ISSN 2229-5518

The Artificial Intelligence Role in COV-19 Diagnosis

Deeksha Kashyap

Student of Sharda University, Greater Noida

Mrs. Megha Chhabra, Mr. Akash Bhasney, Mr. Sunil Dalal

Assistant Professor of Sharda University

[1]2021383431.deeksha@pg.sharda.ac.in, [2]megha.chhabra@sharda.ac.in, [3]akash.bhasney@sharda.ac.in, [4]sunil.dalal@sharda.ac.in

Abstract: - The pandemic of COV-19 sickness 2019 (Coronavirus) is spreading from one side of the planet to the other. Clinical imaging, for example, X-ray and Computed Tomography (CT), is critical in the global fight against the coronavirus; however, as of late, emerging artificial consciousness (artificial intelligence) technologies enhance the power of imaging technology and aid clinically educated specialists. As a result, we examine the local responses of clinical imaging (assisted by artificial intelligence) to the coronavirus. This research proposes an Artificial Intelligence-based solution to combat the virus. Some "DL (Deep Learning) approaches, such as GANs (Generative Antagonistic Organizations)", "ELM (Extreme Learning Machine), and LSTM (Long/Short Term Memory)", have been used to achieve this aim. In this study, the clinical approach of "machine learning and deep learning" in the detection of coronaviruses includes clinical attributes, electronic clinical records, and CT, X-ray, ultrasound, and so on (like clinical images). The current difficulties and future points of view given in this survey can be utilized to coordinate an optimal organization of computer-based intelligence innovation in a pandemic.

Key words: - “artificial intelligence”, “machine learning” (ML), COV-19, “deep learning” (DL).

ISSN 2229-5518

1. Introduction

According to statistics from the 12th of January 2021, COV-19, or Coronavirus Disease 2019, has over "90.9 million confirmed cases". It is caused by the use of the coronavirus "severe acute respiratory syndrome coronavirus 2" (SARS-COV-2 extreme acute respiratory syndrome-2)", a "single-stranded RNA virus" that causes respiratory contamination in people. "SARS-COV-2" has a far higher rate of infectivity than the previous strains that caused "SARS (severe acute respiratory syndrome)" and "MERS (middle Japanese respiratory syndrome)" illnesses, allowing it to spread globally. However, it has a far lower mortality rate of 4.73 percent (March 2020) and 7.7 percent (end of April 2020), compared to 11 percent for SARS and 37 percent for MERS. [4].

Let's see how quickly it spreads. The virus that causes the Coronavirus of 2019 is spread mostly by droplets produced when an infected person exhales, sneezes, or coughs. These drops are far too large to give any thought to where they should be placed, and they fall quickly on surfaces or floors. People can become inflamed by contacting a contaminated floor and, occasionally, their mouth, nose, or eyes can become inflamed by breathing in the infection if they are in close proximity to someone who has COV-19. [9]. COV-19 has several effects on different kinds of people. The majority of infected people will have mild to moderate side effects. Dyspnea, weariness, fever, hiccups, and dry cough are all notable symptoms. Some people like nasal congestion and pains, aches, and diarrhea, sore throats, and runny noses. [5].

The examination of COV-19 is currently a difficult task due to the widespread detachment of the investigation system, which is producing worry. We really wish to rely on diverse end measures because of the limited availability of coronavirus testing units. [10]. We can utilize CT images and X-beam to examine the adequacy of a patient's lungs since COV-19 targets the epithelial cells that line their study respiratory tract. [7]. Clinical specialists utilize CT filter images and X-beam to dissect pneumonia, lung exacerbations, abscesses, and developed lymph nodes every now and then. [1].

Furthermore, practically all clinical centres have X-shaft imaging equipment; it's feasible that COV-19 might be tested using X-beam and CT imaging instead of the more dangerous test kits. Furthermore, such common imaging procedures have downsides, such as requiring a radiology professional and taking valuable time, which is critical when individuals are moved all over the world. As a result, building a robotized examination system is essential for healthcare experts to save time. [7].

There are a few concerns that need to be addressed in the administration of COV-19, which can be addressed with the help of "AI" (artificial intelligence). In addition, coronavirus causes influenza-like symptoms and pneumonia, making it difficult to distinguish it from other types of respiratory infections in the early stages, especially in the absence of large-scale screening programmes. Because of the lack of early detection, there is a significant risk of local area spread. With the present levels of COV-19 dissemination, it is believed that medical services specialists' efforts alone are insufficient in controlling the outbreak, especially because a major portion of the therapeutics and antibodies are still in the clinical preliminary stage. AI advancements assist doctors in reducing challenges encountered during COV-19 administration, such as "risk of self-pollution" in some cases, limitations with quick decision making in stressful situations, and overburdening." [3].

Artificial intelligence is defined as the ability of robots to recreate human understanding without the use of supplementary commands. It is used for positive case screening; autonomous representation of prophetic and perceptive models; therapy is developing, among other things, a prognosis of fortune sickness and vaccine improvement during the COV-19 pandemic emergency. It's crucial that AI platforms like Bluedot Worldwide predict COV-19's global expansion before the outbreak in China. While "AI is commonly utilized for prediction," its application to analysis and therapy in the development of COV is still restricted. Furthermore, its applications in high-risk populations are unclear. [3].

