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Exploration of Coronavirus (Covid-19) Outbreak, Empowered with Deep Learning Algorithms: Challenges and Research Opportunities

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ABSTRACT

Globally, the coronavirus outbreak has had a significant impact on people and healthcare systems. The need for quick and efficient screening techniques to identify COVID-19 infections at an early stage is critical. Thirty (30) research articles that investigate the use of different deep learning models for COVID-19 infection identification and classification are carefully evaluated in this review. Using reliable scholarly databases, targeted keywords, relevance, publication dates ranging from 2019 to 2023, and language requirements, the review conducts a methodical literature search. The algorithms employed, their contributions, performance measures, and limits were taken into consideration when reviewing and analyzing each chosen study. A number of noteworthy restrictions were noted, such as the use of small COVID-19 sample datasets. As a result, augmentation and preprocessing techniques were used, including image sharing, zooming, rotating, resizing, and standardization, to reduce overfitting and increase dataset size. The results showed encouraging accuracy. Moreover, some studies solely focused on coronavirus binary classification that is, either positive or negative which limited the study of multi-class classification that might differentiate between other respiratory diseases, including bacterial pneumonia and other viral infections. Additionally, a thorough assessment was lacking in certain research. Because explainable AI (XAI) is still lacking, it is difficult to use these models in real-world healthcare systems. Robust, scalable, and flexible solutions are needed. This is because users must be able to comprehend and trust the outcomes. These discoveries are essential for subsequent investigations focused on creating more reliable and workable methods for the early identification and categorization of coronavirus diseases.

Keywords: Coronavirus outbreak, Disease identification, Disease classification, Deep learning techniques, Convolutional neural network

1.0 INTRODUCTION

In November 2019, Wuhan, Hubei Province, China, reported the first detection of the new coronavirus disease. By December, it was identified as (SARS-CoV-2) by the World Health Organization (WHO), which recognized it as a virus that might cause respiratory sickness, which is characterized by symptoms including cough, fever, and lung inflammation. COVID-19 originated in China, but it quickly spread to other parts of the world (Maghdid et al., 2021). The WHO designated it a global health emergency on January 30th, 2020, stressing the disease's widespread impact on daily life throughout the world due to its rapid transmission and high fatality rates. Between the time the virus was first discovered and March 30, 2020, more than 750,000 cases and 36,000 fatalities were documented globally. China's mortality rate was lower than that of Italy, the US, and Spain. Prior to the Chinese Spring Festival, there was a lot of travel and population movement in China, which combined with the novel coronavirus's quick spread inside the country to cause serious sickness and fatalities. The People's Republic of China's National Health Commission announced 3,311 verified SARS-CoV-2 fatalities and 82,447 confirmed cases as of March 29, 2020, at midnight. The epidemic started in Hubei province, which accounted for 82.2% (67,801 cases) of all cases in China. Of those instances, Wuhan alone accounted for 73.8% (50,006 cases) of the total cases in Hubei (Wang et al., 2020).

Global healthcare systems and people have been profoundly impacted by the COVID-19 epidemic. Research suggests that the virus most likely came from an animal source before spreading to people. The original COVID-19 epidemic center has been determined to be Wuhan, China. Because COVID-19 is a new virus and there is no prior immunity in the population, there is anxiety around the world. This explains the sudden increase in COVID-19 positive patients. As a result, quick and reliable screening methods are desperately needed to identify COVID-19 patients and allow for immediate isolation and treatment (Gunraj et al., 2020).

With symptoms including respiratory problems, fever, coughing, breathing difficulties, and viral pneumonia that frequently manifest in an indiscriminate manner, our understanding of COVID-19 in humans is still lacking. Due to restricted testing capabilities in epidemic regions and insufficient supply of nucleic acid detection kits, the daily surge in new and suspected cases has made diagnosis increasingly difficult in large hospitals. For the purpose of identifying and diagnosing COVID-19, computed tomography and radiography have thus become essential. High false positive rates, however, are a result of both the sheer volume of patients and the relative lack of radiologists. Consequently, precise confirmation of suspected cases, patient screening, and viral monitoring all require sophisticated computer-aided lung computed tomography diagnostic equipment (Song et al., 2021).

The resilience of public health infrastructure is impacted by the (COVID-19), which presents a serious threat to international healthcare systems. Incorporating deep learning models has recently surfaced as a promising method for quickly detecting and classifying coronavirus infections and their symptoms. The purpose of this review of the literature is to critically evaluate and summarize the results of thirty (30) studies that look at various deep learning algorithm models for COVID-19 detection and classification.

CNN and other deep learning techniques have become popular in the field of medical image analysis. This is ascribed to their ability to comprehend complex aspects, remember information, and utilize it in other linked models, allowing for the creation of very accurate frameworks. Deep learning techniques include a variety of models, including Multilayer Perceptrons, Radial Basis Function Networks, and Convolutional Neural Networks (CNNs), and they are inspired by the neural processes seen in the human brain. Because of their convolution action, which allows for the application of various filter functions for tasks like greyscale transformation, edge detection, and contrast enhancement, CNNs stand out among these in image processing and classification applications. CNNs are therefore regarded as the most promising technology in contemporary public health systems (Meedeniya et al., 2022).

Our goal in doing this evaluation is to evaluate the benefits and drawbacks of different methods in an effort to forward the development of trustworthy and practical methods for patient coronavirus detection. The next sections will examine the approaches taken, emphasize the main advantages, and closely examine the drawbacks of every study that has been evaluated, with an emphasis on the algorithms utilized. Lastly, the study will be concluded.

2.0 RESEARCH METHODOLOGY

The study methodology portion of this document describes the procedure that was used to evaluate the application of deep learning algorithm approaches in the fight against the pandemic thus far. We guarantee a cogent analysis by doing a comprehensive search utilizing the subsequent criteria that are pertinent to the identification of coronavirus (COVID-19) diseases:

2.1 Reputable Academic Databases:

Using targeted keywords, we searched reputable academic databases for relevant material. The Association for Computing Machinery, Science Direct, ResearchGate, Google Scholar, PubMed, Scopus, SpringerLink, and Tech Science databases are among those that were used. Database searches produced duplicate entries, which were eliminated. The several academic databases that were used to get the information for this research are listed in Table 1.

