

COVID-19 Detection from X-Ray Images using Convoluted Neural Networks: A Literature Review

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Abstract—This paper reviews a host of other peer-reviewed articles related to the detection of COVID-19 infection from X-ray images using Convoluted Neural Network (CNN) approaches. It stems from a background of a pandemic that has hit the world and negatively affected all spheres of life. The currently available testing mechanisms are invasive, expensive, time-consuming, and not everywhere. The paper considered 33 main articles supported by several other articles. The measurement metrics considered in this review are accuracy, precision, recall, F1-score, and specificity. The inclusion criteria for studies was that the article should have been written after the pandemic began, deliberates on CNN, and attempts to detect the disease from X-ray images. Findings suggest that transfer learning, support vector machines, long short-term memory, and other CNN approaches are highly effective in predicting the likelihood of the disease from X-rays. However, multi-class predictions seemed to score lowly on the accuracy score relative to their binary counterparts. Also, data augmentation significantly improved the performance of the models. Hence, the paper concluded that all reviewed approaches are effective. Recommendations are that analysts should integrate transfer learning procedures in the model formulation process, engage in data augmentation practices, and focus on classifying data based on binary classes.

Keywords—*Convoluted neural networks; COVID-19; chest x-ray; transfer learning; support vector machines; long short-term memory*

I. INTRODUCTION

COVID-19 is a respiratory disease caused by a relatively new virus belonging to the coronavirus family. It was discovered in late 2019, and it has since wreaked havoc globally [1] and compromised the global health system by clogging it with patients [2]. It has had a catastrophic effect on the economy, social lives, education, and other sectors of life. While the proportion of deaths resulting from this disease is low on average, the absolute number of deaths stands at 5.41 million [3]. One of the major issues aggravating the spread of COVID-19 is the fact that testing is not universally available to everyone [4, 5]. Governments prioritize persons with flu signs to take these tests. If one is detected positive, they are advised to quarantine and or hospitalized. This approach has helped arrest cases that would have spread undetected. The limitation with the testing approach is that there are limited testing equipment because of the novelty of the virus. Additionally, these testing systems are not available everywhere because some locations are remote. The tests are also invasive and time-consuming [6]. Artificial intelligence in

the form of convoluted neural networks comes in as a more convenient substitute [7]. It works by consolidating X-ray data from previously tested individuals and checking new ones against this database. The X-ray technology is available almost everywhere, which makes it a good candidate for a more inclusive testing system. With the right level of accuracy, it is possible for this new testing approach to become just as reliable.

The study investigates the effectiveness of different deep learning approaches in the detection of COVID-19 using X-ray images. The study is significant to stakeholders in the medical sector because the problem of testing individuals for the virus is clear [8, 9]. By presenting and discussing the effectiveness of different approaches, these practitioners will be able to objectively decide which approaches to adopt in enhancing the accuracy and reliability of their test results. The study is also significant to future researchers who may wish to read the comparisons between the selected approaches in detecting COVID-19 from examining X-ray images. The field of deep learning allows researchers to use several models in modeling problems and solutions. Not all models fit to all problem scenarios. Hence, this study will examine the approaches featuring prominently in the previous studies examining that have examined COVID-19 scenarios, which are CNN with transfer learning, CNN with support vector machines, CNN with Long Short-Term Memory, and other CNN approaches.

The first three approaches seem to be the basis of the majority of studies within the selected studies. The approaches have also been in use for quite some time, hence explaining the number of studies willing to integrate them into their models. Approaches that the researcher did not find to be thematically feature in many studies were consolidate in the fourth group of ‘other CNN approaches.’ A myriad of studies comprised this group. However, there was no central theme in the approaches considered within them. Finally, the study will investigate sundry approaches used in the detection of the virus from X-ray images. Ultimately, the study will compare the usefulness of these approaches with respect to their performance in precision, recall, F1-score, support, accuracy, sensitivity, specificity scores.

II. BACKGROUND

The COVID-19 pandemic is the worst pandemic that has plagued the world in recent times. It has succeeded in bringing the world to a halt in almost of spheres of life and has had a

devastating effect on the global population [10]. The economy has taken the biggest hit as estimates indicate that the global economy will have declined by about 5.7% in 2021 measured in GDP [11]. Social lives have also not been the same with stringent measures imposed on the public on how to interact with each other on top of travel restrictions. Places of worship have also experienced several restrictions from governing authorities [12]. But the most important statistics related to the number of people that have contracted the disease and those that have succumbed as a result. The World Health Organization estimates that there have been 274 million cases, while the number of deaths stands at 5.41 million [3]. Evidently, all people wish that this virus disappears because of the disastrous impact it has had on their lives and livelihoods.

To the time of writing, scientists have been successful in discovering an array of vaccines, which continue to be distributed across the world. The effectiveness of these vaccines to end the pandemic has been questioned because of several factors such as limited supply, vaccine hesitancy, and the rise of new variants like the most recent Omicron variant [13]. It seems that scientists have to strongly rely on testing and quarantining infected persons as a formidable way of arresting the virus. The challenges bedeviling this approach are many and significant. Firstly, the cost of testing is way beyond what ordinary people would afford, especially periodically [14]. Secondly, testing equipment is costly and limited in number. Thirdly, the tests take long before they are verified. The reading time taken by radiologists also needs to be reduced for efficiency purposes [15]. For these reasons (and many more), deep learning enthusiasts have been challenging themselves to map X-ray images from persons tested using the conventional approaches and mapping them to their results [16]. As a result, they have come up with models attempting to classify and predict one's COVID-19 status based on their chest X-ray scans.