2. COV-19 and Artificial Intelligence

The current topic focuses on the presentation of a few significant "AI-based approaches that can support existing quality strategies" for COV-19 management in medical services all over the world. With the goal of emphasizing the enhanced viability of these approaches and tactics, their development has been informed by and in light of the most current AI-related distributed clinical updates, as well as COV-19 findings. [1]. As a result, this section discusses ideas for improving and speeding up ANN-based procedures in order to further expand treatment techniques and board well-being, as well as acknowledgement and determination. But, the optimal sufficiency of AI devices during the COV-19 epidemic is determined by the amount of human data and the cooperative effort apathetic occupations that people perform. On the other hand, information regarding AI skills and limitations remains with information researchers, "who play an important role primarily because they are the ones who design AI structures." [4].

Various steps in the deployment of "AI-based strategies utilized to conquer COV-19 difficulties are introduced in the flowchart". The initial step is the readiness of the information, which is vital for information mining during information understanding, information planning, and enormous information [1]. Clinical data, such as "clinical reports, records, and photographs", as well as other sorts of data that may be transformed into information that a computer can understand, are included in this discussion. Understanding information credits and recognizing the concept are two goals of information comprehension. Information volume and the total number of elements to summarize the data are two qualities to consider. Prior to handling and inquiry, there is information arrangement, which is the process of refining and changing raw data. In general, it's an interaction in which data gets reformatted, corrected, and linked to new data [4]. Gathering, breaking down, and using "consumer, patient, physical, and clinical data" are examples of data closure in massive amounts of data. Human mediation, as part of AI techniques, occurs at this step, when professionals study and dissect the material to separate the material with the excellent structures, instances, and elements [9].

"Artificial intelligence" (AI) might be the eccentric preparation needed to meet this problem. Thanks to large tagged datasets and modern GPUs, deep learning algorithms have achieved amazing performance in select PC vision assignments, such as picture categorization and object recognition. In some clinical picture-finding tasks, such as lung ailments, ongoing research demonstrates that AI computations may match or even outperform the performance of human doctors. In comparison to other lung illnesses such as "lung knob detection," tuberculosis detection, and cellular breakdown in the lungs screening, distinguishing COV-19 from other pneumonia presents new challenges, such as the high similarity of pneumonia of various kinds (particularly in the early stages) and enormous variations in various phases of a similar sort. [2]. It is therefore critical to promote an AI analytical calculation that is specific to COV-19. High effectiveness, high repeatability, and a straightforward enormous scope arrangement are all advantages of AI conclusion computation. There is now various scattered research on COV-19, discovering frameworks based on CT. Here, we take a look at a few agent studies that make use of rather large datasets. [11].

"Zhang et al. developed a COV-19" discovery framework that can distinguish COV-19 from other pneumonias and usual solids with an "AUC of 0.9797". The categorization was based on the injury division results and the sore division DICE in their framework. [2].

The file has a resolution of 0.662, which is clearly not an accurate representation of sores. Another issue is that making division covers by hand is a costly process. On a dataset of 3322 participants, including COV-19, CAP, and sound people, "Li et al. developed an AI framework" and obtained an "AUC of 0.96 for COV-19 discovery." Their structures are linked. [2]. Items were cut into volume levels, which increased memory, appeal while obviating the need to separate more informative 3D highlights. A few cut-level analysis procedures that were extremely similar to their work were offered. Although 3D convolution neural networks were used in some AI frameworks, they were mostly regarded as a simple two-classification grouping. There are a few COV-19 identification frameworks that use CXR30, but the number of participants with COV-19 in these studies is much lower than in CT studies, and no study has quantitively evaluated "CXR and CT" exhibitions using matched data [2].

In this paper, we provide a clinical agent massive scope dataset with 11,356 CT tests from three Chinese locations and four publicly accessible databases, which is significantly larger than previous studies. We establish both "CT-based and CXR-based" conclusion frameworks and test them using matched data, which has not been concentrated before, to understand relative displays of "CT and CXR" for differentiating COV-19's [2]. We compare their study "CT-based" analysis framework's indicative presentation to that of five radiologists in pursuer investigations, and the results demonstrate that the framework's exhibition is greater than that of experienced radiologists. Similarly, we identify damage locations in COV-19 patients based on the expected score on each CT volume cut and conduct a quantifiable analysis of several subgroups of patients. To understand the imaging properties of COV-19, a translation organization and radionics investigation are used to follow the specific phenotypic premise of the analysis yield [16].

3. Research Methodology

The organic nervous system, which functions similarly to the brain in terms of information processing, served as the inspiration for the Artificial Neural Network (ANN). The innovative structure of the information processing system is the fundamental component of this concept. The system is composed of several highly linked processing units known as neurons that cooperate to find a solution.

ANNs learn via imitation, much like humans do. The neural network is configured to carry out particular tasks, such as recognizing patterns and classifying data, throughout a learning process. In biological systems, synaptic connections between neurons control learning. Neural networks also employ this technique. ANNs learn by transferring knowledge or a law underlying the data to the network structure through the analysis of experimental data. In essence, the most significant characteristic of such a smart system is its learning capacity. A learning system is more adaptable and simpler to plan, allowing it to respond better to new problems and adjustments in workflow.

