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Neural Networks for the Diagnosis of Covid-19 in Chest X-ray Images: A Systematic Review and Meta-Analysis

Daniel Cristobal Andrade-Girón[1], William Joel Marín-Rodriguez[1, 2, *], Flor de María Lioo-Jordán[1], Gladis Jane Villanueva-Cadenas[1], Flor de María Garivay-Torres de Salinas[1]

[1] Universidad Nacional José Faustino Sánchez Carrión. Huacho, Lima, Perú.
[2] Universidad Tecnologica del Perú. Lima, Perú.

Abstract

Introduction: The COVID-19 pandemic has triggered a global crisis with significant repercussions in terms of mortality and an ever-increasing demand for urgent medical care, particularly in emergency care settings. This demand arises mainly from the prevailing need to carry out real-time diagnoses and provide immediate care to patients at high risk of serious complications. With the purpose of addressing this problem in a rigorous manner, we have carried out a systematic review focused on evaluating the effectiveness of models based on neural networks for the diagnosis of COVID-19 from chest x-ray images.
Methods: This review has been carried out through an exhaustive search in various renowned electronic bibliographic databases, such as Scopus, IEEE Xplore, PubMed and ScienceDirect. The search period has been extended until September 2023, culminating in the identification of a total of 1,250 relevant articles.
Results: The culminating phase of our review involved the inclusion of 37 studies that met rigorously established selection criteria. These studies have been the subject of a thorough analysis, where various performance metrics such as accuracy/precision, sensitivity/recall, specificity and the F1 value (F1-score) have been evaluated.
Conclusions: Our results reveal that the VGG16 (Visual Geometry Group 16) model, based on neural networks, has emerged as the most widely adopted, manifesting itself in 13.04% of the total models analyzed and in 16.21% of the models supported by the 37 studies. selected. Notably, this algorithm has exhibited an impressive accuracy of over 99% in predicting the diagnosis of patients with suspected COVID-19.

Keywords: prediction, COVID-19, model VGG16, deep learning.

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1. Introduction

In recent years, the pandemic caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), commonly known as COVID-19, has posed a considerable threat to global health. This phenomenon has been characterized by its rapid epidemiological spread (1-4), leading the World Health Organization (WHO) to declare it a pandemic on March 11, 2020, based on its rapid spread and high virulence (5-9).
The COVID-19 pandemic has resulted in a high number of deaths globally, largely due to a lack of knowledge, early diagnosis, and timely care for vulnerable patients, as well as a shortage of healthcare resources (10-13). In this context, one of the primary challenges is the urgent need for early diagnoses, which in turn allows for timely treatment. To

*Corresponding author. Email: wmarin@unjfsc.edu.pe; C25859@utp.edu.pe

address this urgency, preventive strategies are required that play a crucial role in mitigating the virus's spread in the community, in addition to effective case isolation and community containment (14-18).

In the field of healthcare, a wide clinical spectrum has been observed in COVID-19-affected patients, ranging from asymptomatic cases to the development of acute respiratory distress syndrome (ARDS), and even fatality (19-21). The lack of early diagnosis and subsequent late therapeutic intervention has significantly increased the clinical risk for COVID-19 patients, resulting in a high percentage of fatalities (22-25).

In this context, timely action in the diagnosis of COVID-19 is critical within healthcare systems, as the identification of clinical risks and the immediate and appropriate implementation of treatments contribute significantly to reducing mortality rates (26-29).

In emergency medical services, the early prediction of the diagnosis and clinical severity of COVID-19 patients is of vital importance (30-33), as many of these patients present multiple comorbidities, poly-pathologies, and specific symptoms (34-38). In this regard, global research efforts have been undertaken to achieve timely predictions regarding the clinical status of patients (40-42).