Table 1: Academic Database Used

Academic Database	**Link**
IEEE	https://ieeexplore.ieee.org/
Scientific Report	https://www.nature.com/scientificreport
Springer Link	https://link.springer.com
Google Scholar	https://scholar.google.com
Tech Science	https://www.techscience.com
Plose One	https://journals.plos.org/plose
Scopus	https://www.scopus.com
Science Direct	https://www.sciencedirect.com
Research Gate	https://www.researchgate.net/search
ACM	https://dl.acm.org

2.2 Search Keywords:

While searching and requesting pertinent content from the aforementioned academic databases, we carefully considered, picked, and employed certain search terms that aligned with our study goals. We created a number of keywords using novel terminology found in numerous relevant studies carried out by other scholars. The keywords used in this research were "COVID-19 outbreak", "deep learning application, CNN, pandemic", "LSTM", "artificial neural network, COVID - 19", "machine learning", "algorithms for coronavirus detection", "Diagnostic tools for COVID-19", alongside with "recent work on COVID-19". Using these search criteria, relevant papers written by well-known academics that were included in the academic databases stated above were found.

2.3 Relevance:

The articles were chosen according to how much they addressed using deep learning models for COVID-19 detection and classification. Since the review is solely focused on COVID-19, only articles from respectable, indexable journals were included. Articles that used machine learning methods, deep learning algorithms, and pertinent journals to fight COVID-19 were taken into consideration for inclusion.

2.4 Publication Date:

We concentrated on recent publications from 2019 to 2023 to incorporate the most recent developments in the field, taking into account the causes of the COVID-19 epidemic in Wuhan city, Hubei Province, China (Maghdid et al., 2021).

2.5 Language:

One of the primary factors we looked at while searching the academic databases for pertinent resources was the language employed in the published article. To expedite the review process, articles published in English were included, whereas those written in other languages were not. After surfing was done, we carefully reviewed what we had surfed and retrieved pertinent articles from the academic databases that had been indexed for a suitable screening procedure. Methodically, key material was gathered from each selected research article, with an emphasis on the models of deep learning algorithms used, datasets used, experimental setups, important conclusions, and limits of the work. A total of thirty (30) research publications were chosen, thoroughly examined, and categorized according to common topics and techniques. By highlighting current advancements in the area, this classification was meant to expedite the review procedure. The algorithms used, contributions, strengths, and weaknesses of each category were then examined. Figure 1 below shows our research selection process.

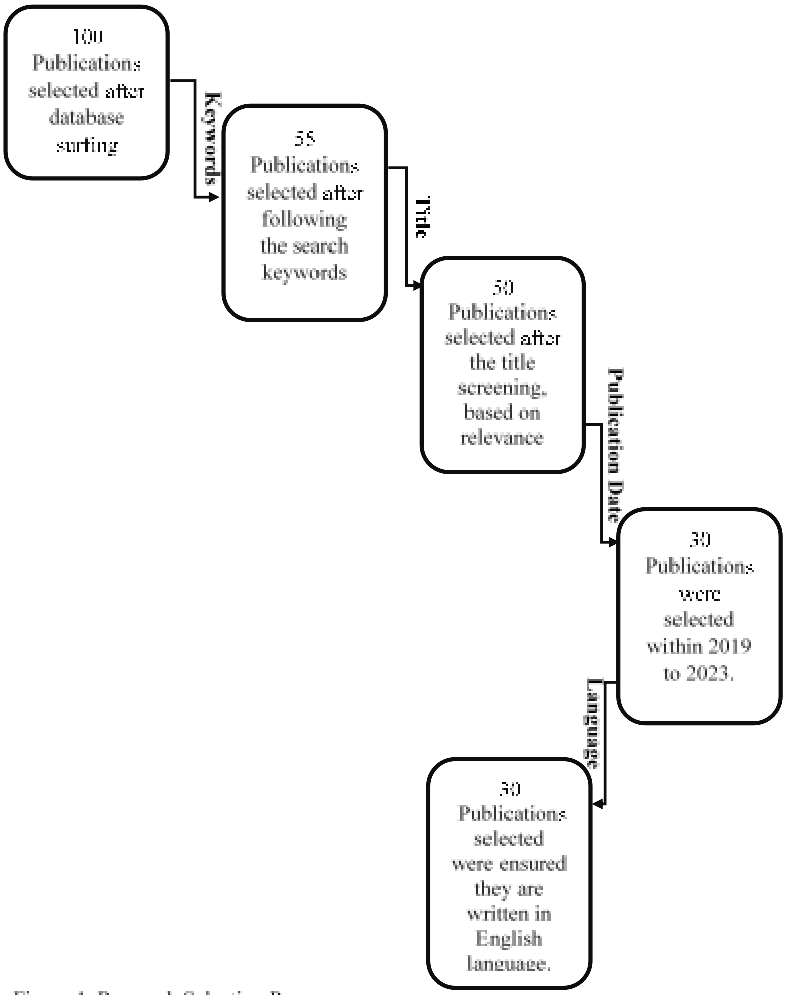

Figure 1: Research Selection Process

3.0 THEORETICAL BACKGROUND OF DEEP LEARNING ALGORITHMS

This section delves further into the main deep learning algorithms that can be used to help patients fight COVID-19. To ensure that our study is as thorough as possible, we want to clarify the basic ideas behind these algorithms and how they work, especially for inexperienced researchers. Among the important deep learning models that were covered were Long Short-Term Memory, Radial Basis Function Networks, Recurrent Neural Networks, Multilayer Perceptrons, and Convolutional Neural Networks.

3.1 Convolutional Neural Network

The CNN is now a popular deep learning model for classifying medical images, thanks in part to its advantages over other models in weight sharing and its capacity to learn intricate features with fewer parameters. CNN architectures created especially for COVID-19 and pneumonia classification in medical pictures have been adopted in a number of research (Meedeniya et al., 2022). Convolutional Neural Network (CNN) stands out for its frequent use and its series of convolutional and pooling layers. CNN's sparse interaction, fair representation, and parameter sharing are among of its main advantages (Rizwan I Haque & Neubert, 2020). within CNN, Pooling layers are used to decrease the size of the feature map, which prevents overfitting and speeds up training. Two popular methods of pooling are average and maximal pooling. Consequently, the prediction procedure frequently uses fully linked SoftMax layers (Zhao et al., 2019).

3.2 Restricted Boltzmann Machines

The majority of Boltzmann Machines are neural networks, which are created using the ideas of energy-based models (EBMs). By giving scalar energy to every possible configuration of the variables, energy-based models incorporate interdependence between them. Inference or prediction usually involves using the values of the observed variables to infer the values of the other variables in an energy-efficient way. By establishing an energy function that produces a low energy for right values of residual variables and a greater energy for wrong values, RBMs facilitate learning. Loss functions are continually reduced as a measure of how well the existing energy functions are working during the learning process (Rizwan I Haque & Neubert, 2020). A Restricted Boltzmann Machine's (RBM) fundamental design is shown in Figure 2, which also highlights the machine's straightforward structure.