With the use of programming skills, a data structure that can mimic a neuron is created for ANNs. A node is the name of this data structure. This structure uses an educational approach to train the network connecting these nodes. Each edge (or synapse, or link between nodes) in this neural network or memory has a weight, and each node has two active states (on or off), one inactive state (off), and two active states (on or off). Negative weights block or deactivate the next linked node, whereas positive weights excite the following dormant node (if active). The input A_p for neural cell x in the ANN architecture comes from cell p before it.

The input A_{px}'s weight in relation to cell c is represented by wpc, and the sum of the inputs' weights is represented by B_x:

$$B_x = \sum W_{px} A_{px}$$

A c is given a nonlinear function, C. In light of this, Ac may be computed as

$$\text{Ac} = \theta c(bc)$$

The output of c to n is the Acn, and wcn is the weight of the Acn. W is the totality of the neural network's weights as a set. HW(x) is the neural network's output for input x and output y. learning these weights is essential to lowering the error values between y and HW(x).

To minimize the cost function, the desired outcome is Q (W), Equation.

$$\text{W (Q)} = \frac{1}{2}\sum_{j=1}^{a}(x - u)^2$$

The correlation coefficient and root mean square error (RMSE) were used for evaluation. These statistics compute a score as a measure of the effectiveness and precision of the proposed procedures by comparing the goal and output values. It presents the formulae for the assessment criteria.

$$\text{Correlation coefficient} = \frac{M\sum(BP) - \sum(P)}{\sqrt{[M\sum B^2 - (\sum B)^2][M\sum P^2 - (\sum BP)^2]}}$$

$$\text{RMSE} = \sqrt{\frac{1}{M}\sum(B - P)^2}$$

On the chest CT scans, several tests have been conducted, taking into account the suggested detection approach as well as current rival techniques. According to experimental findings, the suggested detection strategy works better than

ISSN 2229-5518

more current methods since it introduces the highest accuracy rate.

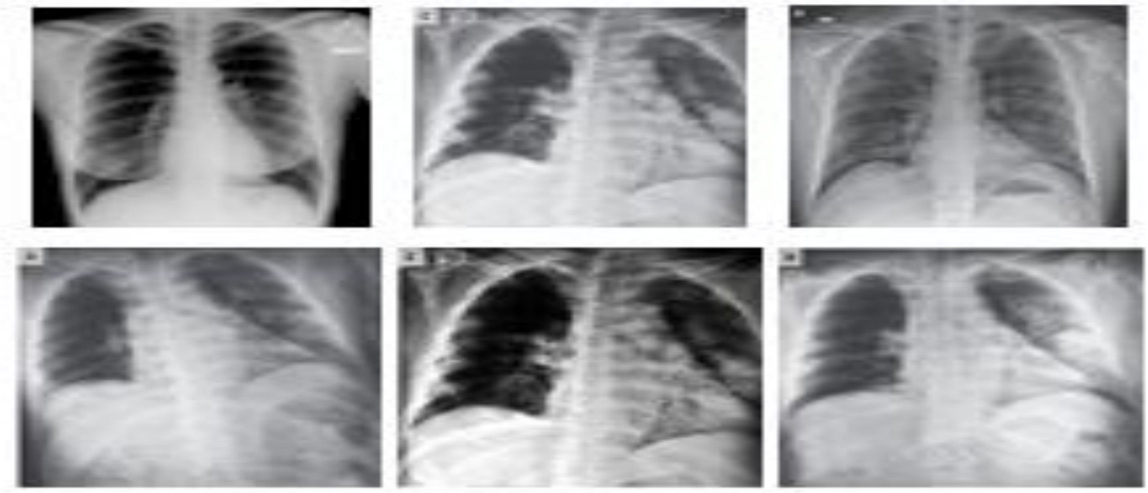

Figure1: Sample images from the normal and pneumonia classes

Each item's strength (training example) is determined. The degree of the item's connection to its hosting class is indicated by the item's strength. All objects are initially projected onto the assumed n-dimensional feature space, with n features and m target classes, in order to determine the strength of each item. The center of each class with t samples in the n-dimensional feature space may then be achieved using

$$C = \left\{ \frac{\sum_{q=1}^{t} V^1}{t}, \frac{\sum_{q=1}^{t} V^2}{t}, \dots, \frac{\sum_{q=1}^{t} V^n}{t} \right\}$$

Where t is the number of instances inside the class, C is the class center in the examined n-dimensional feature space, and V^i_q is the value of the qth example's ith dimension. Lastly, it is possible to determine item I_j strength using