However, the application of conventional statistical algorithms, such as maximum likelihood-based classification, presents limitations arising from assumptions about normal distribution and constraints imposed by input data (43-46). Likewise, in the field of artificial intelligence, although it is possible to train multiple machine learning or deep learning models with different parameters, this does not guarantee the attainment of an optimal model (47-53). This challenge arises, firstly, when the learning algorithm exhibits trends toward diverse local optima, and there is limited training data available (54-57). Secondly, by discarding models that produce divergent results from the global optimum, there is a risk of losing potentially valuable information for prediction (58-62).

Despite research efforts in the field of artificial intelligence applied to early COVID-19 diagnosis, creating architectures based on automated diagnostic models remains a complex challenge (63-67). A promising alternative is the use of deep convolutional neural networks (CNN) for the precise and automated diagnosis of COVID-19 based on chest computed tomography images (68-71). Therefore, it is imperative to investigate emerging technologies in this context, with a particular focus on clinical data (72-75).

To address this issue, the main objective of this study is to conduct a systematic review of the application of deep convolutional neural networks (CNN) in the precise and automated diagnosis of COVID-19 using chest computed tomography images, aiming to predict the diagnosis of patients with suspected COVID-19.

2. Methods

The present research was carried out following the systematic review methodology, as proposed in the literature (76-78). This methodology has been based on the guidelines established by PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), as documented by Serrano, Navarro & Gonzalez (2022) and Schwarzer, Carpenter & Rücker (2015), as well as the recommendations of Alexander (2020) (79-80).

In this context, a structured literature review has been performed with the purpose of analyzing the most recent publications comprised in the period from years 2000 to 2023. The execution of this systematic review has required meticulous planning, in line with the guidelines outlined by Brereton, Budgen, Turner, Bailey and Linkmen (2009).

A critical step in this process has been the formulation of the research question, since clarity in the questions and their components is presented as a fundamental and determining element in conducting a successful systematic review.

Table 01. Criteria for writing systematic research questions.

-	Criteria	-	Detail
-	Population	-	Patients suspected of having COVID-19
-	Intervention	-	Prediction models based on neural networks
-	Outcome	-	Diagnostic optimization

Source: own elaboration

In accordance with the previously outlined criteria, the following research questions were formulated: Which models exhibit the ability to improve performance in predicting the diagnosis of suspected COVID-19 patients?

To conduct this study, a detailed research protocol was developed that comprehensively established the systematic review design. This protocol has rigorously addressed the following aspects: the criteria for study selection, the sources of information used in the literature search, the research strategies implemented, and the procedures for both the collection and analysis of the data obtained.

Table 02. Databases consulted

-	**IDE**	-	**Database**	-	**N**	-	**%**
-	DB1	-	Scopus	-	294	-	23.52
-	DB2	-	IEEE Xplore Digital Library	-	737	-	58.96
-	DB3	-	ScienceDirect	-	63	-	5.04
-	DB4	-	PubMed	-	156	-	12.48
-		-	TOTAL	-	1,250	-	100

Source: own elaboration

In order to carry out the systematic review, a thorough search of specialized databases was undertaken to locate relevant information to support our research. Table 3 details precisely the search strategy implemented.

Table 3. Search formula for each database

Database	Search Strategy
Scopus	TITLE("Neural Networks") OR TITLE(diagnosis) OR TITLE(classification) AND TITLE(Covid-19) AND TITLE("Chest X-ray Images")
IEEE Xplore Digital Library	TITLE("Neural Networks") OR TITLE(diagnosis) AND TITLE(Covid-19) AND TITLE("Chest X-ray Images")
ScienceDirect	TITLE("Neural Networks") OR TITLE(diagnosis) OR TITLE(classification) AND TITLE(Covid-19) AND TITLE("Chest X-ray Images")
PubMed	("Neural Networks") AND (diagnosis) AND (Covid-19) AND ("Chest X-ray Images")

Source: own elaboration

Inclusion and exclusion criteria

Inclusion and exclusion criteria in the context of the present scientific research refer to the predefined patterns and guidelines that are applied for the purpose of discerning which studies or papers will be incorporated into the systematic review and which will be excluded. These guidelines are based on the research objectives themselves and on the study question being addressed.

