNs.

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A novel ACNN network employing two optimizer networks, Rms prop and SGD[19] [13] with momentum, has been proposed, implemented on both CPU and GPU platforms to expedite processing time. This collection includes X-ray pictures of individuals with COVID-19, other pneumonia, and no results. The network was pre-trained on the ImageNet dataset, which included natural pictures, and then fine-tuned for COVID-19 identification on chest X-ray images. In this study [15], we provide a basic CNN-based deep learning model, Grad-CAM CNN (GCNN) [16], that can detect new coronavirus infections from chest X-ray images. When combined with Grad-CAM visualization, it is feasible to generate a heat map that identifies regions of coronavirus infection inside a chest X-ray. Through these methodologies [20], we strive to enhance diagnostic accuracy and expedite COVID-19 detection, offering valuable tools in the global fight against the pandemic.

III. IMPLEMENTATION OF PROPOSED METHOD

This work introduces a Mask R-CNN model and a corresponding dataset designed specifically for detecting crowds and groups of people within a shopping area in Indonesia during the COVID-19 pandemic. The dataset captures real-world behaviors of people amidst the pandemic. The model utilizes Mask R-CNN, a state-of-the-art technique for object detection, with a dynamic learning rate specifically tailored for detecting COVID-19 related behaviors. The main contribution lies in presenting a comprehensive workflow for implementing the Mask R-CNN model, which can be utilized for crowd detection. This workflow sets the foundation for building an automatic monitoring system.

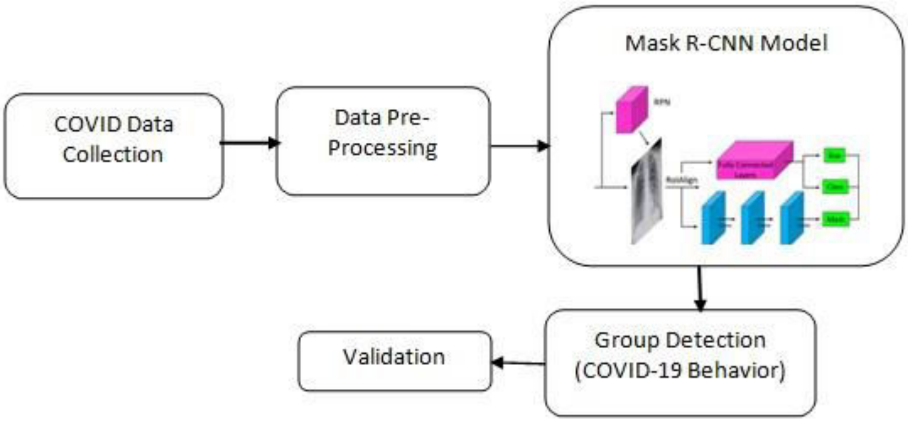

Fig 2: Block Diagram of proposed method

Additionally, the paper explores the utilization of chest image datasets to implement a CNN model for deep learning. This CNN model is applied in a medical context for automatically detecting COVID-19 class from chest images, showcasing classification results in terms of accuracy. In this paper offers a practical approach for crowd detection using Mask R-CNN and provides insights into its potential application in creating automated monitoring systems, while also demonstrating the adaptability of deep learning techniques like CNNs for medical image analysis, particularly in the context of COVID-19 detection from chest images.

A. COVID Dataset Collection

Gathering X-ray image datasets for COVID-19 detection involves sourcing images from various medical facilities or repositories containing X-ray scans of patients suspected or confirmed to have COVID-19. This process entails obtaining consent and ensuring compliance with ethical guidelines regarding patient privacy and data usage. The collected X-ray images should encompass a diverse range of cases, including images of patients with confirmed COVID-19 infections, patients with other respiratory illnesses, and healthy individuals for comparison. Additionally, metadata such as patient demographics, clinical history, and diagnosis should be recorded to provide context for the images. Careful curation of the dataset is essential to ensure its representativeness and reliability. This may involve collaborating with healthcare professionals to verify the accuracy of diagnoses and annotations associated with each image. The goal is to create a comprehensive and well-annotated dataset that reflects the variability of COVID-19 manifestations in X-ray imaging.