$$IS\ (I_i) = \frac{[\propto * ISX(I) + \beta * IS(I)]}{2}$$

$$IS_X\ (I_i) = \sum_{i \neq k} \frac{1}{Dis(I_i, I_k)}$$

$$IS_Y\ (I_i) = \frac{1}{Dis(I_i, C)}$$

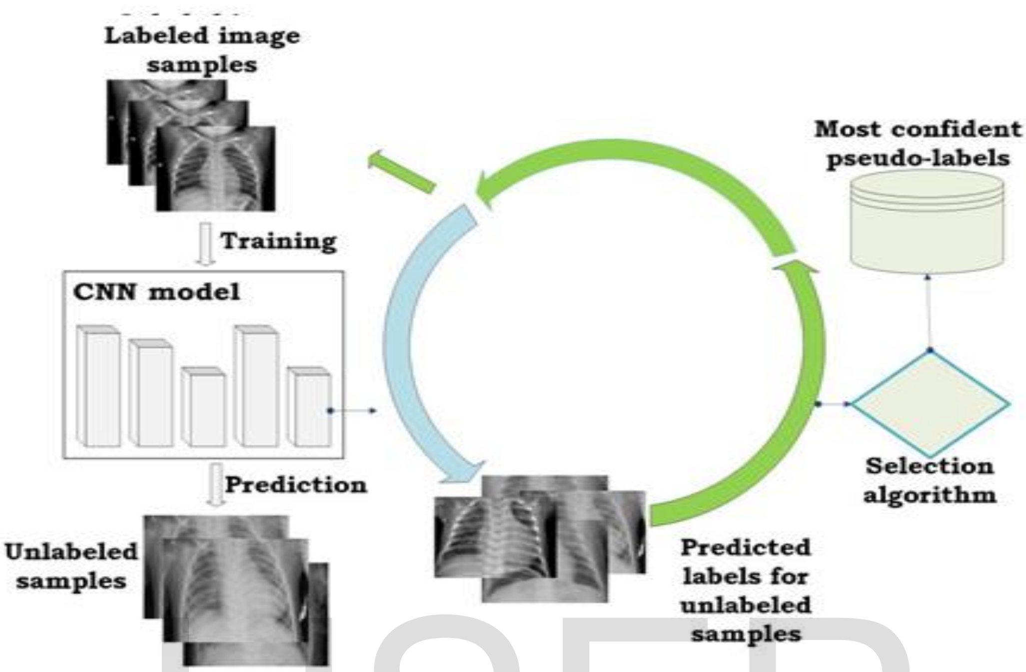

Figure2: Algorithm workflow of the proposed approach

Study limitations and Practical effects

The study has certain limitations in addition to producing some intriguing results. The study's design is not optimal because its primary goal was to document the initial response to issues brought on by a pandemic. The research participants are not as varied as would be ideal, to start. Most of them have college degrees, and they are generally well off, which may have an impact on how they see the pandemic scenario [52]. Additionally, because the research participants' additional contacts were searched for throughout the recruiting process, there is a chance that everyone who was questioned shared a similar background [54].

The offered study has a wide range of real-world applications. The COV-19 pandemic crisis can be analyzed by state decision-makers in a way that prevents a dire situation involving other infectious illnesses in the future. The findings of our study, which highlight the pandemic's most upsetting consequences on individuals, can be used to inform the creation of measures for coping with the crisis' repercussions and preventing a future decline in the general public's mental health [51].

It would be required to perform research that also examines how those who are already dealing with more challenging circumstances in life before the epidemic begins to respond. Additionally, it might be beneficial to focus on the interviewers themselves [48]. Although differences in the establishment of relationships between men and women and gender effects on the quality of the interviews were not noted during the debriefing process because all of the moderators were female, the literature frequently discusses gender effects on the outcomes of qualitative research [53].

Because of the decreased social interaction during the COV-19 pandemic, especially during the lockdown times, the findings of the analysis revealed that many people are particularly affected by these events. On the other hand, social connections serve as a means of crisis transfer that is also more seamless. Given this information, decision-makers should come up with strategies for ensuring pandemic safety without severely restricting social interactions and provide options that offer individuals a sense of control (instead of depriving them of it) [43]. By offering such alternatives, one might lessen the psychological effects of a pandemic and assist people in coping with it. It would have been crucial to include male moderators in the study to capture any disparities in interpersonal dynamics, even though the researchers approached the procedure with reflection and self-criticism at all phases [41].

The findings of their study can also be used as direction for future communications concerning limits in order to ensure their acceptance and respect (for example, by giving rational explanations of the reasons for introducing particular restrictions). The findings of their study can also be a source of advice on how to handle any difficulties that might develop in the event of reoccurring COV-19 pandemic as well as other potential calamities [39].

4. Artificial Intelligence Assisted Diagnosis

COV-19 patients in epidemic areas are in serious need of ‘interpretation and cure’. "X-rays and CT scans" are often utilized because they are quick to acquire and provide confirmation to radiologists. On the other hand, CT scans, particularly chest CT scans, include hundreds of slices and might take a long time to complete. The specialists took a long time to make a diagnosis. The COV-19infection is also a novel illness with symptoms that are similar to those of earlier diseases like pneumonia, necessitating the collection of a significant number of pictures by radiologists [11]. You'll need a lot of experience to deliver solid medical diagnosis performance. As a result, medical imaging is extensively desired for AI-assisted diagnosis. The most recent high-level development research on this issue direction is summarized in Table 1 [10].

X-ray scans are more anaesthetized than "3D chest computed tomography (CT)" pictures, regardless of being the most common treatment imaging dataset used for COV-19’ [5]. According to recent research, X-rays with early or mild sickness seem normal. At the time of admission, "69 percent of patients have abnormal chest radiographs, and 80 percent" of patients have abnormal chest radiographs at some point throughout their hospital stay [4]. X-ray scans are more anaesthetized than "3D chest CT pictures", regardless of being in the most common treatment imaging dataset used for COV-19 sufferers. According to recent research, X-rays with early or mild sickness seem normal. At the time of admission, "69 percent of patients have abnormal chest radiographs, and 80 percent of patients have abnormal chest X-rays at some point throughout their hospital stay." [7].