Table 4. Inclusion and exclusion criteria

Feature	Inclusion	Exclusion
Method	Method based on neural networks	Unbiased method in neural networks
Participants	Patients with suspicion of COVID-19	Non-educational institutions of higher education
Time Period	Studies: from 2000 to 2023	Studies outside this time interval
Data Base	Data based on Chest X-Ray images	Non-image based data.

Source: own elaboration

After meticulous application of the inclusion and exclusion criteria, we proceeded to carry out a rigorous restriction of the sample with the primary objective of analyzing only those papers that provided relevant information consistent with the research objectives. As detailed in the attached flow chart (Figure 1), the initial process revealed the presence of 1250 papers in the three databases examined. Subsequently, by eliminating duplicate papers and applying the aforementioned criteria, this figure was reduced to a set of 112 papers. From this initial selection, additional exclusions were made based on multiple reasons. As a result of this thorough screening process, a set of 37 papers was finally included for subsequent analysis.

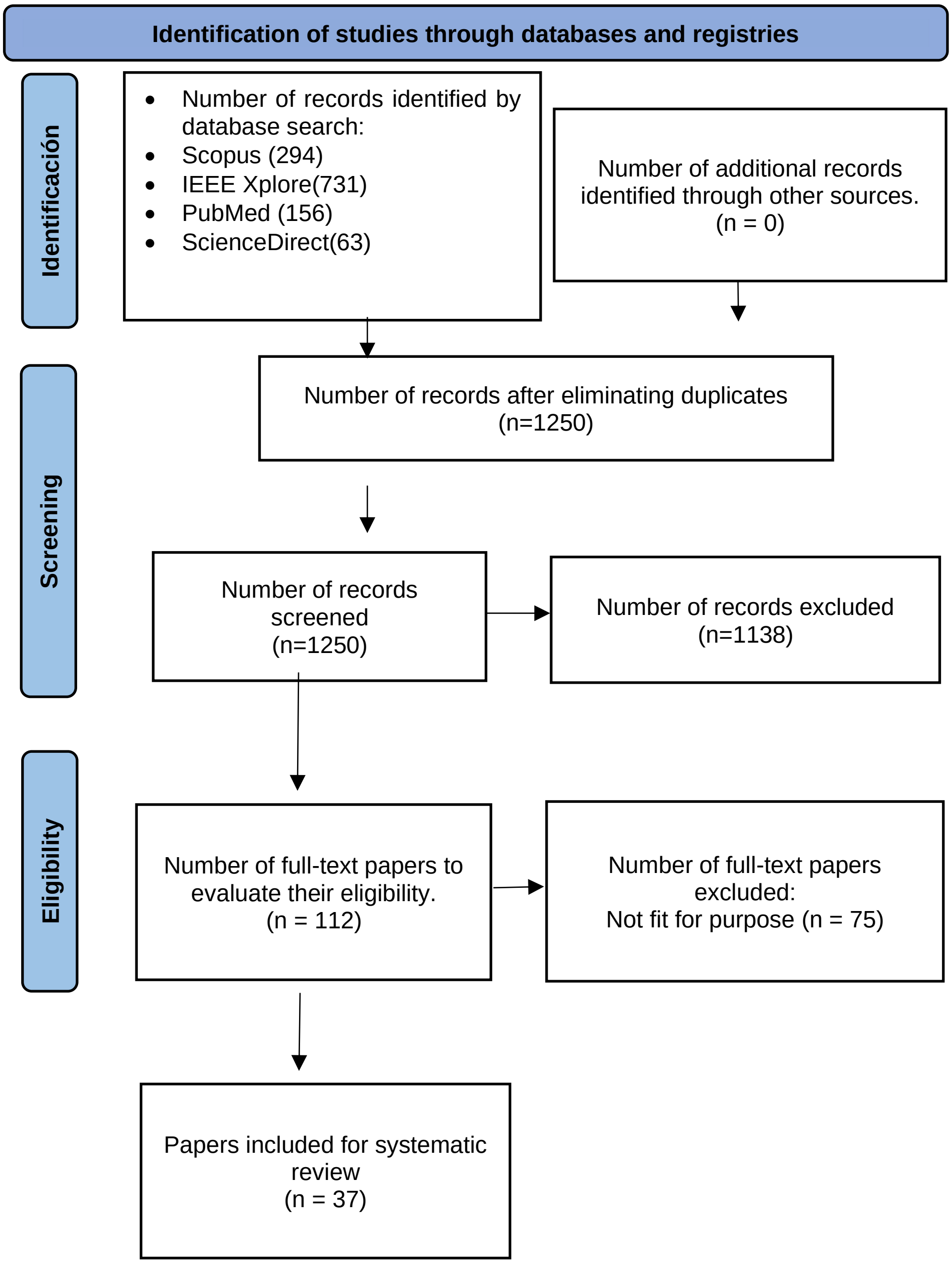


Figure 1: Flowchart of the systematic review reference search and selection method.

3. Results and Discussions

Table 6 shows the most relevant characteristics in the context of the systematic review undertaken. In this analysis, different crucial attributes have been considered, namely: authorship, year of publication, geographical location of the studies, models used in the investigations, specific model selected and various evaluation metrics, namely: accuracy, precision, specificity and f1-score.

The results derived from this study show the geographical distribution of the selected papers according to their country of origin. The outstanding contribution of the papers from India, representing 51.35% of the total sample, is noteworthy. In addition, there is a significant presence of Chinese contributions, representing 13.51%, and Turkish, with 10.81%. Other nations, such as Saudi Arabia, Australia and the United States, have contributed 5.40% each to the data set analyzed. Finally, the participation of Bangladesh, Spain and Korea is identified, with a contribution of 2.70% of the sample in each case.