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B. Denoising filters for Data Preprocessing

Preprocessing an X-ray image dataset entails numerous procedures to ensure that the data is ready for efficient deep learning model training. First, pictures are scaled to a consistent resolution and normalized by adjusting intensity values to account for differences in capture settings and equipment. Augmentation techniques can be used to improve the diversity and resilience of datasets. These methods include random rotations, translations, and inversions to imitate variations in patient location and picture capture angles. Boosting reduces overfitting and increases the model's capacity to generalize.

Algorithm Steps

Step 1: Define the size of the Gaussian kernel and the standard deviation.
Step 2: Iterate over each pixel in the image. And apply the Gaussian kernel to the neighborhood of each pixel using convolution.
Step 3: Compute the values of the Gaussian kernel based on the selected size and standard deviation.
Step 4: Typically, the Gaussian kernel is a 2D matrix with symmetrical values centered around the kernel's midpoint.
Step 5: Handle boundary conditions by applying appropriate padding to the image to ensure consistent filtering across the entire image.
Step 6: Common padding methods include zero-padding, symmetric padding, or replicating the image boundaries.

```
functionGaussianFilter(image, kernel_size, sigma):
kernel = CreateGaussianKernel(kernel_size, sigma)
filtered_image = Convolution(image, kernel)
returnfiltered_image
functionCreateGaussianKernel(kernel_size, sigma):
midpoint = kernel_size / 2
kernel = new Matrix(kernel_size, kernel_size)
sum_weights = 0
for i from 0 to kernel_size-1:
for j from 0 to kernel_size-1:
x = i - midpoint
y = j - midpoint
weight = (1 / (2 * pi * sigma^2)) * exp(-(x^2 + y^2) / (2 * sigma^2))
kernel[i][j] = weight
sum_weights += weight
for i from 0 to kernel_size-1:
for j from 0 to kernel_size-1:
kernel[i][j] = kernel[i][j] / sum_weights
return kernel
function Convolution(image, kernel):
output_image = new Image(image.width, image.height)
        for each pixel (x, y) in image:
weighted_sum = 0
for i from 0 to kernel.width-1:
for j from 0 to kernel.height-1:
nx = x + i - (kernel.width / 2)
                        ny = y + j - (kernel.height / 2)
                        ifnx>= 0 and nx<image.width and ny>= 0 and ny<image.height:
                                weighted_sum += kernel[i][j] * image[nx][ny]
                                        output_image[x][y] = weighted_sum
                                        returnoutput_image
                                End
                        End
                End
        End
```

Additionally, preprocessing may involve noise reduction and artifact removal to enhance the quality of the dataset. Techniques such as denoising filters and image enhancement algorithms can be applied to reduce noise and improve the clarity of X-ray images, ensuring better performance during model training and inference. The preprocessing pipeline

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should be carefully designed to preserve clinically relevant features while minimizing artifacts and distortions that may adversely affect the model's performance.

C. Mask R-CNN Model

Mask R-CNN is a powerful deep learning architecture capable of simultaneously detecting objects and segmenting them at the pixel level. In the context of COVID-19 detection from X-ray images, Mask R-CNN can be adapted to identify regions of pneumonia associated with the virus. The model is initialized with pre-trained weights on large-scale image datasets and fine-tuned on the COVID-19 X-ray dataset to adapt it to the task of pneumonia detection. During training, the model learns to differentiate between normal lung anatomy and areas of abnormal opacity indicative of pneumonia. The loss function is optimized using gradient descent algorithms such as Adam or SGD, with hyperparameters tuned to optimize model performance. Validation is performed iteratively during training to monitor the model's performance on unseen data and prevent overfitting. The test set is reserved for final evaluation, assessing the model's accuracy, sensitivity, specificity, and other performance metrics.

