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DEEP LEARNING TECHNIQUES FOR COVID-19 DISEASE DETECTION: A META-ANALYSIS

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Abstract
Deep learning has gained tremendous recognition as a prospective tool to support medical decision-making in various disorders, including localized and diffuse forms of COVID-19 disease.These methods have the ability for processing the complexity and large amount of imaging data also, like CT scans and X-ray images. The current study intends to assess the precision of deep learning methods in the detection of COVID-19. An organized search algorithm was devised to investigate three well-known databases, specifically Web of Science, PubMed, and Google Scholar to find studies that were publicly accessible from January 1st to December 15th, 2020. The meta-analysis was performed using the 22 shortlisted studies, comprising 4595 chest X-ray images obtained from the patients of COVID-19. The value for pooled sensitivity obtained was 0.91 with a 95% CI of 0.89-0.94 and for pooled specificity was 0.94 with a 95% CI of 0.90-0.96. The value of heterogeneity was obtained $I^2 = 78\%$, ($p < 0.01$). Our findings demonstrate that deep learning models have a great potential for appropriately classifying COVID-19 cases and separating them from patients suffering from other types of pneumonia as well as healthy people. An accurate and careful implementation of deep learning-based methods can surely help radiologists detect COVID-19 correctly and promptly. Health practitioners can benefit from artificial intelligence and deep learning systems to make faster and more efficient decisions.

Keywords: Artificial Intelligence, COVID-19, Diagnostic Accuracy, Sensitivity, Specificity

Introduction
COVID-19 is a dangerous worldwide contagious disease that spread at an alarming rate all over the world [1, 2]. The virus appears to be transmitted mostly through respiratory droplets [3]. Some people infected with COVID-19 exhibit a myriad of symptoms while others remain asymptomatic. Symptomatic patients have symptoms such as breathing difficulties, coughing, taste or smell loss, mild or severe fever, etc. COVID-19 was declared a pandemic when the World Health Organization (WHO) designated it as a public health emergency of global concern. A severe respiratory infection is common in such patients [4]. Imaging methods for the chest, such as computed tomography (CT) scans or chest X-ray radiography, are recommended as the initial screening methods to diagnose COVID-19 patients [5]. These are the frequently employed tools for a rapid diagnosis of pneumonia

[6, 7]. COVID-19 patients' CT scan pictures demonstrate the involvement of multilobar and peripheral airspace, with primarily ground-glass opacities [8, 9]. Patients with SARS-CoV-2 infection have also been observed to develop asymmetric patchy or diffuse airspace opacities [10]. Several studies have demonstrated the use of deep learning methods for the detection and identification of novel COVID-19 using radiography images [11].

At the initial stage of illness, a CT scan generally shows no evidence of lung involvement [12]. The diagnosis of vascular nodules with the help of CT scan images of patient's lungs is a challenge due to the complex and irregular structures within the images [13]. Consequently, the utilization of computer-assisted approaches, especially artificial intelligence and deep learning, has gained notable importance in the realm of medical decision-making. These innovative techniques have proven to be invaluable in enhancing the accuracy and efficacy of diagnosing vascular nodules in CT scans of the lungs, offering healthcare professionals an additional layer of support and guidance in their diagnostic endeavors.

The current research literature reveals that computer-assisted techniques like artificial intelligence can accurately detect COVID-19 from pneumonia and with higher accuracy [18]. However, there are certain limitations in published research, including limited sample size, a scarcity of external validation, a lack of comparative analysis to radiologist performance, etc. [19–21]. Deep learning algorithms have the ability to significantly improve decision-making in health care. However, the effective deployment of these advanced methods requires great attention to the underlying principles of each information system [22]. The integration of deep learning in medical diagnostics involves many challenges including the availability of quality data and the availability of various algorithms etc. Another concern is the variability in the performance of different methods across different healthcare settings [23]. The main purpose of this study is to critically evaluate the performance of various deep-learning methods that have been used to detect COVID-19 disease. More specifically, the performance of the deep learning methods is compared using the pooled accuracy, pooled specificity of the algorithms, and combined estimate for the odds ratio, and the most prevalent findings are provided.

