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Literature Review on A Deep Learning Method for Identification of Viral Infections from CT Scan Images

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Abstract— The coronavirus disease, or COVID-19, is a pandemic viral disease that we are all currently redealing with. Being close to or far from an infected individual effectively spreads this disease, making it dangerous. The number of people affected with this coronavirus sickness is growing daily. Only by identifying and analysing this pandemic COVID-19 sickness can we slow the rate at which this contagious virus spreads. The principal testing method for coronavirus disease diagnosis is the Real-Time Reverse Transcription Polymerase Chain Reaction (RT-PCR). However, the RT-PCR detection method is a time-consuming and expensive procedure. Thus, there is a need to design other ways to detect and diagnose COVID-19. Data-driven science relies heavily on deep learning. In deep learning modelling, the data extraction process is carried out automatically, however in machine learning, we must select attributes and images. The improved form of machine learning is called data learning. Convolutional neural networks, or CNNs, are mostly employed for illness detection, and deep learning is used to converge with them. This essay will outline the fundamentals of deep learning (DL) methods and how they are being used in the context of the COVID-19 pandemic. As Corona virus spread over the world, so doctors and researcher work on this topic. Their researched help to physicians for detect the diseases and give the treatment according to condition of patient. In this paper, a deep learning approaches for detecting chest infections through CT images. Various pre-trained neural network architectures, such as ResNet50, InceptionV3, N-VGG19, and Xception, were evaluated using the Adamax optimizer and data augmentation techniques. A deep learning-based framework was developed for the automatic detection of COVID-19 and its severity. It can assist healthcare professionals in patient care planning, determining the need for ICU facilities, and assessing ventilator requirements. Such a computer-aided system can be instrumental in managing the high volume of patients during crises.

Keywords— Corona virus, covid-19, deep learning, supervised learning, CT scan.

I. INTRODUCTION

One new coronavirus is the COVID-19. One infectious disease that can typically pass from person to person is coronavirus 2019 (high-rate transmission). Similar to other respiratory diseases, this coronavirus disease is spread through sneezing, coughing, and breathing. One subset of machine learning is deep learning. Deep Learning DL often makes use of deep artificial neural networks. A neural network is used to finish deep learning. A collection of machine learning methods known as "deep learning" makes use of multiple layers of non-linear information processing for both monitored and unmonitored feature extraction and transformation, as well as design analysis and classification.

II. SYSTEM OVERVIEW

The In this section research paper of different authors are discussed. And their outputs are very helpful to doctors to give treatment to patient and guideline to human for prevent Corona virus surrounding them. During my work I read more than 70 papers some papers are given below.

Junko Kuritaet al,(2020),they discuss the Prediction of the COVID-19 epidemic represents a matter of concern not only for public health or medicine but also for Earth's general population. In their study predicts outbreaks in Wuhan and in Japan as of 11 February, 2020.Method: They applied a simple SIR model to data published by Hubei public health authorities. Moreover, into the model, incorporate mild and asymptomatic cases from experiences of Japanese residents of Wuhan up to the outbreak. Finally, the predict an outbreak in Japan based on 10,000 iterations of a simulation conducted under the assumption of infected people including mild cases visiting Japan according to the estimated distribution of patients in Wuhan since the date on which the initial case occurred to the date when travel from Wuhan to Japan was suspended. In this paper,Results suggest the basic reproduction number, R0, as 2.84; its 95% confidence interval (CI) was [2.35, 3.33]. The peak is estimated to be reached on March 11. Its 95% CI peak date is 29 February to 27 March. The 95% CI peak date in Japan is 26 April to 2 May. The greatest number of patients at the peak with severe symptoms was estimated as 858.3 thousand.

Catharine I. Paules, MD et al(2020), in this paper they discuss about the corona virus. Coronaviruses are large, enveloped, positive-strand RNA viruses that can be divided into 4 genera: alpha, beta, delta, and gamma, of which alpha and beta CoVs are known to infect humans.1 Four HCoVs (HCoV 229E, NL63, OC43, and HKU1) are endemic globally and account for 10% to 30% of upper respiratory tract infections in adults. Coronaviruses are ecologically diverse with the greatest variety seen in bats, suggesting that they are the reservoirs for many of these viruses. Additionally, biomedical researchers are initiating countermeasure development for 2019-nCoV using SARS-CoV and MERS-CoV as prototypes. For example, platform diagnostic modalities are being rapidly adapted to include 2019-nCoV, allowing early recognition and isolation of cases. Broad-spectrum antivirals, such as remdesivir, an RNA polymerase inhibitor, as well as lopinavir/ritonavir and interferon beta have shown promise against MERS-CoV in animal models and are being assessed for activity against 2019-nCoV.5 Vaccines, which have adapted approaches used for SARS-CoV or MERS-CoV, are also being pursued. For example, scientists at the National Institute of Allergy and Infectious Diseases Vaccine Research Center have used nucleic acid vaccine platform approaches.6 During SARS, researchers moved from obtaining the genomic sequence of SARS-CoV to a phase 1 clinical trial of a DNA vaccine in 20 months and have since compressed that timeline to 3.25 months for other viral diseases. For 2019-nCoV, they hope to move even faster, using messenger RNA (mRNA) vaccine technology. Other researchers are similarly poised to construct viral vectors and subunit vaccines.