Algorithm Steps:

Step 1: Initialize the Mask R-CNN architecture with pre-trained weights on a large-scale image dataset (e.g., COCO dataset).
Step 2: Load the X-ray image dataset.
Step 3: Split the dataset into training, validation, and test sets.
Step 4: Forward pass: Input the images into the network to obtain predictions for bounding boxes, class labels, and segmentation masks.
Step 5: initialize Mask R-CNN model with pre-trained weights and load X-ray image dataset. split dataset into training, validation, and test sets
Step 6: for each epoch in training:

```
        for each batch in training data:
            forward pass: predictions = Mask R-CNN(images)
            compute loss: loss = calculate_loss(predictions, ground_truth)
            backward pass: update_parameters(loss)
        end
    end
for each batch in validation/test data:
            forward pass: predictions = Mask R-CNN(images)
            evaluate performance: metrics = evaluate (predictions, ground_truth)
integrate and deploy Mask R-CNN model for COVID-19 detection
```

Step 7: Compute the loss function, including classification loss, bounding box regression loss, and mask segmentation loss.
Step 8: Back propagate gradients and update the model's parameters using an optimization algorithm (e.g., stochastic gradient descent).

Once trained, the Mask R-CNN model can be integrated into clinical workflows to assist radiologists in identifying COVID-19 pneumonia from X-ray images. The model's predictions can be visualized as overlays on the original images, highlighting regions of abnormal opacity for further examination. Evaluation of the model's performance involves comparing its predictions with ground truth annotations and assessing metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). Additionally, clinical validation studies may be conducted to assess the model's impact on diagnostic accuracy and patient outcomes. Continuous monitoring and refinement of the model are essential to ensure its effectiveness in real-world clinical settings. Feedback from healthcare professionals and ongoing data collection efforts can inform model updates and improvements over time. This integrated workflow demonstrates how Mask R-CNN can be utilized in conjunction with X-ray image datasets for COVID-19 detection, enhancing the accuracy and efficiency of diagnostic processes in healthcare settings.

IV. RESULT AND DISCUSSION

To validate this process, simulation analysis utilizes a publicly available dataset from the Open repository. The experimental results employ k-fold cross-validation to assess the performance of the proposed work by training and testing the given dataset. The dataset is divided into training and test sets using different ratios, such as 70/30, 75/25, and 80/20 (referred to as A, B, and C). The comparison involves the Mask R-CNN method against existing methods

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such as Support Conventional Neural Network (CNN), Attention-based Recurrent Neural Network (ARNN), and Random Forest (RF).

The RCNN method exhibits consistent performance across 10 folds of evaluation for COVID-19 analysis, with an average precision of approximately 0.82, indicating that around 82% of positive predictions were accurate. The average recall of approximately 0.75 suggests that the model correctly identified 75% of actual positive cases. Additionally, the F1-score, averaging around 0.77, reflects a balanced measure of precision and recall.