Materials and Methods

Search Strategies

The studies included in this article are searched from three different databases; ISI Web of Science, Google Scholar, and PubMed. The published studies within the duration of 1st January, 2020 and December 15, 2020, were collected. Using these three search databases, altogether, 462 studies were retrieved and two independent authors extracted the data from all qualifying articles.

Selection Criteria for Studies

Searching different databases and examining reference lists provided a total of 462 studies. We eliminated 255 duplicate studies as well as 192 papers that didn't meet the selection criteria. We assessed 31 full-text papers and eliminated 9 others for diffeent reasons. Three studies used machine learning, three studies merged chest CT and chest X-ray datasets. Three studies failed to provide relevant parameters for evaluating the detection accuracy of deep learning methods. As a result, all these nine studies were also excluded from the final analysis. Finally, 22 research studies comprising 4595 COVID-19 images of the patients are included in the meta-analysis. All this information is summarized in Figure 1.

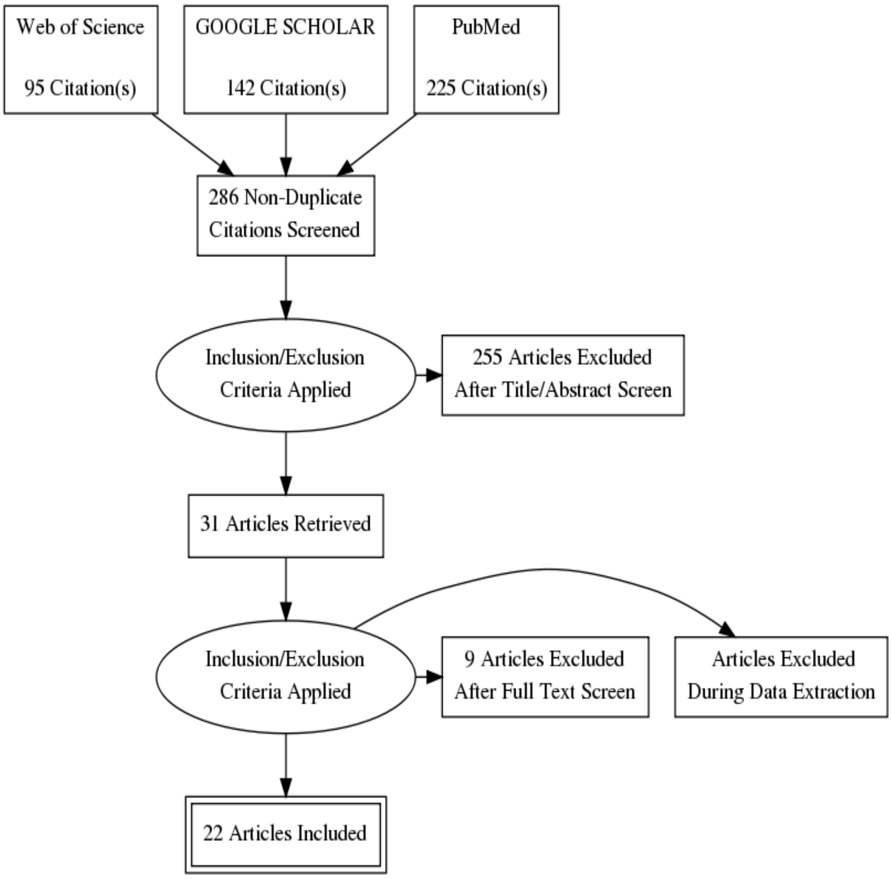

Figure 1: PRISMA flowchart

Statistical Analysis

The meta-analysis was performed for the evaluation of the diagnostic ability of different deep-learning algorithms. In this comprehensive review, both the pooled sensitivity and the pooled specificity were meticulously calculated, and their respective 95% confidence intervals were established to provide a clear understanding of the algorithms' diagnostic capabilities. To address the potential variability across the different studies, Cochran's Q-statistic test was employed as a measure to measure the significance of heterogeneity among the collected data. This test played a crucial role in determining whether to apply a fixed-effects or a random-effects model when consolidating the study estimates. The choice between these models was dependent upon the outcomes of the Q-statistic.