It is important to note that a geographical bias has been detected in the distribution of the documents, and there is an absence of publications related to the research topic in Latin America. This disparity could possibly be due to the limited presence of artificial intelligence laboratories focused on COVID-19 related applications in the regions where no publications have been recorded.

These results highlight the global relevance of research linked to COVID-19 prediction using neural networks. However, it is imperative to recognize that the choice of the database used in the selection process could have exerted a determining influence on the observed geographical distribution.

With regard to the analysis of the prediction models used in the studies reviewed, a total of 69 different models were identified. Within this set, 13.04% of the models applied correspond to VGG16, while 11.59% are represented by VGG19. On the other hand, ResNet50, XceptionNet and DensoNet21 models have individually contributed 10.14% of the applications. In addition, ResNet101 has been used in 7.24% of the cases, while InceptionV3 has been used in 5.79%. The CNN, ResNet, ResNet18 and EfficientNet models were applied in 4.34% of the studies each. Likewise, SqueezeNet, DarkCOVIDNet, U-net, MobileNet v2, NasNet Large and LW-CBRGPNet each contributed 2.89% to the set of models analyzed. Finally, the remaining models individually contributed 1.44% of the applications.

In each of the reviewed studies, an optimal model has been proposed based on a comparison between the selected models. In this regard, 16.21% of the studies have recommended the use of the VGG16 model as the most suitable for their purposes. In addition, 5.40% of the studies have suggested the use of the LW-CBRGPNet model. The other models, such as Inception V3, TSRNet, KNN, DensoNet161, DensoNet121, SKICU-Net, CoroNet, Xception + EfficientnetB0, DarkCoviNet, VGG19, nCoVnet, CapsNet, RestNet, Aplilado Model, NasNet Large, FC-DenseNet03, OptCoNet, EfficientnetB0, InasNet, Modified MobileNetV2, LW-CORONert, Inception V4, MLD, RND-CNN, XCOVNet, CovNNN and MLES-Net56-GAPFC, Bayes-SqueezeNet, have been recommended in 2. 70% of the cases each.