The use of neural networks in classifying X-ray images of possible COVID-19 patients has been an ongoing research endeavor that has attracted the scholarly attention of several scholars, thereby creating a body of scholarly research that is growing by the day. These researchers have engaged with different methods, approaches, and techniques to improve the accuracy score of their models [5]. An examination of these approaches, techniques, and methods should inform the progress that has been made in this regard. It also gives other researchers the motivation to join the race for the attainment of 100% accuracy scores across the precision, recall, F1-score, support, accuracy, sensitivity, specificity scores [17]. This study reviews some of the most significant research papers that have engaged in this field, and therefore, compares the approaches used by the researchers.

III. METHODOLOGY

A. Study Design

The study adopts the design of a systematic literature review of peer-reviewed papers submitted and published in prominent journals. The review compares and contrasts findings reported in these studies and therefore gives an objective analysis on the same. The performance scores of the tests and procedures carried out in these analyses inform the

reliability of the approaches taken this study examines the accuracy, precision, recall/sensitivity, F1-score, specificity scores obtained in running the tests and suggests whether the approaches taken are reliable. These comparisons are the basis of the study recommending specific approaches while casting aspersions on the testing reliability of others.

B. Measurement Metrics

1) *Accuracy*: Accuracy refers to the level of correctness with which a model identifies the positives and negatives during classification. In a confusion matrix, True Positives and True Negatives are added and their ratio to the total number of subjects computed to give the accuracy score [18]. Many studies rely on this measure to determine the validity of their results.

2) *Precision*: Precision refers to the level of correctness with which a model identifies the positive cases out of all the positive cases detected. This computation involves taking the ratio of True Positives and False Positives from the confusion matrix [19]. It is a measurement metric that also features prominently in several studies.

3) *Recall (Sensitivity)*: Recall (otherwise known as sensitivity) refers to the proportion of correctly labelled positive cases against the total number of actual positive cases. It determines how accurately a model correctly detects positive cases [17]. The numerator is the number of positively labelled cases, while the denominator is the number of all positive cases regardless of whether they were detected as positive or not.

4) *F1-Score*: The F1-Score refers to a compromise between the precision and recall values. It is the harmonic mean between the two metrics [20]. The metric is reliable only if there is some balance between the two. Otherwise, if there is a tradeoff between them, the F1-Score is not likely to be high.

5) *Specificity*: Specificity refers to the proportion of actual negative cases that were predicted as negative by the model. It is the same as recall or sensitivity only that this time the group in focus contains negative cases.

C. Inclusion and Exclusion Criteria

The number of studies considered in this approach is 33, with additional studies backing up these papers by providing context. The researcher procedurally filtered out articles to remain with the ultimate 33 papers based on several criteria. On the criterion of relevance, several parameters were considered. Firstly, a study was considered only if it was about detecting COVID-19. Secondly, a study should be using CNN approaches for it to qualify. Thirdly, the CNN approaches should take chest X-ray images. On the time criterion, a study should have been conducted between 2019 and 2021. Since the disease was discovered in 2019, this filter did little to reduce the number of studies. Finally, the study considered the credibility criterion where a study was only considered if it was peer-reviewed. This filter was also responsible for eliminating web-based studies, those that did not have clear sources of data, and papers whose methodological approaches seemed flawed. Fig. 1 shows the paper search procedure, while Fig. 2 illustrates how the studies were filtered out.

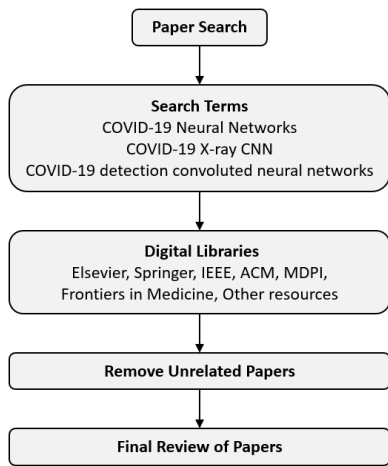


Fig. 1. Paper Search Procedure.

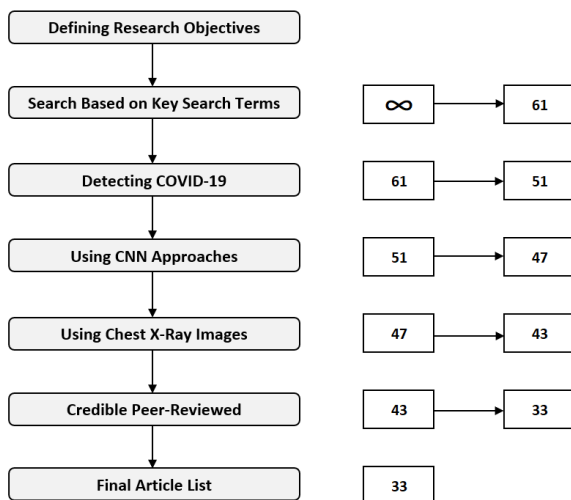


Fig. 2. Filtering Out Studies.