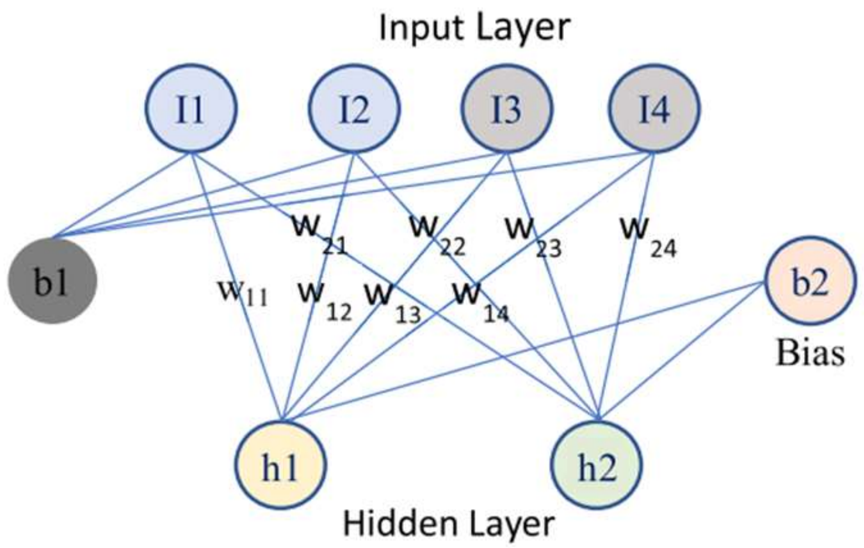

Figure 2: Graphical Representation of Restricted Boltzmann Machines architecture

Source: (Rizwan I Haque & Neubert, 2020).

3.3 Recurrent Neural Networks

The management of input sequences with an arbitrary input size is the special function of recurrent neural networks. Unlike situations when there are several inputs, a series input affects surrounding values in RNNs, therefore the network must understand this relationship. The capacity of RNNs to calculate the current output from both the current input and previously learnt values across time is one of its distinguishing features. The network incorporates prior input data and stores it in a hidden state vector. The network becomes recurrent as a consequence of identical inputs having the potential to create various outputs based on inputs that came before them in the sequence. This recurrence occurs iteratively when different input sequences are processed by the network, producing unique fixed-size output vectors. Usually, each input that is received updates the concealed state. Increasing the number of hidden state layers, adding extra layers inside the hidden state layers and the output layer, inserting nonlinear hidden layers between the input and hidden state levels, or using a mix of all three layers may all be used to modify the depth of RNNs (Rizwan I Haque & Neubert, 2020).

3.4 Long Short-Term Memory Networks

Recurrent neural networks, such as Long Short-Term Memory networks, are basically able to preserve data characteristics over a variety of time intervals. It was mainly developed to solve the problem of the vanishing gradient that conventional recurrent neural networks faced. The hidden layers of long short-term memory networks (LSTM) are thought of as memory cells that enable the network to efficiently handle correlations that are both short- and long-term in nature within a time series. The first LSTM design included input and output gates, memory cells, and no forget gate. The forget gate was then included to enhance the LSTM's capacity for continuous task learning by resetting its state. Many LSTM units with input, output, forget, and memory cells are included in the redesigned architecture (Liu et al., 2019). The architecture of Long Short-Term Memory Networks (LSTM) is shown in Figure 3 below. Among its many uses, LSTM is a particularly powerful artificial neural network (ANN) architecture that may be used for time series analysis, text and music production, handwriting recognition, picture captioning, and disease subtype identification (Okut, H. 2021).

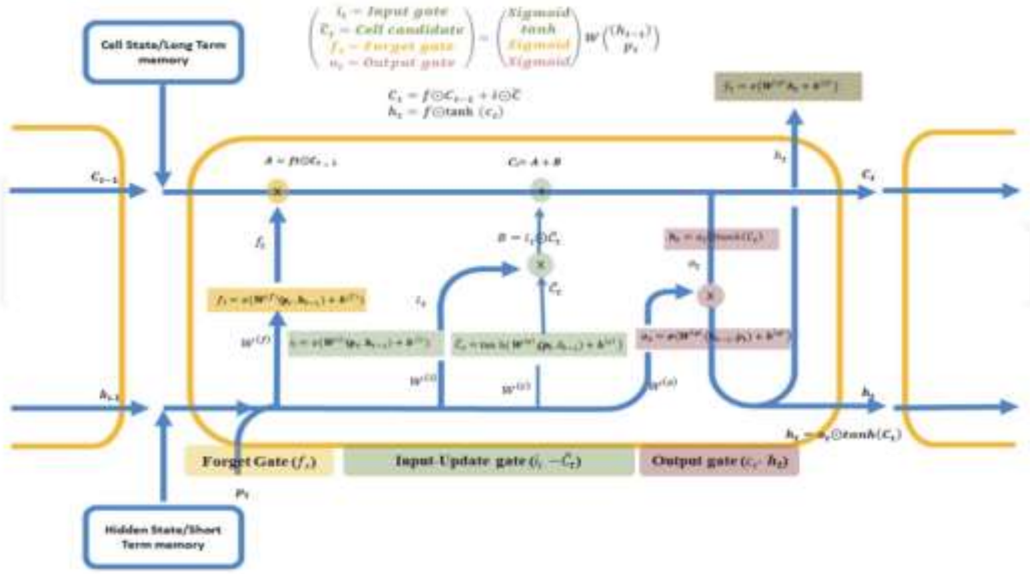

Figure 3: Graphical Representation of Long Short-Term Memory Networks architecture.

Source: (Okut, H. 2021)

3.5 Generative Adversarial Networks

The idea of employing a neural network to create a generator is at the core of Generative Adversarial Networks, or GANs. During its training phase, this generator is educated to convert a random input variable into a function that roughly approximates the desired distribution. Simultaneously, a discriminator network is trained to distinguish between created and genuine data. The discriminator tries to reduce the final classification error between produced and actual data, whereas the generator wants to increase it. In essence, these two networks are rivals. As such, during each training cycle iteration, both networks get better (Rizwan I Haque & Neubert, 2020).