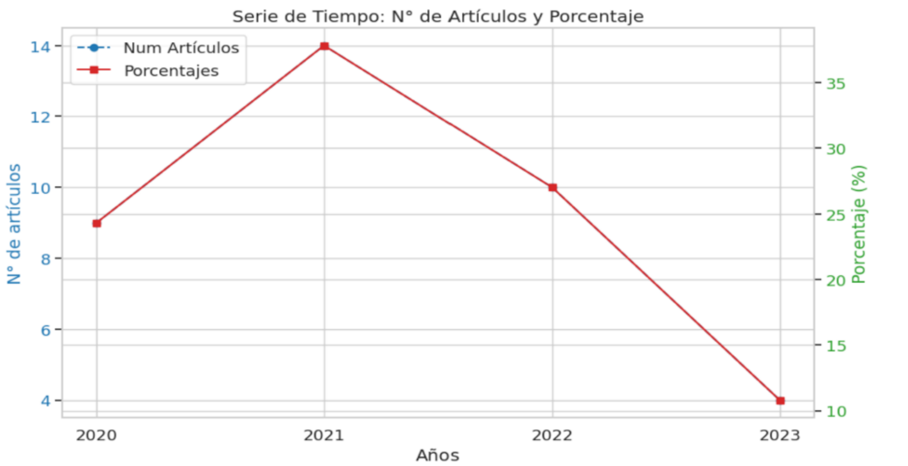
Among the proposed models, we identified those that demonstrated outstanding performance, characterized by an accuracy index (accuracy) that falls in the [99, 100] range. These models include Inception V3, TRSNet, VGG16, Xception + EfficientnetB0 and ResNet, representing 13.51% of the total set of proposed models. On the other hand, models whose accuracy was located in the interval [98, 99) were found, comprising DarkCoviNet, VGG19, NasNet Large, DarkNet, DarkNet, Modified MobileNetV2, LW-CORONert, Inception V4, DenseNet121, XCOVNet, CovNN, LW-CBRGPNet and Bayes-SqueezeNet, representing 32.43% of the total set of proposed models. It is important to note that 55% of the proposed models presented an accuracy lower than 98%.

In addition to the evaluation of models, the systematic review also includes an analysis of the frequency of publications in relation to the year of publication. The detailed results of this analysis are presented in the table and graph below.

Table 5. Publication selected for the study by year of publication

-	Interval of years	-	N	-	%
-	2020	-	09	-	24.32
-	2021	-	14	-	37.83
-	2022	-	10	-	27.02
-	2023	-	04	-	10.81
-	Total	-	37	-	100%

Source: own elaboration



Trend of the scientific production of Neural Networks for the diagnosis of Covid-19 in Chest X-ray images.

A growth trend in the dynamics of publications is evidenced over various time intervals. Initially, in the year 2020, a proportion of 24.32% of the publications is recorded. In the following year, 2021, a notable increase is observed, reaching

37.83% of total publications. However, in the year 2022, a decrease is experienced, reaching 27.02%, equivalent to the percentage observed in the year 2020. Until August 2023, a new decrease to 10.81% is reported, showing that the most pronounced growth occurred in 2021.

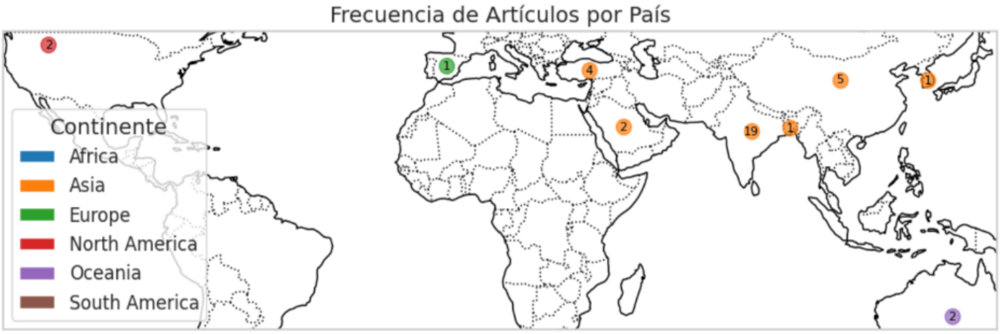


Figure 3 : Shows the number of papers published on the map.