D. Definition of Key Terms and Abbreviations

ACGAN Auxiliary Classifier Generative Adversarial Network

ARIMA AutoRegressive Integrated Moving Average

AUC Area Under the Curve

Bayesnet Classifier A Bayesian network that is applied to CNN classification

CapsNet Capsule Neural Network

CFS Correlation-Based Feature Selection

CNN Convoluted Neural Networks

CNN-RF A hybrid of Convoluted Neural Network and Random Forest classifier

CNN-Softmax Convoluted Neural Network mostly applicable in a multi-class setting

Coro-Net One of the many models designed to detect coronavirus from xray images using CNN

DarkNet An open source high performance framework used to implement neural networks

DenseNet-121 It is a deep learning architecture that enable deep learning networks to to have a deeper reach but still maintain efficiency in its training

DTL Deep transfer learning

GDP Gross Domestic Product

Inception-ResNetV2 It builds on the inception family while also incorporating residual connections

InceptionV3 It is a CNN that assists in the detection of images and analysis of images

LSTM Long short-term memory

MobileNetV2 It is an architecture that assumes an inverted residual structure in which the input-output are thick bottleneck layers, and are not the expanded representation of the input

PA The Prophet Algorithm

ResNet It is an artificial neural network that works by stacking residual blocks to eventually form a network

ResNet101 A ResNet that is 101 layers deep

ResNet152 A ResNet that is 152 layers deep

ResNet18 A ResNet that is 18 layers deep

ResNet50 A ResNet that is 50 layers deep

ResNet50V2 A better performing version of ResNet50

RT-PCR Reverse transcription polymerase chain reaction

SqueezeNet It is a CNN that actively uses fire modules to reduce the number of parameters

SVM Support vector machines

VGG16 16 layers deep CNN

VGG19 19 layers deep CNN

Xception A CNN whose depth traverses 71 layers

IV. RESULTS

This section analyzes the application of three main CNN approaches in predicting COVID-19 positivity using X-ray images. The methods analyzed herein are transfer learning, support vector machines, and long-term short-term memory. Other minor CNN approaches are also analyzed in the fourth subsection. The goal is to establish their performance and with respect to the performance metrics discussed in the previous sections of this paper.

A. CNN with Transfer Learning

Several studies combined the convoluted neural networks with transfer learning to examine the model's outcome. In [21], the study applied a dense convoluted network with transfer learning and considered three labels, namely patients with COVID-19, with Pneumonia, and Normal. The study

worked with 112,120 chest X-ray images, which were obtained from 30,805 patients. The specific transfer learning approach adopted was known as twice-transfer learning whereby the study used the NIH ChestX-ray14 dataset as the intermediate step. The study reported an improvement in the model's effectiveness and the performance of the deep neural network, which is consistent with the findings established in [22]. Results indicated that the researchers were able to attain an accuracy of 100% on the dataset, which affirms the role played by transfer learning. These findings are similar to [23], whereby, the study employed the transfer learning approach with VGG19, MobileNetV2, Inception, Xception, and Inception-ResNetV2. The researchers assembled 1427 X-ray images. Accordingly, the study found that the application of the approach yielded remarkable positive results. The outcome yielded an accuracy of 96.78%, 98.66% sensitivity, and 96.46% specificity.

Some studies were prudent enough to mitigate the issue of small sample sizes by applying the transfer learning approach. The investigation by [24] is one such study, and it examined X-ray images to determine the effectiveness of deep learning and convoluted networks in detecting COVID-19. The dataset used consisted of 112 X-rays from each of the three classes – with COVID-19, with Pneumonia, and normal. Using transfer learning, the researchers successfully extracted knowledge from pre-trained models and used it on the model to be trained. Ultimately, the two best models by the study scored an accuracy of 95%. Sensitivity scores for the two best models VGG16 and VGG19 were 96% and 92%. Fig. 3 shows training loss, validation loss, training accuracy, and validation accuracy of the two top-performing epochs.

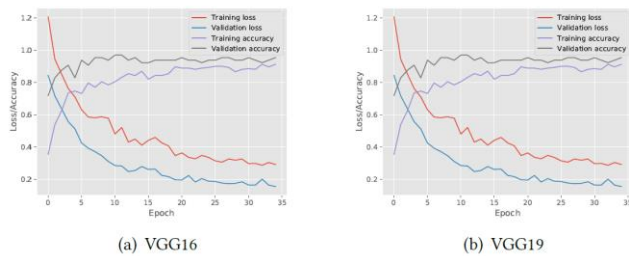


Fig. 3. Comparing VGG16 and VGG19 [24].

The investigation further constructed the confusion matrices for the models it ran, and the matrices for the two-top models VGG16 and VGG19 are shown in Fig. 4.

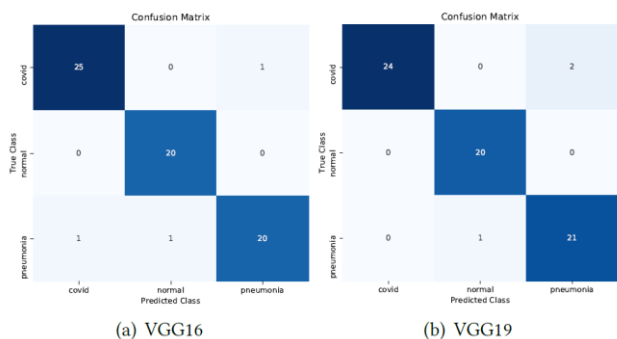


Fig. 4. Comparing Confusion Matrices between VGG16 and VGG19 [24].