3.6 Multilayer Perceptrons

When compared to more intricate techniques, Multilayer Perceptrons (MLPs) are renowned for producing high-quality models with comparatively shorter training times. Essentially, MLPs use the summation of weighted outputs from neurons in the layer above that are linked to the current layer to determine the values of the neurons in that layer. Regression is limited to a single value in MLP regressors. It is necessary to use a modular model made up of several models when solving issues with various output values. Furthermore, MLPs might not be the best choice in nonlinear situations, even though they are capable of handling linear issues that arise in a single perceptron (Car et al., 2020).

3.7 Radial Basis Function Networks

Three layers make up the Radial Basis Function Network (RBFN): Input (IL), Hidden (HL), and Output (OL). Weight vectors that are originally allocated at random serve as the link between the Hidden and Output layers. A nonlinear activation function is applied at each hidden layer node via RBFN. Since each category variable in the input layer is represented by one neuron, the number of IL nodes vary based on the form of the picture as it enters the network. This suggests that the number of IL nodes varies dynamically according on the form of the input picture, resulting in the RBFN being designed as a Dynamic Radial Basis Function Network (DRBFN). Only when the standardized EF pixel values are non-zero does each IL node become active. The Radial Basis Function Network is structured similarly to a traditional regular network (Chattopadhyay, 2021).

3.8Autoencoders

Using the backpropagation technique, the autoencoder neural network compresses input data into a latent-space representation with similar target values to the inputs, hence serving as an unsupervised learning process. Neural networks called autoencoders are used to compress and recreate data. In order to accomplish compression, the network must be under completed, meaning that the hidden layer must have less dimensions than the input layer. The network is able to extract the most significant characteristics from the training set due to the hidden layer's decreased dimensionality. In autoencoder-based deep learning techniques, pictures are usually down-sampled to provide a latent representation with fewer dimensions. This allows the autoencoder to be trained and learn from the images in their compressed form (Rizwan I Haque & Neubert, 2020).

4.0 RELATED WORK

A customized pre-trained AlexNet model and a convolutional neural network (CNN) were built for the purpose of identifying coronavirus from x-ray and computed tomography scan pictures (Maghdid et al., 2021). This strategy was motivated by the shortcomings of RT-PCR testing, which made the pandemic worse even in the face of lockdown measures. These shortcomings included limited capacity, the possibility of false negative results, delays in processing results, and logistical problems. To train and verify the models, a dataset including 356 computed tomography scan pictures and 170 x-ray images was assembled from five sources. There were training and validation sets of the data. A total of 339 computed tomography scan pictures (192 positive and 147 normal of COVID-19) and 120 chest x-ray images of (60 positive and 60 normal COVID-19) made up the training set. Fifty (50) chest x-ray pictures of (25 positive and 25 normal of coronavirus) and seventeen (17) computed tomography scan images of (11 positive and 6 normal of coronavirus) made up the validation set. The suggested CNN was able to identify objects in x-ray pictures with 94.0% accuracy, 100% sensitivity, and 88.0% specificity, and in computed tomography scan images with 94.1% accuracy, 90.0% sensitivity, and 100% specificity. For x-ray pictures, the AlexNet model yielded a 98.0% accuracy rate with 100% sensitivity and 96.0% specificity, while for computed tomography scan images, it produced an 82.0% accuracy rate with 72.0% sensitivity and 100% specificity.

(Hosny et al., 2021) presented two affordable image classifier models that could run on an embedded Linux machine called a Raspberry Pi. These models are intended to identify COVID-19 instances from chest computed tomography and X-ray pictures automatically. The objective was to create a cost-effective and portable COVID-19 diagnostic tool. This resulted from developing a classification model that fits on a Raspberry Pi and only needs about 3 MB of RAM. Global features from chest X-rays or computed tomography scans were acquired using multi-channel fractional-order Legendre-Fourier moments (MFrLFMs), whereas local characteristics were first recovered by the model using the local binary pattern (LBP) approach. The study made use of datasets from computed tomography scans (with 2,482 pictures) and chest X-rays (1,926 images), which were divided into two groups: COVID-19 (class one) and other lung disorders (class two). The models outperformed state-of-the-art techniques, obtaining an accuracy of 99.3±0.2% for chest X-rays and 93.2±0.3% for computed tomography scans. The findings were encouraging. Nevertheless, the model's capacity to categorize different lung conditions was constrained.

(AlMohimeed et al., 2023) presented a stacking ensemble deep learning model in their study which uses datasets of COVID-19 symptoms and chest X-ray images to predict and detect COVID-19. The study presented two distinct models, one based on symptoms of COVID-19 and the other on pictures from chest X-rays. Four distinct pre-trained deep learning ensemble models were combined in the first model: MLP, RNN, LSTM, and GRU. The second model was created by combining the results of previously trained models, including InceptionV3i, ResNet152V2, DenseNet201, VGG16, and MobileNetV2. This model trained and evaluated a meta-learner (SVM) for final predictions utilizing chest X-ray datasets through stacking. Using the same datasets, the researchers compared their suggested model with other deep learning models, demonstrating encouraging performance outcomes. A 99.62% accuracy rate was attained by the suggested model on two COVID-19 chest X-ray datasets. The accuracy on two datasets of COVID-19 symptoms was 99.30%. These outcomes demonstrated how well the model generalized its predictions. The quantity of the datasets, however, hampered the study, and no explainable AI (XAI) approaches were used, which would have made the conclusions easier for users to comprehend and believe.

(Panwar et al., 2020) sought to speed up the identification of COVID-19 utilizing chest X-ray and computed tomography scan images by focusing on binary image classification to distinguish COVID-19 from non-COVID-19 positive patients. To increase the interpretability and explainability of the deep learning model's output, the researchers merged a Grad-CAM color visualization method with a Deep Transfer Learning algorithm. Three datasets were used: the SARS-COV-2 computed tomography-scan dataset, which included 1,252 computed tomography scans of COVID-19 positive patients and 1,230 computed tomography scans of non-COVID patients, the COVID-chest X-ray dataset, which included 673 radiology images from 342 unique patients, and the Chest X-Ray Images (Pneumonia) dataset, which included 5,856 images of pneumonia and normal patients. In comparison to conventional RT-PCR testing, the suggested approach proved to be substantially quicker, achieving an overall accuracy of 95.61% in detecting COVID-19 cases. Furthermore, the model's training weights on CT scan pictures were successfully applied to the analysis of CXR images. The system reliably extracted fundamental characteristics and recognized patterns in COVID-19 instances from both CXR and CT scan pictures using pre-trained weights. One noteworthy feature of the suggested approach is the incorporation of five extra layers into the VGG-19 model to improve connection.