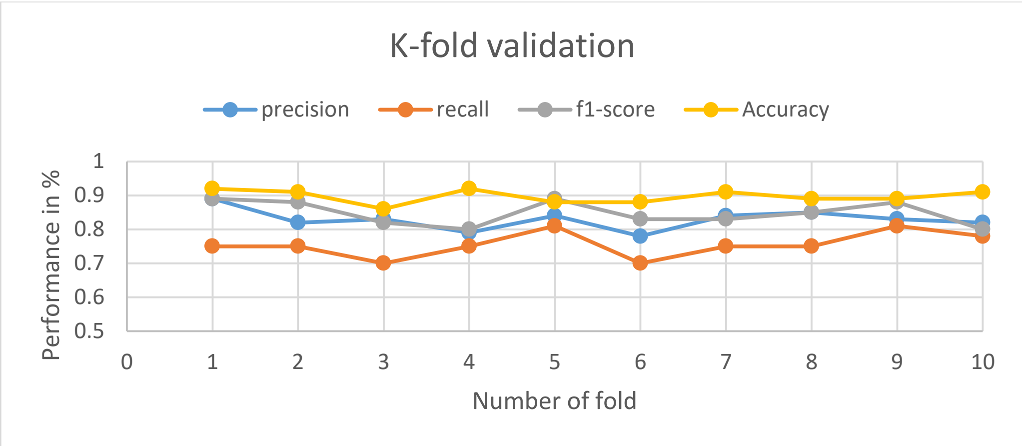

Fig 3: k fold validation performance analysis

The k-fold validation for split the data into the different datasets to analyze the system performance. With an average accuracy of approximately 0.89, the model demonstrates its ability to correctly classify 89% of the cases. These findings collectively indicate the RCNN method's effectiveness in COVID-19 analysis across multiple folds, highlighting its potential as a valuable tool in disease diagnosis and classification tasks.Table1 presents a comparison of proposed Masked R-CNN method test sets software defect prediction performance of f1-score, recall, precision and accuracy.The test sets A, B, and C demonstrate consistent performance across multiple evaluation metrics for the given task.

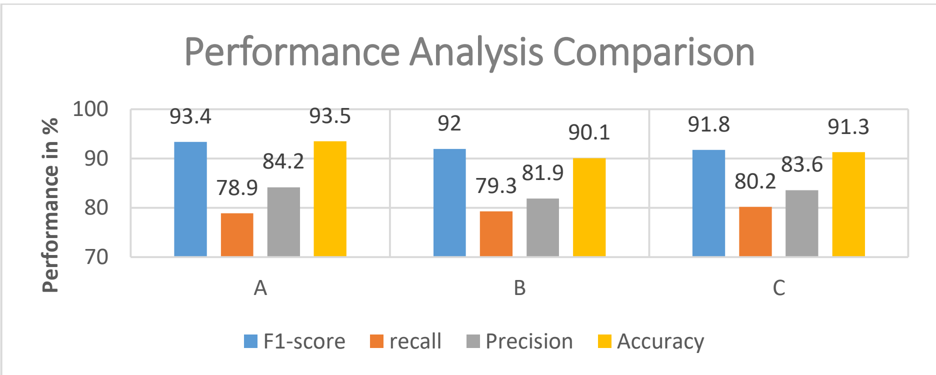

Fig 4: Proposed method Analysis

Test set A achieves the highest F1-score of 93.4%, indicating a strong balance between precision and recall, with recall at 78.9% and precision at 84.2%. Additionally, test set A exhibits high accuracy, scoring 93.5%. Test sets B and C also perform well, with F1-scores of 92.0% and 91.8%, respectively, showcasing robustness in model performance. Both sets B and C maintain similar levels of recall and precision, with recall values around 79% and precision values around 82%. While test set B slightly lags in accuracy compared to A and C, at 90.1%, all sets demonstrate commendable performance, underlining the reliability and effectiveness of the models on diverse datasets.

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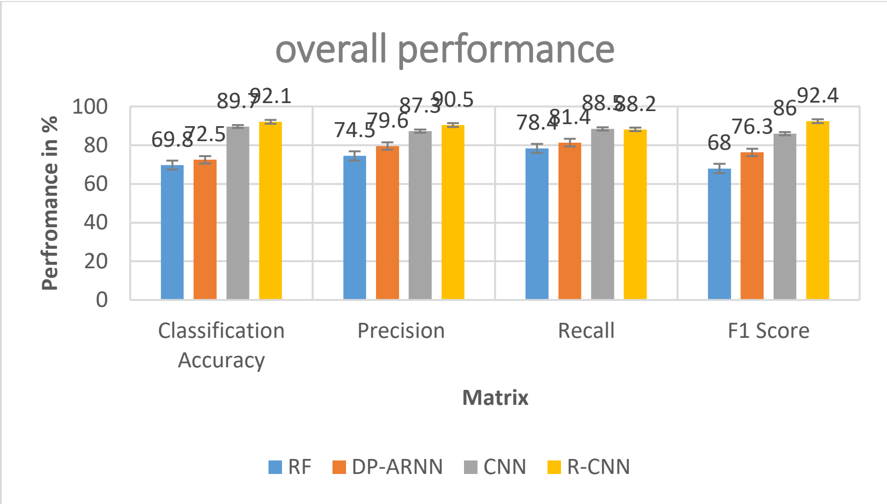