Similar studies were conducted that reported findings resonating with those established in the above study. The research by [25] finds that transfer learning is an impeccable approach to boost the effectiveness of neural network models that predict COVID-19 from X-ray, ultrasound, and CT scan images. Using the VGG19 model, the study found that ultrasound images had the highest precision, which was 100%, followed by X-ray (86%), and CT scans (84%). Transfer learning algorithms are critical to the improvement of model results in neural networks [26]. Using publicly available datasets, the researchers report an accuracy of 96.3%, which they consider to be very high and reliable. The sample size employed was quite minimal as it comprised images from 65 male and 45 female sources, which totals 110. The confusion matrix suggests that out of the 34 sick patients, the model managed to correctly predict 33. On the other hand, out of the 75 normal cases, the model correctly predicted 72. Transfer learning was essential to attain these results because the approach extrapolates training models from other successful pre-trained data.

Transfer learning has also been used with InceptionV3 and ResNet50 models to predict COVID-19 based on X-ray images. The study by [27] developed a deep transfer learning (DTL) where they employed convoluted neural networks using X-ray data obtained from Kaggle. The dataset used comprised 160 COVID-19 X-ray images and another 160 normal X-ray images. The InceptionV3 model scored a 99.01% accuracy, while ResNet50 model managed to score an accuracy of 98.03%. The models' performance was slightly higher than other models against which the study was benchmarking its results. In [28], the study considered more than the two models encompassed in the study above. Specifically, the investigation considered DenseNet-121, SqueezeNet, ResNet18, and ResNet50. The dataset contained 5000 X-ray images. These neural networks were trained using the transfer learning approach on a subset of 2000 radiograms. 3000 images were used in validating the model. Findings suggested that the model's sensitivity rate was 98%, while its specificity rate was 90%.

Some studies have used the transfer learning approach to investigate the effectiveness of neural networks in predicting COVID-19 from X-ray images. The investigation by [20] examined VGG16 and VGG19 to establish which one maximizes the effectiveness of the model. Like many other studies, this investigation also used image data from public repositories, which had images classified into three groups, namely COVID-19, pneumonia, and normal. The highest AUC value was found to be 0.950 (95.0%) – VGG16. The VGG16 neural network achieved higher performance scores, where it obtained an accuracy of 95.9%, sensitivity of 92.5%, and specificity of 97.5%. Fig. 5 shows the accuracy level of the two neural networks across the number of fine-tuned convolutional blocks.

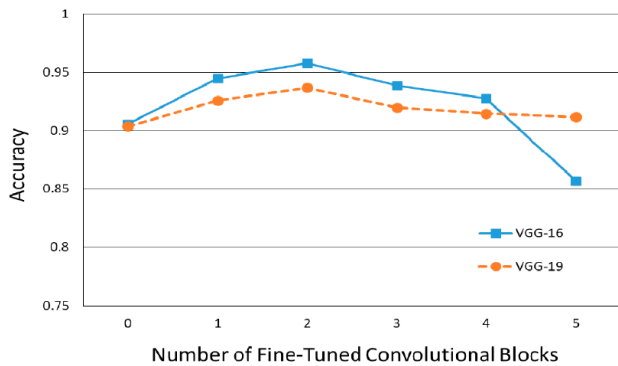


Fig. 5. Comparing the Accuracy of VGG16 and VGG19 Models [20].

Transfer learning can also be useful in building models that classify image data into more than three categories. In [29], the study employed this approach in classifying images into six diseases. The goal was to use X-ray data for known six diseases and determine whether or not the patients had COVID-19 too. The study used a dataset containing 3905 X-ray images. The specific neural network used in this investigation was MobileNetV2, which was trained using the data from patients suffering from the six diseases. Results showed that the classification accuracy was 87.66%. Other measures were accuracy (99.18%), sensitivity (97.36%), and specificity (99.42%). Table I shows the outcomes against the specific diseases.

TABLE I. CONFUSION MATRIX RESULTS [29]

	Actual classes						
	Covi d19	Ede ma	Effus ion	Emph ys ema	Fibr osis	Pneum onia	Nor mal
Predicted classes							
Covid19	21	0	1	1	0	1	0
Edema	270	254	210	199	155	171	136
Effusion	4	5	24	4	6	0	1
Emphysema	15	16	34	49	31	4	7
Fibrosis	46	17	35	50	78	3	18
Pneumonia	91	1	3	4	2	712	287
Normal	8	0	4	8	8	19	892

B. CNN with Support Vector Machines (SVMs)

Support vector machines have been in use to detect the likelihood of patients having the virus causing COVID-19. The study by [30] faults the generic means through which clinicians test for the virus, which is known as the real-time reverse transcription-polymerase chain reaction (RT-PCR) method. According to the source, the approach yields low positivity rates among persons who have recently contracted the virus. Hence, the study considers the method unreliable for such cases. Instead, the source suggests the use of CNN with support vector machines to conduct these tests. This method is

said to be effective because regardless of when one contracted the virus, chest X-rays of a normal person, that of a pneumonic person, and that of a COVID-19 infected person shall always be different. The dataset used for the analysis is from the first worldly available dataset on the same. The number of cases in the selected dataset was 71, where 48 were for COVID-19 infected persons, while the rest (23) were from normal people. The dataset also underwent augmentation to avoid possible overfitting by the model. This specific study reported an accuracy score of 90.5%. This value was acceptable but it was lower than that of using the CNN-SoftMax model. However, the selected approach scored a higher accuracy compared to the CNN-RF method. Table II compares the accuracy, sensitivity, specificity, and precision scores as reported in the study.