From the geographical analysis carried out, it can be seen that an overwhelming proportion of 86.48% of the papers submitted for evaluation originate from the Asian continent. In addition, a percentage equivalent to 5.40% corresponds to both the North American continent and the oceanic continent. In contrast, only 2.70% of the papers came from the European continent, while no publications from the African or South American continent were found. These findings reveal an evident publication bias, characterized by a lack of homogeneity in the distribution of publications across the various continents analyzed.

Table 06. Descriptive characteristics of the included studies.

Author	**Country**	**Models**	**Proposed model**	**Classification results of the proposed model**			
				Accuracy	**Specificity**	**Sensitivity**	**F1-scord**
(Jin, Dong, Dong, & Ye, 2021)	China	InceptionV3,SqueezeNet,VGG19 ,ResNet50, ResNet101	InceptionV3	99,082 ± 0,335 %	98,412 ± 0,577 %	98,650 ± 0,950 %	98,528 ± 0,540 %
(Sun, Peng, Chaosheng, Wang, & Zhang, 2022)	China	DarkCOVIDNet, Deep-COVID, NAGNN, COVID-ResNet, CNN	TSRNet	99,57%	100%	99,18%	99,59%
(Chandra, Verma, Singh, Jain, & Netam, 2021)	India	KNN	KNN	72,09%	76,74%	67,44%	70,73%
(Li, Tan, Liu, Zhou, & Yang, 2021)	China	VGG16, VGG19	VGG16	93,57%	93,93%	94,21%	91,74%
(Biswas, y otros, 2021)	India	VGG16, ResNet50, Xceptión	VGG16	98,39%	98,39%	98,39%	98,39%
(Afif, Hafsa, Ali, Alhumam, & Alsalman, 2021)	Saudi Arabia	ReseNet18, DensoNet161, Inicio V4.0	DenseNet161	92,4%	91,2%	NaN	91,9%
(Sadik, Dastider, Subah, Mahmud, & Fattah, 2022)	Bangladesh	FCN, U-Net, SKICU-Net	SKICU-Net	93,5%	99,1%	94,2%	96,6%
(Khan, Shah, & Bhat, 2020)	India	CoroNet	CoroNet	93,17%	97,9%	98,25%	95,61%
(Marques, Agarwal, & De la Torre Díez, 2020)	Spain	EfficientNet	Xception + EfficientnetB0	99,62%	99,64%	99,63%	99,62
(Ozturk T. , Talo, Yildirim, & Baloglu, 2020)	Turkey	DarkCovidNet	DarkCovinet	98,08	95,3	95,13	96,51
(Apostolopoulos & Mpesiana, 2020)	Australia	VGG19, MobileNet v2	VGG19	98,75	98,75%	92,85	
(Panwar, Gupta, Siddiqui, Morales-Menendez, & Singh, 2020)	India	nCoVnet	nCoVnet	88,10%	97,06%	82,00%	89,13%