An improved convolutional neural network called COVID-Net CT-2 was unveiled by (Gunraj et al., 2022) with the express purpose of identifying COVID-19 from chest computed tomography scans. Furthermore, as a component of the open-source COVID-Net program, they provided an extensive benchmark dataset of 1,489 patient cases. COVID-Net CT-2 is one of the biggest and most diverse global cohorts accessible, including data from 4,501 patients across at least sixteen nations, published in an open-access format. Two new CT benchmark datasets were also utilized to train the system. Additionally, COVID-Net CT S—a unique lightweight neural network architecture—was unveiled. It is noticeably quicker and smaller than COVID-Net CT, the earlier version. The encouraging findings of the study demonstrate the great potential of deep neural networks for computer-assisted COVID-19 evaluation. The findings revealed a 99.0% accuracy rate, a 99.1% COVID-19 sensitivity rate, and a 98.0% positive predictive value. Significant potential for clinical use in computer-aided COVID-19 evaluation was shown by the validation procedure, which used explainable methodologies and showed a solid alignment between the decision-making process of COVID-Net CT-2 and radiologist interpretations.

A study by (Jain et al., 2021) evaluated the performance of many convolutional neural network models, such as Xception, ResNeXt, and Inception V3, in categorizing coronavirus patients according to chest X-ray images. The researchers collected a total of 6,432 samples from Kaggle datasets using Posteroanterior (PA) views of chest X-ray images from both COVID-19 patients and healthy persons. Of these, 965 samples were utilized for validation and 5,467 samples for training. In comparison to the other models, the Xception model performed better, recognizing COVID-19 in chest X-ray pictures with the greatest accuracy of 97.97%. By utilizing LeakyReLU activation rather than the more conventional ReLU, this model presented a novel strategy that sped up training and lessened the issue of dead neurons. To avoid overfitting, other data augmentation techniques were used, such as rotating, flipping, and zooming photos.

CoroNet, a deep convolutional neural network model based on the Xception architecture, was presented by (Khan et al., 2020) Its purpose is to automatically identify COVID-19 infection from chest X-ray pictures. After the model was trained on the ImageNet dataset, it was then trained on a carefully selected dataset that included one thousand two hundred and three (1,203) normal cases, six thousand six hundred and sixty (660) instances of bacterial pneumonia, and nine hundred and thirsty one (931) cases of viral pneumonia. The Kaggle repository Chest X-Ray photos (Pneumonia) had one thousand three hundred (1,300) photos in this dataset, including COVID-19 and other images linked to pneumonia. With an astounding 89.60% total test accuracy, CoroNet performed admirably. While the initial outcomes seem encouraging, significant advancements are expected as additional training data becomes accessible.

DarkCovidNet, a deep learning model created to identify and categorize COVID-19 instances using chest X-ray pictures, was presented by (Ozturk et al., 2020). In order to overcome the lack of radiologists, this completely automated, end-to-end model was used in distant areas of COVID-19-affected nations. It does away with the necessity for manual feature extraction. However, the tiny dataset of COVID-19 X-ray pictures presented challenges for the investigation. 43 female and 82 male COVID-19 positive subjects' X-ray pictures from two repositories were included in the dataset. The model was created for multi-class classification (COVID vs. No-Findings vs. Pneumonia) as well as binary classification (COVID vs. No-Findings). With 98.08% for binary classification and 87.02% for multi-class scenarios, it attained noteworthy classification accuracy.

Deep learning techniques were used by (Shaik et al., 2022) to identify COVID-19 in chest X-ray pictures. Their dataset comprised X-ray pictures of one thousand, five hundred and eighty-three (1,583) healthy patients, four thousand, two hundred and ninety-two (4,292) pneumonia cases, and two hundred and twenty-five (225) verified COVID-19 cases. These images were utilized to train both deep learning and machine learning classifiers. They employed 14 pre-trained networks for transfer learning, ten (10) trials using machine learning models, and 38 experiments with convolutional neural networks (CNNs). ConvNets, a CNN design that the researchers presented, not only illustrated the topologies under consideration but also decreased computing costs while preserving good performance with the dataset pictures. They obtained remarkable results using ConvNets, recognizing COVID-19 in X-ray pictures with an area under the curve score of 96.51%, a specificity of 99.18%, and an accuracy of 98.50%.

(Bushra et al., 2021) created an Android-specific 150-layer CNN model for coronavirus detection in chest X-ray pictures. The model was transformed into a TFLite model, and this TFLite model was used to construct an Android application for COVID-19 identification. There were one thousand, one hundred and eighty-four (1,184) X-ray pictures in their collection, of which five hundred and ninety-two (592) were of the coronavirus disease and five hundred and ninety-two (592) were of the regular kind. They obtained an average precision of 98.81% and accuracy of 98.65% via thorough examination.

Transfer learning was used by (Apostolopoulos & Mpesiana, 2020) to assess the performance of pre-trained convolutional neural network architectures created in the last few years. Using two datasets of chest X-ray pictures that they obtained from different public medical archives, they evaluated the performance of VGG19, Inception, Inception ResNet v2, MobileNet v2, and Xception. Five hundred (500) chest X-ray pictures of normal people, two hundred and twenty-four (224) chest X-ray photos of COVID-19, and seven hundred (700) chest X-ray images of bacterial pneumonia were included in the initial dataset. The second dataset included three hundred and fourteen (314) chest X-ray photos showing both viral and bacterial pneumonia (314 viral and 400 bacterial cases), five hundred and four (504) normal chest X-ray images, and two hundred and twenty-four (224) coronavirus chest X-ray images. During the examination of the first dataset, VGG19 and MobileNet v2 demonstrated encouraging accuracy rates of 98.75% and 97.40%, respectively. They also demonstrated sensitivities of 92.85% and 99.10%, specificities of 98.75% with 97.09%. With results of 96.78%, 98.66%, and 96.46%, respectively, MobileNet v2 showed the greatest accuracy, sensitivity, and specificity on the second dataset.