TABLE II. PERFORMANCE METRICS AGAINST DIFFERENT MODELS [30]

Classifier	Accuracy	Sensitivity	Specificity	Precision
CNN-Softmax	95.2%	93.3%	100%	100%
CNN-SVM	90.5%	86.7%	100%	100%
CNN-RF	81%	76.5%	100%	100%

The Support vector machines method has been used with kernel functions such as Gaussian, linear, cubic, and quadratic. In the study by [31], the goal was to establish the effectiveness of using support vector machines and neural networks in detecting COVID-19 in X-ray images. The model employed pre-trained models in training the data. The pretrained models that were used are the VGG16, the VGG19, the ResNet18, the ResNet50, and the ResNet101. The dataset contained 380 images data, 200 of which were for normally healthy persons, and the other 180 were from persons infected with the novel coronavirus. The ResNet50 fine-tuned model produced results with an accuracy of 92.6%. However, the ResNet50 when used with linear kernel produced an accuracy of 94.7%. The findings indicated that the deep learning methodologies are more efficient in detecting COVID-19 compared to the descriptors of local texture. These findings are also consistent with [32] and [33], which came to similar conclusions. Table III is a summary table comparing the performance of the selected neural network models in terms of their accuracy scores.

The confusion matrix below illustrates that out of the possible 45 COVID-19 cases, the model accurately predicted 43. On the other hand, out of the possible 50 non-COVID-19 cases, the model accurately predicted 45. Fig. 6 shows the confusion matrix associated with this analysis.

TABLE III. COMPARING ACCURACY SCORES ACROSS DEEP CNN MODELS [31]

Fine-tuning	Accuracy
VGG16	85.26%
ResNet18	88.42%
ResNet50	92.63%
ResNet101	87.37%
VGG19	89.47%

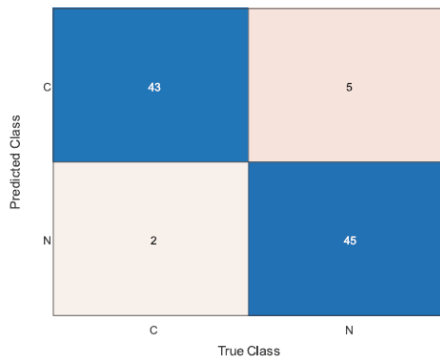


Fig. 6. Confusion Matrix [31].

At times, separating the classes into two (infected and not infected) can have a significant positive effect on the outcomes of models using the support vector matrix. In the study conducted by [34], the researchers used CNN to conduct feature extraction and support vector matrix as the classification method. Using InceptionV3, ResNet50, ResNet101, and Inception-ResNetV2 as the pre-trained models of choice, the study attempted to classify the data into two (infected versus not infected) and into three (COVID-19, pneumonia, and normal). The accuracy of the instrument was 97.33% when the researcher considered three classes, while it rose to 100% when the cases were separated into two. These findings suggest that the accuracy scores of a model can be significantly affected by the number of classification categories required. Fewer categories seem to produce more accurate results by the support vector-matrix model. Outcomes also suggested that the two top models were ResNet50 and ResNet101. Their confusion matrices as shown in Fig. 7.

C. CNN with Long Short-Term Memory (LSTM)

Some studies combined CNN with Long Short-Term Memory approach to predict the likelihood of a subject having COVID-19 based on their X-ray images. It is an architecture in the artificial recurrent neural network commonly used in deep learning [35]. It is different from conventional feedforward neural networks in that Long Short-Term Memory approach has feedback connections [36]. For this reason, the network can process entire data sequences as opposed to processing a single data sequence. Its name is inspired by the fact that programs use short term memory structures to generate long-term memory. The complexity of LSTM models has made them perfect candidates for solving complex machine learning problems such as speech recognition, machine translation, and many more. In image classification, LSTM has also been a formidable and reliable approach as noted in [37]. The study finds that the proposed classification method using LSTM is far more effective in classifying images than other state-of-the-art classification methods.

The use of CNN and LSTM has been found to result in high levels of accuracy. In [38], the study introduced a combined CNN-LSTM model of predicting the likelihood of COVID-19 infection given X-ray images. CNN was responsible for extracting features from the images, while LSTM was the method used to classify these images. The

research utilized 4575 X-rays from random subjects. Among the images, 1525 were for confirmed COVID-19 cases. Another 1525 were from patients with regular pneumonia, while the other 1525 from for normal patients without pneumonia and COVID-19. The outcome suggested that the accuracy of this model stands at 99.4%. Its AUC was 99.9%, F1-Score 98.9%, sensitivity 99.3%, and a specificity of 99.2%. The performance of the combined model was far more effective compared to if LSTM was not used. Fig. 8 shows the confusion matrices obtained from running the model on the data comparing the usage of LSTM and the lack of it. Evidently, using LSTM improved the model's performance by reducing incorrectly predicted COVID-19 cases from 3 to 2.

LSTM has been used alongside other methods to predict COVID-19 infection based on X-ray images. One study used CNN with LSTM, autoregressive integrated moving average (ARIMA), and the Prophet Algorithm (PA) [39]. Overall results suggest that the accuracy of the models ranged between 92.33% and 99.94% when predicting confirmed cases. The models seemed to perform relatively poor in predicting recovered and death cases. For the recovered cases, the best model attained an accuracy of 90.29%, while the worst model achieved an accuracy metric of 63.52%. Regarding death cases, the best model attained 94.18% as its accuracy value, while the worst model attained an accuracy value of 78.02%. Findings from the study established that while LSTM did well to predict confirmed and death cases, the model performed relatively poor in predicting recovered cases. All the same, LSTM seemed more effective in predictions compared to ARIMA. However, the Prophet Algorithm was the best model of the three in predicting all of confirmed, recovered, and death cases. Other studies that have affirmed the reliability of LSTM in COVID-19 prediction are [40] and [41]. Table IV compares the performance of the various models used in the study.