Furthermore, the I^2 statistic was utilized as an additional tool to quantify the extent of heterogeneity present in the study results. The significance of the I^2 statistic was ascertained through its corresponding p-value. A significant p-value would suggest that the observed variability in study findings is more likely due to underlying differences in study design or population rather than random chance. This level of detailed analysis is critical for interpreting the meta-analysis results and for understanding the performance of deep learning algorithms in a diagnostic context.

Results and Discussion

The diagnostic performance of deep learning algorithms to detect COVID-19 patients was determined based on the 22 studies [18, 20, 21, 24–42]. This evaluation yielded a high pooled sensitivity rate of 0.91, with a 95 percent confidence interval ranging from 0.89 to 0.94, indicating a strong ability of the algorithms to correctly identify positive cases. In addition, the algorithms yielded a pooled specificity rate of 0.94 (with a 95 percent confidence interval between 0.90 to 0.96), reflecting their effectiveness in accurately excluding individuals who do not have the disease.

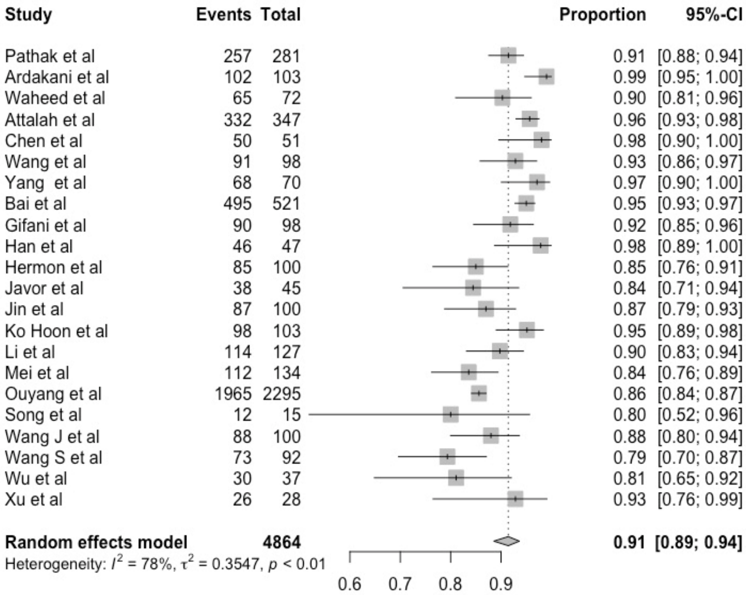

Figure 2: Pooled sensitivity: Evaluating Different Deep Learning Techniques in Diagnosing COVID-19 Patients.

The graphical representations of all these aggregated metrics are provided in Figures 2 and 3, which illustrate the combined sensitivity and specificity, respectively. Further, Figure 4 presents the aggregated results for the overall diagnostic accuracy of these tests, showing an odds ratio (OR) of 140.28, with a wide 95 percent confidence interval from 69.77 to 282.05. This odds ratio quantifies the likelihood of deep learning algorithms successfully distinguishing between COVID-19 patients and non-patients compared to chance.

The heterogeneity among the studies measured by the I^2 statistic was found to be 90% which is a considerably high level. It indicates a significant variability in the study outcomes as the p-value obtained was less than 0.01, underscoring the heterogeneity's statistical significance. Despite this variation, the pooled odds ratio still provides valuable insight into the diagnostic power of the algorithms, as visualized in Figure 4.