A convolutional neural network model was created by (Ismael & Şengür, 2021) to distinguish between COVID-19 and normal chest X-rays. They employed end-to-end training, feature extraction, and CNN models that had already been trained as deep learning approaches. The study employed pre-trained CNN models, including Visual Geometry Group 19, ResNet18, VGG16, ResNet50, and ResNet101for the purposes of deep feature extraction and fine-tuning. They also used a variety of kernel functions to identify the retrieved deep learning features using SVM. One hundred and eighty (180) coronavirus cases and two hundred (200) healthy X-ray pictures made up the three and eighty (380) chest X-ray images in their collection. According to the trial findings, ResNet50 had the greatest average accuracy, coming in at 92.6%. In particular, VGG16, ResNet101, VGG19, and ResNet18 had average accuracies of 89.8%, 89.5%, 88.1%, and 87.4% in COVID-19 identification, respectively. With an average accuracy of 92.63% for COVID classification, ResNet50 outperformed VGG19, ResNet18, ResNet101, and VGG16, which had average accuracies of 89.47%, 88.42%, 87.37%, and 85.26%, respectively.

(Kumar ECED et al., 2022) improved the accuracy of categorizing human chest X-rays into normal and coronavirus infected patients by incorporating VGG16 and InceptionV3 into an ensemble of convolutional neural networks. These models served as the ensemble model's pre-trained constituents. Pre-trained and transfer learning models have the benefit of applying to a variety of datasets since they leverage pre-existing information instead of creating it from start. A collection of seven hundred and twenty (720) X-ray scans of normal and COVID-positive patients was used in their analysis. Eighty percent (80%) of this dataset was used to train the model, while the remaining twenty percent was set aside for testing. The ensemble model generated a promising confusion matrix and showed an amazing accuracy of 99.31%. Nevertheless, the researchers used data augmentation techniques to enlarge the dataset because of its constraints.

(Bhattacharjee et al., 2023) presented DeepCOVNet, a three-convolutional-layer Deep Neural Network intended for the classification of CXR pictures into three groups such as: Coronavirus, Normal, and Pneumonia cases. It functions as a reliable model to differentiate between normal and pneumonia states in COVID-19 chest x-ray pictures. In order to enhance training and results, the study combined datasets into two groups, designated as group A and group B. Group B comprised 6012 photos linked to lung opacity from Kaggle, whereas Group A featured Chest X-Ray scans of COVID-19 patients from GitHub and Kaggle repositories. Using VGG16, InceptionResNet, and XceptionNet, among other deep learning techniques, the suggested model outperformed the rest on both dataset sets. It demonstrated its potential as a quick coronavirus detection technique based on X-ray image analysis with accuracy of 96.77% for group A and 90.25% accuracy for group B.

In order to identify coronavirus illness from chest computed tomography scans, (Li et al., 2020) created and assessed a three-dimensional deep learning model known as the COVID-19 detection neural network (COVNet). With coronavirus and community-acquired pneumonia area under the receiver operating characteristic curves of 0.96 and 0.95, respectively, the model's sensitivity and specificity for COVID-19 identification were 90% and 96%, respectively. To make the model easier to understand, the researchers employed the gradient-weighted class activation mapping approach. A substantial number of computed tomography (CT) scan images of one thousand, two and ninety-two (1292), one thousand seven hundred and thirty-five (1735) community-acquired pneumonia (CAP) CT scans images, and one thousand three hundred and twenty-five (1325) non-pneumonia CT scans images were gathered from many hospitals and included in the datasets. One drawback, though, was that the origin of each COVID-19 case was not confirmed by a laboratory.

(Attaullah et al., 2022) presented a hybrid system that used CNN, Logistic Regression, and Decision Tree algorithms with the goal of early COVID-19 identification. This approach makes early-stage coronavirus identification easier by combining patient symptoms with medical imaging. The testing dataset had eight hundred (800) X-ray pictures of patients as well as eight hundred (800) patient symptoms. These were divided into five classes: normal, early-stage coronavirus, non-coronavirus viral, bacterial, and COVID-19, with two hundred (200), two hundred (200), one hundred and eighty (180), ninety (90), and one hundred and thirty (130) images corresponding to each class, and their accompanying symptoms. With an accuracy of 78.88%, specificity of 94%, and sensitivity of 77%, the study produced encouraging findings. Pre-processing the X-ray pictures and symptom datasets, training CNN and logistic regression models with these pre-processed datasets, and training a decision tree model utilizing the labeled output from the first two models were the steps in the procedure.

(Kassania et al., 2021) evaluated the best way to combine machine learning classifiers with deep learning-based feature extraction frameworks to identify coronavirus illness. For feature extraction, they used a variety of frameworks, such as InceptionV3, InceptionResNetV2, DenseNet201, DenseNet121, Xception, VGG19, VGG16, ResNet50, ResNet152, ResNet101V2, ResNet50V2, ResNet152V2, NASNetMobile, NASNetLarge, MobileNet, and InceptionV3. They used Decision Tree, XGBoost, Random Forest, Bagging classifier, AdaBoost, and LightGBM for classification. For their experiment, they obtained computed tomography and X-ray pictures of the chest from public repositories on GitHub and Kaggle. They preprocessed the images using conventional image normalization to improve quality. Twenty (20) COVID-19 positive computed tomography (CT) scans, twenty healthy CT images, and one hundred and seventeen (117) coronavirus positive chest X-ray images made up the dataset. The combination of DenseNet121 and Bagging classifier showed the best performance after testing, attaining an accuracy of 99%, according to the results. LightGBM and ResNet50 came next, both of which had a 98% accuracy rate.

Using chest X-ray pictures, (Nasiri & Alavi, 2022) presented a deep learning architecture to help radiologists diagnose and identify COVID-19 patients. They extracted features from the X-ray pictures using the pre-trained DenseNet169 model. Analysis of variance (ANOVA) was used in feature selection to pick pertinent characteristics, lowering computing cost and resolving dimensionality concerns, all of which increased accuracy. Following selection, the eXtreme Gradient Boosting (XGBoost) method was used to classify these characteristics. The new method used XGBoost for classification and the pre-trained DenseNet169 model for feature extraction. The ChestX-ray dataset was subjected to this approach for both multiclass (coronavirus, No-findings, Pneumonia) and two-class (coronavirus, No-findings) classification. With an accuracy of 98.72% for two-class classification and 92% for multiclass classification, the suggested model showed remarkable performance. The study was hindered, nonetheless, by the scarcity of COVID-19 samples.