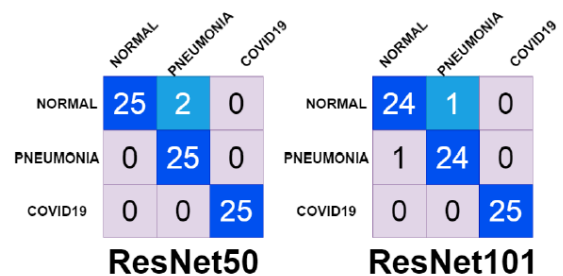


Fig. 7. Comparing Confusion Matrices ResNet50 and ResNet101 [34].

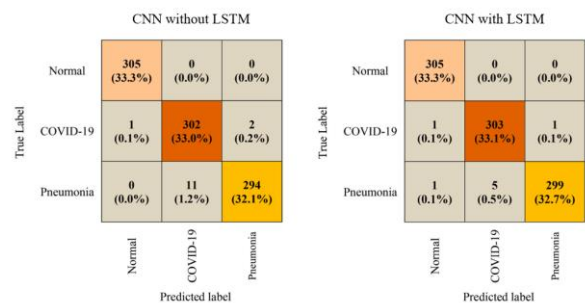


Fig. 8. Comparing Models with and without LSTM [38].

TABLE IV. PA, ARIMA AND LSTM PERFORMANCE SCORES [39]

Prediction Algorithm	Accuracy
PA (confirmed cases)	99.94%
PA (recovered cases)	90.29%
PA (death cases)	94.18%
ARIMA (confirmed cases)	92.33%
ARIMA (recovered cases)	63.52%
ARIMA (death cases)	78.02%
LSTM (confirmed cases)	94.16%
LSTM (recovered cases)	86.44%
LSTM (death cases)	92.76%

D. Other CNN Approaches

Many other studies utilized various approaches in reaching the same goal. The study by [42] found that by leveraging Auxiliary Classifier Generative Adversarial Network (ACGAN), the model’s accuracy improved from 85% to 95%. In another study by [43], the researchers engage in a model utilizing depthwise convolution with fluctuating rates of dilation in a multi-class detection system. The COVID-normal test produced an accuracy score of 97.4%. In [44], the study considered 1215 images sourced online, which were taken through an augmentation process to end up with 1832 images. Furthermore, the study engaged in stage-I and stage-II deep network model designing. Using these methods and techniques, the ultimate model attained an accuracy of 97.7%, a precision value of 97.14%, and a recall value of 97.14%. The conclusion was that the model was effective in predicting COVID-19 infection from X-ray images. Another study reported in [45] developed a model that utilized the concatenation of Xception and ResNet50V2 networks. The researchers trained several deep convolutional networks, while leveraging 11,302 X-ray images sourced online. The proposed model achieved an accuracy of 99.5%. For this reason, the authors find the model effective and reliable in determining whether a patient is infected with COVID-19. Other studies that employed the Xception model and reported similar findings are [46, 47]. It underscores the importance of the pre-trained model in detecting COVID-19 infections.

Some studies have established that there is a big difference when considering binary class and multi-class situations in favor of binary. For example, classifying X-ray images into COVID-19 and non-COVID yields a higher accuracy value compared to if the classes are COVID-19, pneumonia, and healthy. The investigation reported in [48] used the DarkNet model in classifying the X-ray images. Findings from the investigation suggest that classification accuracy when using binary classes was 98.08%, while that obtained in a multi-class situation is 87.02%. Another study that utilized binary classification is [49], which assembled four classes, namely bacterial pneumonia, viral pneumonia, COVID-19, and healthy groups. Studies such as [50] use one pre-trained CNN model, the researchers adopted five pre-trained CNN-based models of ResNet101, ResNet50, ResNet152, Inception-ResNetV2, and InceptionV3. Findings indicated that ResNet50 was the most effective as it resulted in 99.7% in one of the datasets used. It indicates that this pre-trained model is also effective in detecting COVID-19.

In [51], the study used the ResNet101 CNN to examine the effectiveness of deep learning in detecting COVID-19 from X-ray images. The researchers used publicly available chest radiographs in the thousands, some of which were from confirmed COVID-19 patients. Findings established that the accuracy of the resultant model was 71.9%, while its sensitivity and specificity were 77.3% and 71.8%, respectively. The training process involved creating a model that would positively identify radiographs images with chest abnormalities. The study’s strength is that it used mutually exclusive publicly available data and that it used labels with a strong clinical association with COVID-19 cases.

Multi-CNN is another approach used in modeling and classification of image data in artificial intelligence. The approach was used in [49], and it involved utilizing Bayesnet Classifier and Correlation-Based Feature Selection (CFS). Using two datasets, the multi-CNN method was tested. The first dataset contained 453 X-ray images from COVID-19 patients and 497 images from patients without the disease. The accuracy of the model on this dataset was 91.16% and an AUC of 96.3%. The second dataset contained 78 X-ray images; 71 of which were from COVID-19-infected patients. Findings on this data suggested that the accuracy score was 97.44% and an AUC of 91.1%. The study concluded that pre-trained multi-CNN was more effective in detecting the disease compared to using single-CNN approaches.