"Airspace opacities", ground-glass opacity (GGO), and later consolidation are all radiological indicators. The most common distributions are "bilateral, peripheral, and lower zone distributions (80 percent)". When it comes to parenchymal problems, pleural effusion is uncommon (3 percent). COV-19 was tested against different pneumonia strains and healthy people to evaluate how it compared. To estimate the diagnosis, a Bayesian Convolutional Neural Network might be employed. [12].

Table1. Medical research on the detection of COV-19

Author Name	**Dataset**	**Topics**	**Task**	**Result**	**Methods**
Ozturketal. (2020)	X-Ray	80COV-19	Organization : COV-19	92.9%	Convolutional neural network(CNN)
Chaeetal. (2018)	X-Ray	50COV-19, 60 Normal	Organization : COV-19, Normal	98.0%	ResNet 50
Zhan g, Yang et al. (2020)	X-Ray	80COV-19, 1009 Others	Organization : COV-19, Others	98.0% (Sens.) 80.78% (Spec.) 0.953 (AUC)	ResNet
Chen, Wu, et al. (2020)	X-Ray	45COV-19, 941, Bac. Pneu, 670, Vir. Pneu,	Organization : COV-19, Bac. Pneu, Vir. Pneu,	83.5%(Acc,)	Convolutional neural network(CNN)

		1403 Normal	Normal		
Butt et al. (2020)	CT	51COV-19,55 Others	Classification: COV-19, Other	95.2%, 100%, 93.6%	UNet++
Goze a et al. (2020)	CT	51COV-19, Others	Classification: COV-19/ Others	93.7%(Sens.) 92.1%(Spec) 0.969(AUC)	U-Net, CNN
Wang and won g (2020)	CT	313COV-19 ,229 Others	Classification: COV-19/ Others	90.7% (Spens.) 91.1% (Spec.) 0.959 (AUC)	U-Net CNN
Chen, Wu, et al. (2020)	CT	496COV-19 ,1385 Others	Classification: COV-19/ Others	94.1%(Sens.) 95.5%(Spec)	Convolutional neural network(CNN)
Zhan g, Yang et al. (2020)	CT	723COV-19 ,413Others	Classification: COV-19/ Others	97.4% (Sens.) 92.24% (Spec.)	UNet++ CNN
Ozturk et al. (2020)	CT	44COV-19 , 56Vir. Pneu	Classification: COV- 19/ Vir. Pneu.	82.98% (Acc.)	Convolutional neural network(CNN)
Chae et al. (2018)	CT	88COV-19, 100Bac. Pneu, 88 Nor	Classification: COV-19/ Pneu. Bac. Normal	86.0%(Acc)	Res Net-50
Chae et al. (2018)	CT	219COV-19, 234 Influ-A, 174 Normal	Influenza A, COV-19, Normal	86.7% (Acc.)	Convolutional neural network(CNN)

Butt et al. (2020)	CT	468COV-19, 1551CAP, 1445Non-pneu	Classification: COV-19, CAP, Pneu.	90.0% (Sens.) 96.0% (Spec.)	ResNet-50
Wang and won g (2020)	CT	1658COV-19, 1027CAP	COV-19, CAP	88.9% (Acc.) 91.7% (Sens.) 84.30% (Spec.)	RF
Zhan g, Yang et al. (2020)	CT	176COV-19	Severity assessment	87.7 %(Acc.) 95.3%(TPR) 75.5%(TNR)	RF

Dynamic radiological designs on upper body CT scans COV-19 contains four phases, according to the description. In a nutshell, the stage is considered to be in its early stages when the first symptom appears 0–5 days following the onset of the first symptom. GGO was found subpleurally in the lower lobes, one-sided or two-sided. [13].

Diffuse GGO and crazy-paving are included in the progressive stage, which lasts 5-8 days. On both sides, there existed a pattern, and even consolidation, in multi-lobed [14]. During the peak period (9–13 days), intense growth can be seen. Consolidation is becoming more common. When an infection occurs, the absorption stage appears (typically after the control stage). Gradually, consolidation and a crazy-paving pattern emerge. Only GGO remains after it has been assimilated. These X-ray patterns are given critical data for classification based on CT scans and COV-19 severity assessment. [16].

Because ordinary pneumonia, particularly "viral pneumonia" and COV-19 have similar radiological appearances [11], their distinction would be helpful in improving the health assessment procedure in patient-contact experience. As a consequence, a "convolutional neural network (CNN)" pattern is proposed to discriminate between "COV-19 and common viral pneumonia" [14]. The researchers looked at 99 individuals' chest CT scans. As input, the suggested CNN receives slices formed from each 3D CT image [5]. The testing dataset has an overall accuracy of 74.1 percent, a specificity of 68.0 percent, and a sensitivity of 75.0 percent [11].

For COV-19, we've shown that research on COV-19's long-term effects is still limited. As far as we know, only a few efforts have been made. For example, using a visualization tool and a machine learning-based method, "Shanghai United Imaging Intelligence (UII)" researchers are attempting to show how "volume size, density, and other factors" change over time, clinically important factors in the patient's infection locations [1]. These changes are then immediately included in the clinical report as data-driven recommendations for healthcare providers to consider. A COV-19 follow-up solution was also developed by the Perception Vision Company (PVmed) team. They aimed to develop a contrastive model that would represent changes in time-lapse CT scans of the same patient. [10].