(Siddhartha & Santra, 2020) presented a method termed COVIDLite that uses a depth-wise separable convolutional neural network to integrate white balance correction with Contrast Limited Adaptive Histogram Equalization. They employed DSCNN, a model with fewer parameters and a smaller size, for image classification, and CLAHE for image preprocessing to improve the clarity of CXR pictures. One thousand, eight hundred and twenty-three (1,823) photos with annotations for poster-anterior (PA) views of CXR images made up the dataset. It contained labeled computed tomography and OCT scans to distinguish between cases of viral pneumonia and non-pneumonia or normal cases. There were five hundred and thirty-six (536) photos of coronavirus patients, six hundred and nineteen (619) photos of viral pneumonia cases, and six hundred and sixty-eight (668) photos of normal cases in this collection. The research demonstrated remarkable 99.58% accuracy in binary classification and 96.43% accuracy in multi-class classification, outperforming several cutting-edge techniques. Nevertheless, the research revealed many noteworthy shortcomings, including the use of constrained datasets and cases of overfitting.

(Khurana Batra et al., 2022) presented a deep learning model built on the InceptionV3 architecture that uses convolutional neural networks to automate and evaluate the diagnostic process using computed tomography scan and X-ray pictures. The suggested model outperformed the current models and other deep learning models, such as VGG16 and ResNet50V2, in terms of accuracy and other important metrics. Nine hundred and twenty (920) X-ray and seven hundred and fourty-six (746) computed tomography scan pictures were utilized in the study, with the images being divided into coronavirus and non-coronavirus groups. With only a little amount of memory used, the suggested model demonstrated good performance and reached an accuracy of about 96%. The model attained 93.48% sensitivity for chest X-rays (CXRs) and 93% accuracy and 89.81% sensitivity for CT scan pictures. Two of the study's shortcomings were its tiny dataset and scarce computing resources. Notwithstanding these drawbacks, the model was able to identify coronavirus instances on its own without assistance from a person.

(Song et al., 2021) presented DRENet, a deep learning diagnostic system designed to use CT scans to detect COVID-19 patients. To help doctors identify patients, DRENet collected lesion characteristics and produced image-level predictions from computed tomography (CT) scans. To speed up calculation, preprocessing techniques were used to eliminate extremely similar pictures from 3D CT scans. The dataset comprised 86 healthy people with 708 CT pictures, one hundred (100) patients with bacterial pneumonia with five hundred and five (505) CT images, and 88 COVID-19 positive patients with seven hundred and seventy-seven (777) computed tomography images. The model obtained an accuracy of 93%, according to experimental study.

(Toraman et al., 2020) deviated from the original CapsNet implementation and used four convolutional layers to increase the feature map's efficacy. After these layers came a LabelCaps layer with 16D capsules for classes two and three. Using capsule networks and chest X-ray pictures, their novel Convolutional CapsNet artificial neural network type was able to identify COVID-19 illness. Two scenarios were tested with the model: multi-class classification (identifying coronavirus, No-Findings, and Pneumonia cases) and binary classification (separating coronavirus cases from No-Findings). The model performed quite well in spite of the dataset's restrictions, obtaining 97.24% accuracy in binary classification and 84.22% accuracy in multi-class classification, respectively.

A novel deep learning framework called COVIDX-Net was presented by El-Din Hemdan et al. (2020) with the goal of helping radiologists diagnose COVID-19 in X-ray images automatically. The study suggested that VGG19 and DenseNet201 models be used in computer-aided diagnostic (CAD) systems to ascertain the health condition of patients in COVID-19 X-ray pictures. Nevertheless, the dataset employed in the study was small, it included just fifty (50) X-ray pictures split into twenty-five (25) classes, twenty-five (25) positive coronavirus instances and twenty-five (25) normal cases. An eighty percent (80%) training and twenty percent (20%) testing split was used for the assessment. In automatic COVID-19 classification, the VGG19 and DenseNet models performed well and similarly, obtaining F1-scores of 0.89% and 0.91% for normal and COVID-19 cases, respectively. Conversely, the InceptionV3 model performed the worst in terms of categorization, with F1-scores of 0.00% for COVID-19 instances and 0.67% for normal cases.

(Islam et al., 2022) classified X-ray samples into pneumonia, COVID-19, and normal classes and used convolutional neural network and recurrent neural network architectures to diagnose coronavirus patients from chest X-rays. Features from X-ray pictures were extracted using four well-known CNN architectures (VGG19, DenseNet121, InceptionV3, and Inception-ResNetV2) and input into an RNN network for classification. With the use of gradient-weighted class activation mapping, the significance of picture areas for classification was illustrated. Sixty thousand, three hundred and ninety-six (6396) X-ray samples from different sources made up the dataset. In identifying COVID-19 instances, the VGG19-RNN model performed remarkably well, obtaining accuracy of 99.9%. The combined CNN+RNN architectures created for this study worked incredibly well for coronavirus infection case classification.

(Xu et al., 2020) developed a classification network to distinguish influenza, a virus pneumonia (IAVP) from coronavirus. In their network architecture, they used ResNet for feature extraction. This invention offered a cutting-edge approach for applying deep learning techniques to automatically screen for coronavirus in computed tomography scans. A dataset including six hundred and eighteen (618) transverse-section computed tomography samples was used in the investigation. An accuracy percentage of 86.7% was reported for all computed tomography cases combined. Models using a location-attention mechanism shown potential in coronavirus, IAVP, and healthy case classification, providing frontline clinical practitioners with a useful additional diagnostic tool.

To identify coronavirus using computed tomography scan pictures, Kathamuthu et al., (2023) created a transfer learning framework that was improved using convolutional neural network models such as (DenseNet121, VGG16, InceptionV3, Xception, VGG19, and ResNet50). Their dataset, obtained from Kaggle, included two thousand, four hundred and eighty-one (2481) pictures classified into COVID and non-COVID groups. The COVID group included CT scans of patients with COVID-19, while the non-COVID group included scans of healthy individuals. A confusion matrix and a number of performance indicators, including as accuracy, and precision, were used in the assessment procedure. VGG16 stood out from the other models examined in the study because to its accuracy of 98.00%. The VGG16 model's lower parameter set and shorter training time needs are responsible for its better performance.

(Ukwuoma et al., 2023) presented a multi-head self-attention network and a deep learning architecture that is end-to-end with an emphasis on deep feature concatenation. To enhance the COVID-19 identification prediction performance, they utilized a modified Multilayer Perceptron block in conjunction with a multi-head Self-attention network technique. Using the large ImageNet dataset for generic attribute capture, pretrained models (DenseNet, InceptionV3, and VGG-16) analyzed the original chest X-ray pictures. To further improve performance, a Multi-head Self-attention network was also included. Four classes were employed using the open-source COVID-19 Radiography Dataset: COVID-19, pneumonia, lung opacity, and normal. Three thousand, six hundred and sixteen (3,616) coronavirus samples, one thousand, three hundred and fourty-five (1,345) samples of viral pneumonia, six thousand and twelve (6,012) samples of lung opacity (indicating lung infection other than COVID), and 10,192 normal samples were included in this dataset. 96.33% overall multi-classification accuracy and 98.67% binary classification accuracy were attained by the created model.