Fig 5: overall performance of the proposed and existing method

In the context of COVID-19 analysis, comparing the performance of various models, namely Random Forest (RF), ARNN, CNN, and R-CNN, reveals distinct characteristics in their classification abilities. While RF and DP-ARNN exhibit lower classification accuracy rates at 69.8% and 72.5% respectively, CNN and R-CNN showcase significantly higher accuracy levels at 89.7% and 92.1% respectively, underscoring their superior performance in distinguishing COVID-19 cases. Precision scores indicate the proportion of correctly predicted positive cases among all positive predictions, where R-CNN leads with 90.5%, followed closely by CNN at 87.3%. Similarly, in terms of recall, which measures the ratio of correctly identified positive cases to the actual positives, CNN and R-CNN outperform other models, with scores of 88.5% and 88.2% respectively. The F1 Score, a harmonic mean of precision and recall, reflects a balanced measure of a model's performance, with R-CNN achieving the highest score at 92.4%, highlighting its efficacy in COVID-19 analysis tasks. Overall, CNN and R-CNN demonstrate superior performance across multiple evaluation metrics, showcasing their potential as valuable tools for accurate COVID-19 classification.

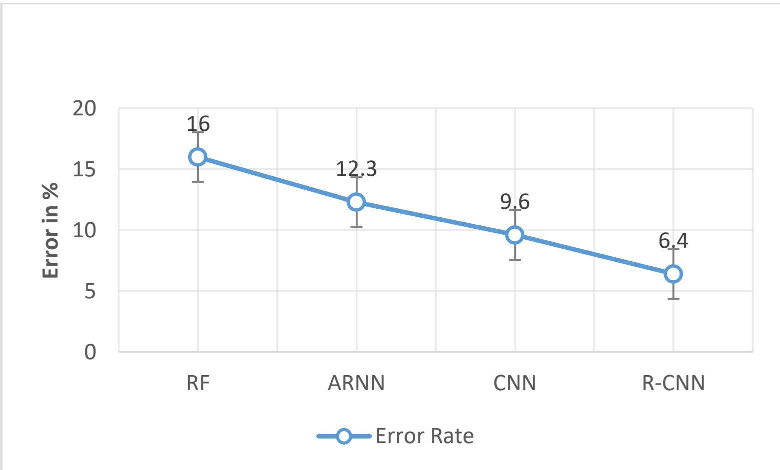

Fig6: Error rate analysis of proposed method

The error rates of various models, including Random Forest (RF), ARNN, CNN, and R-CNN, provide valuable insights into their performance in COVID-19 analysis tasks. With the lowest error rate of 6.4%, R-CNN emerges as the most accurate model, followed by CNN with an error rate of 9.6%. DP-ARNN exhibits a slightly higher error rate at 12.3%, while RF demonstrates the highest error rate at 16%. These findings underscore the superior accuracy and effectiveness of deep learning-based approaches, particularly R-CNN and CNN, in accurately classifying COVID-19 cases. The lower error rates of these models signify their robustness and reliability in disease diagnosis, highlighting their potential as essential tools for healthcare professionals in combating the COVID-19 pandemic.

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V. CONCLUSION

The review of scientific literature reveals significant advancements in automatic COVID-19 classification using RCNNs, with reported performance rates surpassing those of human specialists by over 30 percentage points. However, a critical observation indicates that many studies rely heavily on regions outside the chest area for classification, suggesting a form of shortcut learning. This reliance on non-chest regions may compromise the models' ability to generalize to new datasets. The recent advancements in automatic COVID-19 classification using RCNNs have shown promising performance a rate surpassing those of human specialists, the reliance on regions outside the chest area for classification suggests a potential issue of shortcut learning, compromising the models' generalizability. Furthermore, the absence of evaluation on external datasets in most studies raises concerns about the reliability of the models' learned patterns. Incorporating external dataset evaluation as a standard practice is essential for accurately assessing the generalization power of the models, particularly in biomedical applications where accurate diagnoses are crucial for patient treatment decisions. By ensuring robust validation practices, AI and DL methods can provide valuable assistance to radiologists in disease diagnosis and classification, ultimately improving patient outcomes in critical medical scenarios such as COVID-19.

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