FUTURE WORK AND DISCUSSION

Artificial Intelligence has been used to effectively implement the whole imaging-based diagnosis process for COV-19. However, there are several projects that must be finished in the near future [11]. As previously indicated, AI-assisted image collection has proven to be both very quick and also more successful in safeguarding medical workers against the COV-19 virus. More AI-powered apps will be introduced into the image collection process in the future, resulting in higher diagnostic grade and less radiation consumption by patients. In order to achieve excellent picture quality, more precise "AI-based automatic ISO-centering and scan range determination" is needed [5]. Furthermore, utilizing AI-derived, depending on the patient's body area thickness, X-ray exposure settings may be adjusted, assessed, and modified instinctively, ensuring that the appropriate quantity of radiation is utilized.

Only a small quantity of radioactivity is utilized throughout the sonographer, which is critical for ‘moderate image acquisition.' [1]. In the early stages of the disease, medical imaging frequently displays negative radiological signals; therefore, studying this period is vital to help with clinical diagnostic confusion. [7]. Meanwhile, much of the current AI segmentation and diagnostic research uses tiny samples, which might lead to over-fitting of conclusions. The quality and quantity of data must be enhanced in order for the results to be therapeutically helpful. As a result, new databases containing clinically acquired X-ray and CT images should be created. Deep learning has emerged as the most effective strategy in the fight against COV-19. The picture data in COV-19 applications, on the other hand, may contain labels that are missing, inexact, or incorrect, providing an issue for users. [12].

In this case, poorly supervised deep learning techniques might be employed to establish a precise segmentation and diagnosis network. Additionally, manually categorizing data on imaging is both time-consuming and costly, pushing researchers to investigate transfer-deep-learning methods and self-supervised deep learning. Multicenter COV-19 research should also be promoted [13]. The need for follow-up in identifying COV-19 and assessing therapy cannot be overstated. Despite the fact that there is currently little research, we feel that methodologies from other similar studies may be used.

1) A machine learning-based technique might motivate a follow-up study of COV-19's role in the prognosis of several pneumonia conditions.

2) For COV-19 patients, internal and external follow-up might be combined to establish a long-term tracking system.

3) The whole COV-19 measuring follow-up approach could benefit from multidisciplinary integration, such as medical imaging, natural language processing, cancer, and fusion [9].

CONCLUSION

COV-19 is a virus that has made its way throughout the globe. Intelligent medical imaging has been critical in the fight against COV-19. This research looks at how artificial intelligence (AI) may be used to provide imagery services that are "safe, accurate, and efficient in COV-19 Platforms for intelligent imaging". "Clinical diagnosis and groundbreaking research" are covered in detail in this article [1], which covers the entire AI-powered workflow of COV-19 imaging applications: For example, "X-ray and Computed Tomography (CT) scans" demonstrate the effective COV-19 will use "Artificial Intelligence-assisted medical imaging" [12]. It's worthy to note that imaging only provides you with a limited image of COV-19 patients. It's crucial to keep in mind that imaging data should be connected with "clinical signs and symptoms". Research lab test results to assist in screening and detection "Diagnosis and treatment of COV-19". We believe AI will be beneficial in this situation [5].

Reference

1. Jamshidi, M., Lalbakhsh, A., Talla, J., Peroutka, Z., Hadjilooei, F., Lalbakhsh, P., Jamshidi, M., La Spada, L., Mirmozafari, M., Dehghani, M. and Sabet, A., 2020. Artificial intelligence and COV-19: deep learning approaches for diagnosis and treatment. *Ieee Access*, *8*, pp.109581-109595.
2. Jin, C., Chen, W., Cao, Y., Xu, Z., Tan, Z., Zhang, X., Deng, L., Zheng, C., Zhou, J., Shi, H. and Feng, J., 2020. Development and evaluation of an artificial intelligence system for COV-19 diagnosis. *Nature communications*, *11*(1), pp.1-14.
3. Shi, F., Wang, J., Shi, J., Wu, Z., Wang, Q., Tang, Z., He, K., Shi, Y. and Shen, D., 2020. Review of artificial intelligence techniques in imaging data acquisition, segmentation, and diagnosis for COV-19. *IEEE reviews in biomedical engineering*, *14*, pp.4-15.
4. Rahmatizadeh, S., Valizadeh-Haghi, S. and Dabbagh, A., 2020. The role of artificial intelligence in management of critical COV-19 patients. *Journal of Cellular and Molecular Anesthesia*, *5*(1), pp.16-22.
5. Jamshidi, M., Lalbakhsh, A., Talla, J., Peroutka, Z., Hadjilooei, F., Lalbakhsh, P., Jamshidi, M., La Spada, L., Mirmozafari, M., Dehghani, M. and Sabet, A., 2020. Artificial intelligence and COV-19: deep learning approaches for diagnosis and treatment. *Ieee Access*, *8*, pp.109581-109595.

6. Vinod, D.N. and Prabaharan, S.R.S., 2020. Data science and the role of Artificial Intelligence in achieving the fast diagnosis of COV-19. *Chaos, Solitons & Fractals*, *140*, p.110182.