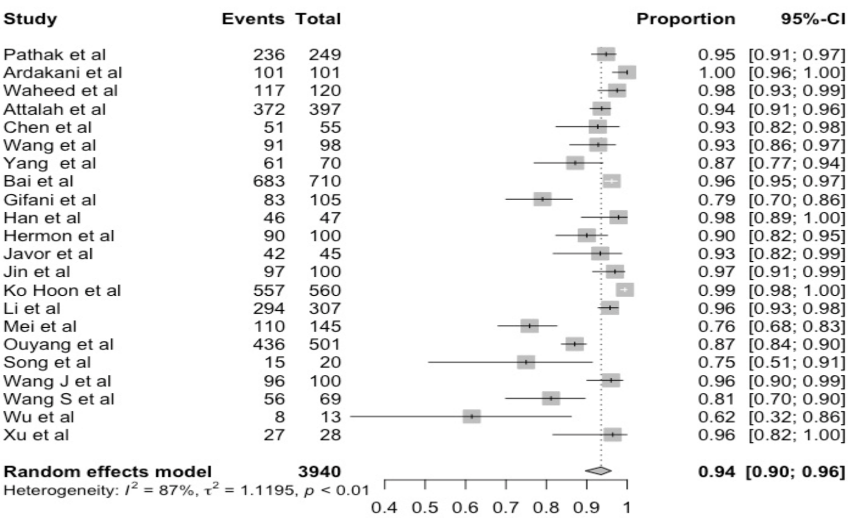

Figure 3: Pooled specificity: Evaluating Different Deep Learning Techniques in Diagnosing COVID-19 Patients.

To address potential publication bias, Figure 5 shows a funnel plot. The plot did not reveal any significant bias because the asymmetry is statistically insignificant (p=0.57). This suggests that the publication bias is not likely to have skewed the results of the meta-analysis regarding the diagnostic performance of deep-learning algorithms for detecting COVID-19.

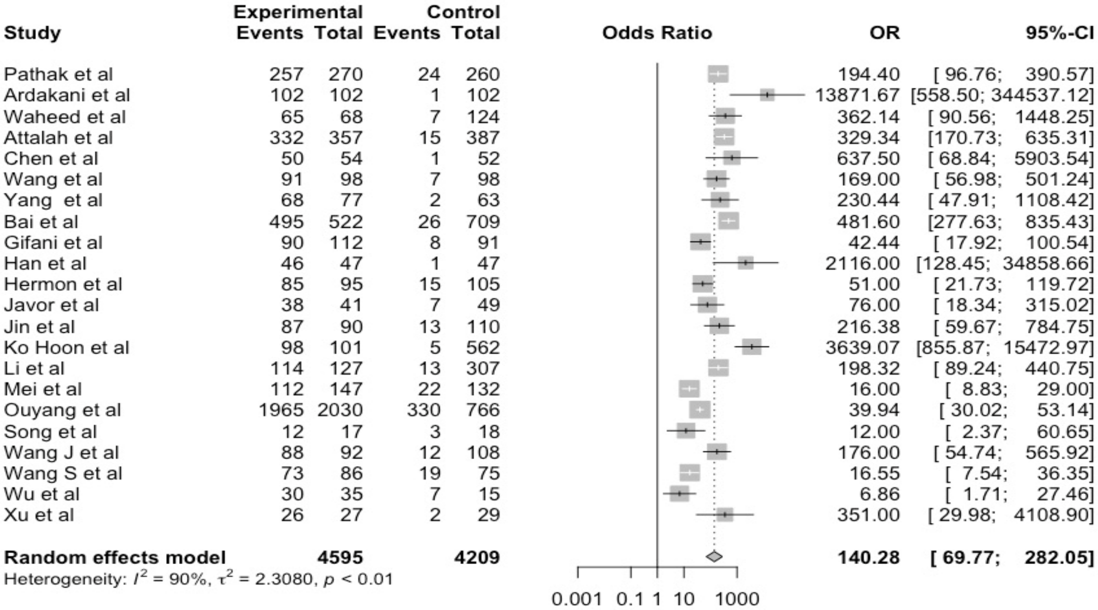

Figure 4: Performance of different methods based on deep-learning algorithms to detect COVID-19 patients

The current article evaluated 22 studies to examine the detection accuracy of deep learning algorithms for identifying COVID-19 disease. The pooled value of diagnostic test accuracy was found to be 0.91 with a 95 percent confidence interval (0.89 to 0.94) and I^2 = 78%. The pooled result for specificity was 0.94 with a 95 percent confidence interval (0.90 to 0.96) and I^2 = 87%. The patients with COVID-19 disease can be successfully identified from other types of pneumonia patients using deep learning methods as evidenced by the high pooled accuracy and specificity of the deep learning methods.