(Toraman, Alakus, & Turkoglu, 2020)	India	CapsNet	CapsNet	97,24%	97,04%	97,42%	97,24%
(Ahuja, Panigrahi, Dey, & Rajinikanth,, 2021)	India	ResNet18, ResNet50, ResNet101, SqueezeNet	RestNet	99,4%	98,6%	100%	99,5%
(Shorfuzzaman, 2023)	Australia	ResNet50V2,Xceptión, DensoNet121,modelo apilado	Modelo apilado	96,58%	99,16	94,02%	96,60%
(Sing Punn & Agarwal, 2021)	India	Basiline REsNet, Inception v2, Inception ResNet v2, DenseNet 169,NASNet Large	NASNet Large	98%	92%	90%	86%
(Oh, Park, & Chul Ye, 2020)	Korea	U-Net,FC-DenseNet67, FC-DenseNet03	FC-DenseNet03	88,9%	96,4%	85,9%	84,4%
(Goel, Murugan, Mirjalili, & Kumar Chakrabartty, 2021)	India	Nonoptimization, GA,pattern search, SA, PSO,WOA, OptCoNet	OptCoNet	97,78%	96,25%	97,75%	95,25%
(Nayak S. R., y otros, 2021)	India	DenseNet-121, ResNet-101, VGG-19, XceptionNet, LW-CBRGPNet	LW-CBRGPNet	98,33%	98,64%	97,31%	97,32%
(Ozturk T. , y otros, 2020)	Turkey	DarkNet	DarkNet	98,08%	95,3%	95,13	96,51
(Gayathri, Abraham, Sujarani, & Nair, 2022)	India	InceptionResnetV2+Xception, InceptionResnetV2+Resnet101, Xception + Resnet101, Darknet53+Resnet101, Xception + EfficientnetB0, Xception, Darknet53, Resnet101, EfficientnetB0, InceptionResnetV2	EfficientnetB0	93,21%	94,52%	91,88%	94,25%
(Perumal, Nayak, Praneetha Sree, & Srinivas, 2022)	India	VggNet, ResNet,InceptionNet, Nasnet, InasNet	InasNet	94%	94,3 %	94%	94%
(Akter, Mehedi Shamrat, Chakraborty, Karim, & Azam, 2021)	INDIA	Modified MobileNetV2 , InceptionV3 ,NFNET ,GoogLeNet ,DenseNet121 ,EfficientNetB7 ,AlexNet ,ResNet50	Modified MobileNetV2	98%	97%	98%	97%
(Nayak S. R., Nayak, Sinha, Arora, & Pachori, 2022)	India	ResNet-101, VGG-19, DenseNet-121, Xception, LW-CORONet	LW-CORONet	98.67%	99.03%	97,93%	97,98%
(Kaur, y otros, 2021)	India	C19D-Net, Inception V4	Inception V4	98,1%	98,2%	97,88%	98%
(Chakraborty, Murali, & Mitra, 2022)	INDIA	DLM	DLM	96,43%	99%	93,68%	93%

(Atitallah, Driss, Boulila, & Ben Ghézala, 2021)	Saudi Arabia	RND-CNN, RU-CNN, CNN-0, VGG16,Xception	RND-CNN	94%	98%	95%	93%
(Madaan, y otros, 2021)	India	XCOVNet	XCOVNet	98.44 %	98.45 %	97,44 %	97.94%
(Sanket, y otros, 2022)	India	ResNet101, VGG19, VGG16, Inception V3, ResNet50V2, InceptionResNet V2, Xception, CovNN	CovNN	98%	97,73%	100%	98%
(Gupta, y otros, 2022)	India	VGG16, MobileNetV2, ResNet18, and AlexNet	VGG16	98%	99%	99%	99%
(Wang, Jiang, Wang, Zhang, & Li, 2022)	China	MLES-Net56- GAPFC (without MLES&SE&SK), MLES-Net56-GAPFC (SE), MLES-Net56-GAPFC (SK), MLES-Net56-GAPFC.	MLES-Net56-GAPFC	95,27%	94,66%	NaN	95,77%
(Ranjan Nayak, y otros, 2023)	India	ResNet-101, VGG-19, DenseNet-121, XceptionNet, Proposed LW-CBRGPNet	LW-CBRGPNet	98,33%	98,64%	97,31%	97,32
(Ucara & Korkmaz, 2020)	Turkey	Bayes-SqueezeNet	Bayes-SqueezeNet	98.3%	99.1%	98.3%	98.3%
(Sahinbas & Catak, 2021)	Turkey	VGG16,VGG19,ResNet,Red Densa, inicio v3	VGG16	80%	80%	80%	80%
(Kogilavani, y otros, 2022)	India	VGG16, DenseNet121,MobileNet, Xception, NASNet, EfficientNet	VGG16	100%		96%	98%
(Yang, y otros, 2021)	China	VGG16,DenseNet121,ResNet50,ResNet152	DenseNet121	83.7%	77.7%	98.2%	86.7%
(Buvana M. , y otros, 2021)	India	VGG16	VGG16	98.87%	96.12%	99.45%	82%

In this present study, the following research question is rigorously and thoroughly addressed: Which neural network-based models are most frequently proposed and demonstrate optimal performance in predicting the diagnosis of patients suspected of COVID-19? Among the analyzed models, VGG16 stands out as the most recommended, with an accuracy equal to or greater than 98%, representing 13.04% of all examined research.