Some studies have utilized capsule neural networks in detecting COVID-19 from X-ray images. Capsule networks are a form of artificial neural networks, and they are known for their ability to fetch spatial information thereby exhibiting great performance. Some studies used the method CapsNet to detect COVID-19 and found that binary classes seem to perform better than multi-class approaches [52, 18]. An analysis of the model’s performance on binary classes obtained an accuracy score of 97.24%, while in the multi-class, the score was 84.22% in [52]. The study concluded that it is a reliable model for physicians to use in conveniently detecting the COVID-19 status of their patients. Fig. 9 shows the confusion matrices comparing the results of the two analyses with binary and multi-class situations.

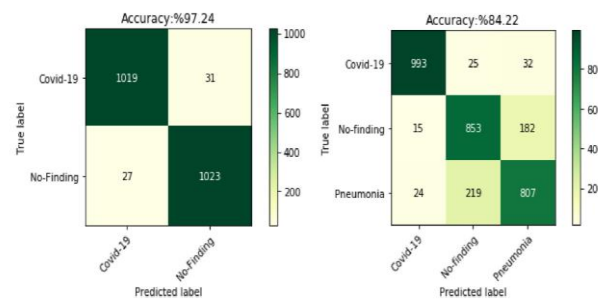


Fig. 9. Comparing Binary and Multi-Class Approaches [52].

The decision tree classifier has also been used in some studies alongside CNN to detect COVID-19 infection from X-ray images. The studies by [53, 54] find the RT-PCR test as inconvenient as it is not time-friendly and it is also not affordable to the populace. The researchers suggest a system that utilizes the decision tree algorithm to separate COVID-19

cases from the rest. The first separation occurs by isolating normal scans from abnormal ones. The second step in the decision tree classification involves telling between those that have signs of tuberculosis among the abnormal scans. The third step is similar to the second step only that this time it does so for COVID-19. The accuracy scores of these steps are 98%, 80%, and 95% for the respective steps.

V. DISCUSSION

Many of the studies adopted transfer learning as their preferred method in attempting to improve the effectiveness of the model. Findings have been quite consistent in establishing that this method boosts the performance scores across accuracy, sensitivity, precision, and F1-scores. According to [27], transfer learning improves model effectiveness by ensuring that the analyst does not spend too much time training new models. Instead, an analyst relies on previously trained models with some few improvements. The study by [23] finds that using transfer learning is a key consideration among many analysts when dealing with CNN. Some studies have reported increased accuracy values running up to 100%. It underscores the need for data analysts to embrace this approach in their endeavors, as it has proven to be reliable. Therefore, it is understandable why several studies settled for this approach. One important take-away from the review of transfer learning approach is that binary-class classification seems to be performing better than multi-class classification. Data augmentation was also prominent in this approach, which also contributed to the heightened effectiveness of the resultant models.

The use of support vector machines in classifying images to detect COVID-19 infections was also clear from this review. This approach has been lauded in [34] as a formidable supervised approach to image classification because of its ability to classify and regress too. When combined with functions such as Gaussian, linear, cubic, and quadratic, its performance increases even further. While it is a relatively new classification method, its adoption in this regard is a

testament to its effectiveness and reliability. The method is highly memory-efficient because its decision function uses a subset of training points. Perhaps, the only disadvantage with the SVM approach is that it is not efficient for large datasets because of the time it would take to train the model. For the case of COVID-19 detection, the required data does not have to be massive. Even here, data augmentation featured significantly, and it also positively affected the strength of the resultant models.

CNN with Long Short-Term Memory also featured prominently in this review. Findings were clear that combining CNN with LSTM significantly improves the accuracy of the trained models. This view is consistent with [36] where the researchers argue that this approach is an area of growing interest because of its effectiveness. The large range of parameters provided by LSTM and the input and output biases strongly argue the case for its adoption in CNN classification models. The method is also a bit insensitive to gap length, which is an advantage it holds against the RNN. Such advantages seem to give the LSTM approach an edge and explain why data scientists would prefer to work on models that encapsulate this approach. LSTM in binary classification seemed to be more accurate than in multi-class classification situations.

CNN has its pre-trained models that some studies have evidently taken advantage of to predict COVID-19 infections. Their usage is evident among the studies encapsulated in the 'other CNN approaches' subsection. Examples of common models are DenseNet-121, SqueezeNet, ResNet18, and ResNet50, among others [50]. They have proven to be highly effective in accurately predicting the disease based on X-ray images. Even here, binary-class classification seems to be performing better than multi-class classification. The use of decision tree classification was outstanding though it could not accurately predict recovery and death rates.

Table V summarizes the findings and limitations of articles consulted throughout this paper.

TABLE V. SUMMARY OF CONSULTED

#	Publication	Author Date	Accuracy	Sensitivity	Specificity	F1-Score	Purpose	Model or Approach	Limitation
1	[21]	(Bassi & Attux, 2021)	100.0%	100.0%	100.0%	100.0%	Detecting COVID-19 using X-ray images	Transfer Learning	Only 150 images
2	[22]	(Heidari, et al., 2020)	94.5%	98.4%	98.0%	-			Only investigates and tests two image preprocessing methods
3	[23]	(Apostolopoulos & Mpesiana, 2020)	96.8%	98.7%	96.5%	-			More patient data needed
4	[24]	(Makris, et al., 2020)	95.0%	-	-	-			None indicated
5	[25]	(Horry, et al., 2020)	86.0%	86.0%	86.0%	86.0%			Inadequate data
6	[26]	(Vaid, et al., 2020)	96.3%	-	-	-			Lack of publicly available and expert labeled images
7	[27]	(Benbrahim, et al., 2020)	98.03% - 99.01%	-	-	-		Transfer Learning, InceptionV3, ResNet50	---