7. Mei, X., Lee, H.C., Diao, K.Y., Huang, M., Lin, B., Liu, C., Xie, Z., Ma, Y., Robson, P.M., Chung, M. and Bernheim, A., 2020. Artificial intelligence–enabled rapid diagnosis of patients with COV-19. *Nature medicine*, *26*(8), pp.1224-1228.

8. Li, L., Qin, L., Xu, Z., Yin, Y., Wang, X., Kong, B., Bai, J., Lu, Y., Fang, Z., Song, Q. and Cao, K., 2020. Using artificial intelligence to detect COV-19 and community-acquired pneumonia based on pulmonary CT: evaluation of the diagnostic accuracy. *Radiology*, *296*(2), pp.E65-E71.

9. Salman, F.M., Abu-Naser, S.S., Alajrami, E., Abu-Nasser, B.S. and Alashqar, B.A., 2020. COV-19 detection using artificial intelligence.

10. Laghi, A., 2020. Cautions about radiologic diagnosis of COV-19 infection driven by artificial intelligence. *The Lancet Digital Health*, *2*(5), p.e225.

11. Lalmuanawma, S., Hussain, J. and Chhakchhuak, L., 2020. Applications of machine learning and artificial intelligence for COV-19 (SARS-CoV-2) pandemic: A review. *Chaos, Solitons & Fractals*, *139*, p.110059.

12. Mohamadou, Y., Halidou, A. and Kapen, P.T., 2020. A review of mathematical modeling, artificial intelligence and datasets used in the study, prediction and management of COV-19. *Applied Intelligence*, *50*(11), pp.3913-3925.

13. Chen, J. and See, K.C., 2020. Artificial intelligence for COV-19: rapid review. *Journal of medical Internet research*, *22*(10), p.e21476.

14. Naudé, W., 2020. Artificial Intelligence against COV-19: An early review.

15. Naseem, M., Akhund, R., Arshad, H. and Ibrahim, M.T., 2020. Exploring the potential of artificial intelligence and machine learning to combat COV-19 and existing opportunities for LMIC: a Scoping review. *Journal of Primary Care & Community Health*, *11*, p.2150132720963634.

16. Ozsahin, I., Sekeroglu, B., Musa, M.S., Mustapha, M.T. and Uzun Ozsahin, D., 2020. Review on diagnosis of COV-19 from chest CT images using artificial intelligence. *Computational and Mathematical Methods in Medicine*, *2020*.

17. JHU CSEE. COV-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University. 2020 [cited 2021 Jun 1].

18. Torales J, O'Higgins M, Castaldelli-Maia JM, Ventriglio A. The outbreak of COV-19 coronavirus and its impact on global mental health. Int J Soc Psychiatry. 2020 Mar 31; 66(4): 317–20. pmid:32233719

19. van Gelder N, Peterman A, Potts A, O'Donnell M, Thompson K, Shah N, et al. COV-19: Reducing the risk of infection might increase the risk of intimate partner violence. EClinicalMedicine. 2020 Apr 13;21. pmid:32292900

20. Li S, Wang Y, Xue J, Zhao N, Zhu T. The impact of COV-19 epidemic declaration on psychological consequences: A study on active Weibo users. Int J Environ Res Public Health. 2020 Mar 19;17(6). pmid:32204411

21. Gerhold L. COV-19: Risk perception and coping strategies. Results from a survey in Germany. PsyArXiv [Preprint]. 2020 Mar 25

22. Nowakowska K. Rok z koronawirusem: Od paniki, przez luz, do fatalizmu. [A year with coronavirus—from panic through chill to fatalism]. Dziennik Gazeta Prawna [Internet]. 2021 Mar 4 [cited 2021 Jun 1].

23. Armour C, McGlinchey E, Butter S, McAloney-Kocaman K, McPherson KE. The COV-19 psychological wellbeing study: Understanding the longitudinal psychosocial impact of the COVID -19 pandemic in the UK; A methodological overview paper. J Psychopathol Behav Assess. 2020 Nov 4;174–90. pmid:33169046

24. McBride O, Murphy J, Shevlin M, Gibson-Miller J, Hartman TK, Hyland P, et al. Monitoring the psychological, social, and economic impact of the COV-19 pandemic in the population: Context, design and conduct of the longitudinal COV-19 psychological research consortium (C19PRC) study. Int J Methods Psychiatr Res. 2020 Nov 9;1–16. pmid:33166018

25. Megías-Robles A, Gutiérrez-Cobo MJ, Cabello R, Gómez-Leal R, Fernández-Berrocal P. A longitudinal study of the influence of concerns about contagion on negative affect during the COV-19 lockdown in adults: The moderating effect of gender and resilience. J Health Psychol. 2021 Feb 4; pmid:33541155

26. Yang Z, Ji LJ, Yang Y, Wang Y, Zhu L, Cai H. Meaning making helps cope with COV-19: A longitudinal study. Pers Individ Dif. 2021 May;174;110670. pmid:33518865

27. Fernandes N. Economic effects of coronavirus outbreak (COV-19) on the world economy. IESE Business School Working Paper No. WP-1240-E. 2020 Mar 23.