VGG16, a convolutional neural network (CNN) architecture developed by the Visual Geometry Group at the University of Oxford, is distinguished by its deep structure and uniform design, which makes it easy to understand and implement (79-81). A key feature of VGG16 is its ability to process input images with a fixed size of 224x224 pixels and three color channels (red, green, and blue). The network consists of 13 convolutional layers organized into five convolutional blocks, each composed of multiple 3x3 convolutional layers followed by a 2x2 max-pooling layer to reduce resolution (82-84). The number of filters in each convolutional layer increases as the network deepens (85-87). Additionally, VGG16 incorporates three fully connected layers with 4096 neurons each, followed by rectified linear unit (ReLU) activation functions (88-90). The final layer is a softmax activation layer with 1000 neurons, corresponding to 1000 ImageNet classes, which produces a probability distribution for image classification (91,92).

One of the key advantages of VGG16, justifying its high recommendation in the analyzed studies, is its simplicity and uniform structure. The use of 3x3 convolutional filters throughout the network contributes to this consistency (93,94). Furthermore, VGG16 benefits from pre-trained weights on large image datasets like ImageNet, facilitating its application in various computer vision tasks through transfer learning (95).

Another distinctive aspect of VGG16 is its depth, which acts as an effective feature extractor. This feature enables the network to learn to represent complex patterns and features in images, making it suitable for tasks beyond classification, such as object detection and segmentation (96).

VGG16 has established a strong performance foundation in image classification tasks. Although more contemporary architectures like ResNet and Inception have surpassed it in certain applications in terms of accuracy and efficiency, VGG16 remains a reliable choice in many COVID-19 diagnostic-related applications (97).

Regarding its performance, the VGG16 model is not only capable of increasing the network's depth but also effectively improving its performance. This simple module consists of a small convolutional core, a small pooling layer, and the ReLU activation function (98).

In the systematic analysis conducted, it has been demonstrated that, when constructing and evaluating numerous models, the VGG16 model significantly outperforms all others. Metrics from all analyzed models have been extracted and their accuracy compared, revealing that VGG16 is the best among those evaluated. Furthermore, when analyzing the losses of these models, it has been observed that VGG16 continues to provide the most outstanding results (81).

4. Conclusions

This systematic review has provided a comprehensive overview of early diagnosis prediction in patients suspected of COVID-19 using neural networks applied to chest X-ray images. The most promising algorithms and their variants have been identified in terms of their predictive ability. Precise anticipation of the diagnosis in COVID-19-infected patients has significant potential to improve treatment effectiveness and ultimately reduce mortality in the field of healthcare.

Through the analysis of 37 scientific works, we have highlighted the application of a diverse set of 69 neural network algorithms for COVID-19 diagnosis in chest X-ray images. Within this sample, the VGG16 model emerges as the most predominant, representing approximately 13.04% of all applied models and an impressive 16.21% of recommended models. In addition to its predominance, models like Inception V3, TRSNet, VGG16, Xception + EfficientnetB0, and ResNet have demonstrated exceptional performance, achieving accuracy rates equal to or greater than 99%.

Despite its advantages, VGG16 has some limitations, including a large number of parameters, making it a computationally expensive and memory-intensive choice. Modern architectures have addressed these issues while maintaining or improving performance. However, VGG16 remains a milestone in the history of deep learning and computer vision.

The study emphasizes the promising capacity of Deep Learning techniques to address the challenge of early diagnosis in patients suspected of COVID-19. The results obtained and recommendations outlined in this article are anticipated to play a fundamental role as a starting point for future research and practical applications in the healthcare field.

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