8	[28]	(Minaee, et al., 2020)	-	98.0%	90.0%	-		Transfer Learning, ResNet18, ResNet50, SqueezeNet, and DenseNet-121	Limited number of COVID-19 images
9	[29]	(Apostolopoulos, et al., 2020)	99.18%	97.36%	99.42%	-		Transfer Learning, MobileNetV2	---
10	[30]	(Alqudah, et al., 2020)	95.2%	93.3%	100.0%	100.0%		SVM	The need for more classifier types
11	[31]	(Ismael & Şengür, 2021)	94.74%	91.0%	98.89%	94.79%		SVM, ResNet50	---
12	[32]	(Saraswati, Wardani, & Indradewi, 2020)	93.91%	98.75%	89.06%	91.26%		SVM	---
13	[33]	(Saygılı, 2021)	94.5%	92.25%	90.00%	-			---
14	[34]	(Novitasari, et al., 2020)	97.3% - 100.0%	-	-	-		SVM, ResNet50, ResNet101	Model time processing is long
15	[36]	(Sherstinsky, 2020)	-	-	-	-	Fundamentals of LSTM		---
16	[37]	(Öztürk & Özkaya, 2021)	-	-	-	-	Image Classification		---
17	[38]	(Islam, et al., 2020)	99.4%	99.3%	99.2%	98.9%		LSTM	Small sample size
18	[39]	(Alazab, et al., 2020)	95.0-99.0%	-	-	95.0-99.0%			---
19	[40]	(Demir, 2021)	100.0%	100.0%	100.0%	-			---
20	[41]	(Naeem & Bin-Salem, 2021)	98.94%	99.00%	99.00%	99.00%			Limited number of COVID-19 images
21	[42]	(Waheed, et al., 2020)	95.0%	90.0%	97.0%	-		ACGAN	Small dataset
22	[43]	(Mahmud, et al., 2020)	97.4%	97.8%	94.7%	97.1%		Inception, VGG-19	---
23	[44]	(Jain, et al., 2020)	98.9%	98.9%	98.7%	98.2%		ResNet50, ResNet101	Limited number of COVID-19 images
24	[45]	(Rahimzadeh & Attar, 2020)	99.5%	80.5%	-	-		ResNet50V2 and Xception	Small dataset
25	[46]	(Khan, et al., 2020)	89.6%	-	-	-	Detecting COVID-19 using X-ray images	Coro-Net, SVM	More testing required
26	[47]	(Singh, et al., 2020)	95.8%	95.6%	-	95.9%		XceptionNet	---
27	[48]	(Ozturk, et al., 2020)	98.1%	95.1%	95.3%	96.5%		DarkNet	Limited number of COVID-19 images
28	[49]	(Abraham & Nair, 2020)	91.2%	85.3%	98.5%	91.4%		Bayesnet Classifier	Not tested in a multi-class environment
29	[50]	(Narin, et al., 2021)	94.2%	95.4%	83.5%	74.8%		ResNet50, ResNet101, ResNet152	Limited number of COVID-19 images
30	[51]	(Che Azemin, et al., 2020)	71.9%	77.3%	71.8%	-		ResNet101	Inadequate data
31	[52]	(Toraman, et al., 2020)	97.4%	97.2%	97.0%	97.2%		CapsNet	Small dataset
32	[53]	(Yoo, et al., 2020)	95.0%	97.5%	90.0%	-		ResNet18	---
33	[54]	(Hassantabar, et al., 2020)	93.2%	96.1%	-	-		CNN-Softmax	---

VI. LIMITATIONS

One of the most significant limitations of this study is that the COVID-19 virus is still mutating. As such, it is difficult to tell whether the virus will mutate into a state that causes different patterns on the X-ray image. If this happens, there will be a need to redo the models to fit this new data. Another limitation is that the data sourced by the various studies is not the same. Some sourced it from public repositories, some did so from private sources, some combined the two, while some engaged in augmentation practices. It would be more valid and reliable if the studies had sourced their data from the same source and applied the different methods. In such a situation, it would be reasonable to compare the accuracy scores and determine which method is more effective. Thirdly, some studies applied multiple methods and approaches to their model building process. It is difficult to tell which of the component approaches contributed mostly to the model's effectiveness or whether they did not.

VII. CONCLUSION AND RECOMMENDATIONS

The study concludes that all the approaches reviewed in the discourse are valid and reliable. The slight differences in accuracy scores are not significant enough to warrant writing off some of the approaches. All of transfer learning, support vector machines, long short-term memory, and other CNN approaches delivered results that were basically above 90%. It explains the growing preference among physicians to use these technological methods in detecting COVID-19 early enough. The methods are all non-invasive, more affordable, and available almost everywhere because the only requirement is a chest X-ray of the subject. For the sake of improving the model's accuracy, the study makes the following recommendations.

1) Integrate transfer learning procedures in the model formulation process. The study has established that transfer learning boosts the formidability of models by allowing them to learn from previously trained models and data.

2) Engage in data augmentation practices. In the pre-processing segment of the data analysis phase, there is a need to augment data, especially where data is scarce. This study has found that data augmentation positively impacts the strength and viability of a CNN model.

3) Focus on classifying data based on binary classes. Throughout this review, whenever a study compared the accuracy scores between binary- and multi-class situations, the binary-class scenario produced better results. Hence, it is prudent to consider it the main focus of model formulation.

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