28. Van Lancker W, Parolin Z. COV-19, school closures, and child poverty: a social crisis in the making. Lancet Public Health. 2020 Apr 7; 5(5):e243–4. pmid:32275858

29. Ho CS, Chee CY, Ho RC. Mental health strategies to combat the psychological impact of COV-19 beyond paranoia and panic. Ann Acad Med Singapore. 2020;49(1):1–3. pmid:32200391

30. Gambin M, Sękowski M, Woźniak-Prus M, Wnuk A, Oleksy T, Cudo A, et al. Generalized anxiety and depressive symptoms in various age groups during the COV-19 lockdown in Poland. Specific predictors and differences in symptoms severity. Compr Psychiatry. 2021 Feb;105(1). pmid:33388494

31. ARC. Praca z domu w polskim wydaniu—badanie na zlecenie Gumtree.pl we współpracy z Randstat Polska [The Polish way of working from home—a study commissioned by Gumtree.pl in collaboration with Randstat Polska]. 2020 [cited 2021 Jun 1]

32. Sierpowska, I. O edukacji w czasie pandemii [On Education during pandemic]. Centrum Prasowe SWPS [Internet]. 2020 Sep 8. [cited 2021 Jun 1].

33. Polish Academy of Sciences. Understanding COV-19. Report by the COV-19 team at the President of the Polish Academy of Sciences. 2020 Sep 14. [Cited 2021 Jun 1].

34. Cinelli M, Quattrociocchi W, Galeazzi A, Valensise CM, Brugnoli E, Lucia A, et al. The COV-19 social media infodemic. Sci Rep. 2020 Oct 6;10(1):16598. pmid:33024152

35. Chryssochoou X, Papastamou S, Prodromitis G. Facing the economic crisis in Greece: The effects of grievances, real and perceived vulnerability, and emotions towards the crisis on reactions to austerity measures. JSSE-Journal Soc Sci Educ. 2013 Mar 27;12(1):41–9.

36. Lonigan CJ, Shannon MP, Taylor CM, Finch A, Sallee FR. Children Exposed to Disaster: II. Risk Factors for the Development of Post-Traumatic Symptomatology. J Am Acad Child Adolesc Psychiatry. 1994; 33(1):94–105. pmid:8138526

37. Karanci NA, Alkan N, Aksit B, Sucuoglu H, Balta E. Gender differences in psychological distress, coping, social support and related variables following the 1995 Dinal (Turkey) earthquake. N Am J Psychol. 1999; 1(2):189–204.

38. Polizzi C, Lynn SJ, Perry A. Stress and coping in the time of COV-19: Pathways to resilience and recovery. Clin Neuropsychiatry. 2020 Mar 31;17(2):59–62.

39. Sakurai M, Chughtai H. Resilience against crises: COV-19 and lessons from natural disasters. Eur J Inf Systs. 2020 Sep 13; 29(5): 585–594.

40. Noy I, Nguyen D. COV-19 cost more in 2020 than the world's combined natural disasters in any of the past 20 years. The Conversation [Internet]. 2021 Apr 19. [Cited 2021 Jun 1].

41. Brown, K. The pandemic is not a natural disaster. The New Yorker [Internet]. 2020 Apr 13 [cited 2021 Jun 1].

42. Lau JTF, Griffiths S, Choi KC, Tsui HY. Avoidance behaviors and negative psychological responses in the general population in the initial stage of the H1N1 pandemic in Hong Kong. BMC Infect Dis. 2010 May 28;10(1):1–13. pmid:20509887

43. Huang L, Xu F, Liu H. Emotional responses and coping strategies in nurses and nursing students during COV-19 outbreak: A comparative study. PLoS ONE. 2020 Aug 7;15(8): e0237303. pmid:32764825

44. Lee SA. Coronavirus Anxiety Scale: A brief mental health screener for COV-19 related anxiety. Death Stud. 2020 Apr 16;44(7):393–401. pmid:32299304

45. Rodriguez-Llanes JM, Vos F, Guha-Sapir D. Measuring psychological resilience to disasters: Are evidence-based indicators an achievable goal? Environ Health. 2013 Dec 20;12(1):2–20. pmid:24359448

46. Reich JW. Three psychological principles of resilience in natural disasters. Disaster Prev Manag. 2006 Oct 1;15(5):793–8.

47. Apgar D, Cadmus T. Using mixed methods to assess the coping and self-regulation skills of undergraduate social work students impacted by COV-19. Clin Soc Work J. 2021 Feb 11;1. pmid:33589848

48. Mathias K, Rawat M, Philip S, Grills N. We've got through hard times before: acute mental distress and coping among disadvantaged groups during COV-19 lockdown in North India—a qualitative study. Int J Equity Health. 2020 Dec 17;19(1):1–12. pmid:33334344

49. Ogueji IA, Okoloba MM, Demoko Ceccaldi BMD. Coping strategies of individuals in the United Kingdom during the COV-19 pandemic. Curr Psychol. 2021 Jan 3;1. pmid:33424202

50. Maison D. Qualitative marketing research. Understanding consumer behaviour. London: Routledge; 2019.

51. Braun V, Clarke V. Using thematic analysis in psychology. Qual Res Psychol. 2006;3(2):77–101.

52. Argyle M. Causes and correlates of happiness. In: Kahneman D, Diener E, Schwarz N, editors. Well-Being: The Foundations of Hedonic Psychology. New York: Russell Sage Foundation; 1999. p. 353–373.

53. Spadaro A. COV-19: Testing the limits of human rights. Eur J Risk Regul. 2020 Apr 7;11(2):317–25.

54. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0258133