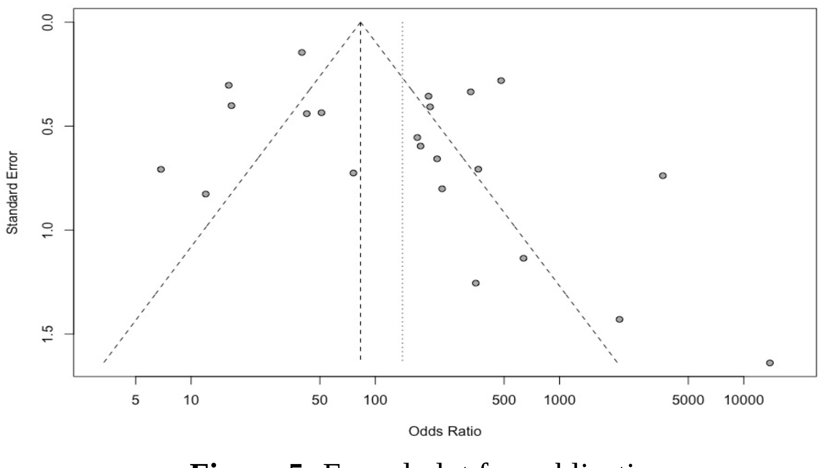

Figure 5: Funnel plot for publication

We compared our findings with some other studies using meta-analysis for the detection of COVID-19 using deep learning methods. Moezzi et al. [12] reported similar results in a prior investigation using deep learning techniques to detect COVID-19 based on 23 studies. They reported a pooled sensitivity of 0.91, specificity of 0.88. When the combined sensitivity was compared to the study of Mahmoud et al. [43] for detection test accuracy of chest radiography to detect COVID-19 using seven studies, the pooled sensitivity was found to be 0.89, which is consistent with a pooled sensitivity of 0.89 observed by Komolafe et al. [44] for detection test of chest CT scans using 36 studies. According to our findings, detection based on deep learning methods attained a better sensitivity. Thus, deep learning methods can detect more COVID-19 than radiologist results from Komolafe et al. [44] and Mahmoud et al. [43]. Furthermore, in comparison to the aggregate result based on seven studies obtained by Vafea et al. [45], our pooled sensitivity increased by around 0.90 percent. Our findings are also consistent with Bao et al. [43] whose findings are based on the pooled sensitivity of thirteen studies.

A slightly higher than our result was obtained by Boger¨ et al. [47] who conducted a meta-analysis using 6 studies and with a pooled sensitivity of 0.92. Similarly, Kim et al. [48] observed a pooled sensitivity of 0.94 in a meta-analysis involving 63 studies, which shows a 3.3 percent increase as compared to our results based on 22 studies using deep learning methods for the detection of COVID-19. These findings are consistent with the compelling observations of Duarte et al. [49], who merged two trials and obtained the pooled sensitivity of 0.953.

When it comes to specificity, the studies based on meta-analysis identification of coronavirus patients utilizing CT scans of chests, rarely mention it. The pooled specificity in our analysis was found to be 0.94. This value remarkably surpasses the finding of Kim et al. [48] using 63 studies, who obtained 0.37, a much lower value pooled specificity. Other studies reporting the pooled specificity include Duarte et al. [49], who reported a pooled specificity of 0.44 which is a 53.2% decrease as compared to our pooled specificity. Similarly, Boger¨ et al. [47] who had previously reported better sensitivity, had a pooled specificity of 0.251, which was exceedingly low (73.3%). These specificities further emphasize the nuanced nature of detection accuracy and the need to consider both sensitivity and specificity in evaluating the performance of deep learning methods for COVID-19 identification.

Conclusions

Deep learning techniques have shown promising results in recognizing indicators of lung involvement in patients with COVID-19 disease. The presence of selection bias and the retrospective design of existing studies suggest a need for further investigation through prospective, real-time trials to solidify the contributions of deep learning techniques in improving the promptness and precision of COVID-19 diagnoses. The results of this research suggest that deep learning methods possess a strong capability to distinguish individuals suffering from COVID-19 from those with pneumonia or from healthy ones. These methods can help radiologists quickly screen for COVID-19 and categorize patients with elevated risk, which could have clinical implications for early patient treatment and resource optimization. An elevated proportion of false negatives may have disastrous consequences for society, and as a result, it's critical to validate model performance with additional, unknown data sets. To evaluate the implementation of artificial intelligence models in real-world healthcare and clinical settings, retrospective evaluation and reliable interpretation of results are crucial.

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