(MLHC-COVID-19), a multilayer hybrid classification model was presented by Phumkuea et al., (2023) for coronavirus detection, and it was assessed using 10-fold cross-validation. There are two levels of binary classification in the model. As a screening stage, the first layer sends unhealthy chest x-ray pictures to the second layer, where they are further divided into coronavirus and non-coronavirus images. This model integrates many machine learning approaches on a large-scale CXR image dataset including of healthy, non-COVID-19 (bacterial and viral pneumonia), and COVID-19 patients. Using chest X-ray scans, the dataset comprised one thousand and fifty (1,050) coronavirus patients, two thousand and hundred (2,100) non-coronavirus cases, and one thousand and fifty (1,050) healthy cases. After training and assessment, the multilayer hybrid classification coronavirus model outperformed other state-of-the-art deep learning approaches with high accuracy scores of 96.2%.

(Ayalew et al., 2023) built a (CNN) model including different classifiers as SoftMax, Random Forest, and SVM to enhance accuracy in identifying coronavirus using X-ray pictures. Their research developed a useful method for identifying coronavirus-infected or normal chest X-ray pictures. The method comprised classifying pictures using SVM, Random Forest, and SoftMax classifiers in accordance with the insights gleaned from the learning model. They used convolutional and max pooling layers on processed images and the (ReLU) activation function. The collection included one thousand, eight hundred (1,800) photos from an online repository and seven hundred (700) photographs respectively. With a training accuracy of 99.8% and a test accuracy of 99.1%, the CNN model demonstrated remarkable performance in its goal of preventing adverse events including mortality by early identification of coronavirus.

(Kumar Sethy et al., 2020) used deep features from ResNet50 and (SVM) to build an approach for early-stage coronavirus identification using X-ray photos. Deep features were extracted using thirteen (13) pre-trained CNN models, and each one was then input into a separate SVM classifier. Each CNN-SVM combination was run twenty (20) times, with the average values noted, in order to improve the robustness of the model. The dataset comprised three and eighty-one (381) chest X-ray frontal view pictures, with one hundred and twenty-seven (127) photos in each of the following categories: COVID-19, pneumonia, and normal X-ray images obtained from GitHub and Kaggle sources. Twenty independent executions yielded an accuracy of 95.33% on average, with 98.66% being the highest.

5.0 LIMITATIONS

The main objective of this study is to identify the gaps in the journals (publications) evaluated on the coronavirus (covid-19) epidemic. One common shortcoming we found in all the research articles we examined for our analysis is the usage of small datasets for model evaluation and training, which has a big impact on the models' validity, generalizability, and dependability. Numerous research that was examined brought attention to issues with representation, interpretation, diversity, and quantity of datasets. Deep learning models may not always be able to generalize well to the variety of COVID-19 detection and classification tasks due to the usage of small datasets.

Other difficulties that researchers encounter include overfitting and a lack of training data. Due to the lack of COVID-19 example datasets, several researchers have expanded their datasets and prevented overfitting by using data augmentation techniques such as rotating, mirroring, and magnifying pictures. The discrepancy between experimental results and practical application in the healthcare industry, as well as the absence of explainable AI (XAI) to support users in comprehending and believing the outcomes, are two other noteworthy drawbacks. Scalability, flexibility, and robustness of the suggested models are challenged when moving from controlled laboratory settings to dynamic field circumstances, especially when COVID-19 could be mistakenly categorized as other illnesses.

Furthermore, a large number of the evaluated studies only address binary classification such as (coronavirus positive or negative), which restricts research into multi-class classification and the ability to differentiate between other respiratory diseases, including bacterial pneumonia, lung diseases, and other viral illnesses.

6.0 DISCUSSION

One notable similarity found in the publications this study analyzed is the application of deep learning architectures for coronavirus (COVID-19) illness detection and classification. Convolutional neural network models were integrated with various machine learning classifiers in several of the examined papers, including the ResNet50 Model and the SVM classifier (Kumar Sethy et al., 2020, and Ismael & Şengür, 2021), to name a few. Several other models were used in the numerous papers that were examined, such as the VGG16 and InceptionV3 Model, an ensemble model for convolutional neural networks, DenseNet121, DenseNet169, ANOVA, the XGBoost Algorithm, and InceptionV3. These research' designs have demonstrated the power and effectiveness of deep learning approaches in handling intricate picture datasets, making it easier to extract useful features for the categorization of coronavirus and related illnesses.

Several authors and researchers augmented their data due to the limitations of the COVID-19 sample datasets, which resulted in zooming, rotating, resizing, standardizing, and sharing of images on the datasets to prevent overfitting occurrence for incrementation of the datasets as required. These also produced some promising accuracy results in the study. The application of data augmentation and preprocessing techniques was common across the reviewed studies.

However, notable variations were found in the experimental setups and methodologies employed by the reviewed studies; some studies concentrated solely on Chest X-ray sample datasets, while others only examined CT image sample datasets; still others focused on using both Chest X-ray sample datasets and CT image sample datasets in their own study to identify and categorize coronavirus (covid-19) disease at an early stage. Other differences were found in the selection of datasets; some researchers used coronavirus (covid-19) datasets that were made publically available, while others looked for and created their own dataset samples.

7.0 FINDINGS/RESULTS

We have thoroughly examined thirty (30) research publications that focus on the use of deep learning models for the identification of coronavirus illness in this review of the literature. After scrutinizing the techniques, constraints, and principal discoveries, we have discerned many recurring patterns and discrepancies. The research findings highlight the flexibility of deep learning in coronavirus disease detection, as well as the persistent difficulties arising from small dataset samples and the necessity for models to transfer well from lab environments to real-world healthcare settings. These findings provide insightful information for next research projects and open the door to the creation of more robust and realistically optimal methods for early-stage coronavirus illness detection and classification.

8.0 CONCLUSION

Global healthcare systems and people have been significantly impacted by the COVID-19 epidemic. Rapid and effective screening strategies to identify coronavirus infection early are desperately needed to tackle this new illness (Maghdid et al., 2021). The research has highlighted a number of deep learning-based techniques that use datasets of computed tomography and chest X-ray images to focus on the early identification and classification of COVID-19 illness. One common method used to diagnose and classify coronavirus illness and other related lung infections is to analyze samples of chest X-rays and computed tomography scan images.

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