Wang, D.et al,(2020), in their study,they describes the sociodemographic and epidemiological characteristics of confirmed COVID-19 cases in Muscat governorate and related outcomes. Materials and Methods: This is a descriptive, exploratory analysis of all lab confirmed COVID 19 cases that were reported from 1st February to 31st May 2020. Data for the study was primarily extracted from notifications system established for surveillance (Tarassud). Secondary data sources were, contact listings and hospital medical records. Results: 11,648 initial cases of confirmed COVID-19 infections were included. The mean age was 35 years, 84.7% (N = 9862) were males, 25.9% (N = 3017) were Omanis, and 74.1% (N = 8631) were expatriates of which Indian origin were the majority (37%). Fever and cough were the most common presentations (46.3% and 29.5% respectively). Diabetes and hypertension were the most common comorbidities (4.9% and 4.6% respectively). Hospital admission was required for 7% (N = 811) of the total reported cases, out of them 171 cases (21%) were admitted to ICU, where 107 (13.2%) were ventilated. Results of this study, determine the transmission trend of COVID-19 in a country with high immigrant population. These findings could be utilised for further response planning in similar settings.

Kokoa Chia Marie Reineetal(2020),in this paper disuss aboutchemostratigraphic.In chemostratigraphic term two megasequences (MS1 and MS2) have been identified. A correlation of chemostratigraphic data completed by the lithology results allowed a subdivision of oil wells that shows two main types of deposits environments. First, a proximal marine environment to continental and to Albian marked by a detrital flow deducted from the concentrations evolution of indicator elements of terrigenous material that are K, Mg, and Rb. On the other hand, a deep to shallow marine environment of Cenomanian to Paleocene marked by the presence of predominantly clay sediments and abundant glauconite in the lower Senonian. Nevertheless, there is a transition or intermediate environment that is characterized by the presence of glauconite and detrital flows.

HarapanHarapan et al (2020), in this paper they discuss the literature review of publicly available information to summarize knowledge about the pathogen and the current epidemic. In this literature review, the causative agent, pathogenesis and immune responses, epidemiology, diagnosis, treatment and management of the disease, control and preventions strategies are all reviewed. They describe the situation of corona virus. In early December 2019, an outbreak of coronavirus disease 2019 (COVID-19), caused by a novel severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), occurred in Wuhan City, Hubei Province, China. On January 30, 2020 the World Health Organization declared the outbreak as a Public Health Emergency of International Concern. As of February 14, 2020, 49,053 laboratory-confirmed and 1,381 deaths have been reported globally. Perceived risk of acquiring disease has led many governments to institute a variety of control measures.

Lu H, Stratton CW et al (2020),in this paper their study evaluated two clusters of COVID-19 in six patients, four of whom (66.7%) tested negative for RNA of SARS-CoV-2 on RT-PCR of nasopharyngeal swabs. All epidemiological, clinical, and laboratory data were collected. The first cluster was a nosocomial infection of four health care providers in early January. One case resulted in a sequential familial cluster of infection. All patients either self-quarantined at home or were admitted to hospital for isolated treatment. All recovered and were anti-SARS-CoV-2 IgG- and/or IgM-positive (100%) for serological detection of SARS-CoV-2 at the recovery stage. Our study provides a cautionary warning that negative results for nasopharyngeal swabs of suspected SARS-CoV-2 infection can increase the risk of nosocomial infection among health care providers. Serologic detection for anti-SARS-CoV-2 IgG and/or IgM is an important test in the diagnosis of COVID-19.

Pardo Lledias et al (2020), The diagnosis of SARS-CoV-2 infection presents some limitations. RT-PCR in nasopharyngeal swabs is considered the gold standard for the diagnosis, although it can have false negative results. We aimed to analyze the accuracy of repeating nasopharyngeal swabs based on different clinical probabilities. Retrospective observational study of the first patients admitted to a two COVID Internal Medicine wards at the University Hospital Marqués de Valdecilla, Santander, from March to April 2020. RT-PCR targering E, N, RdRP and ORFab1 genes and antibody tests detecting IgG.

Gili, A.,et al(2021),they compare the Lumipulse® SARS-CoV-2 antigen test with the gold standard real-time reverse transcription-polymerase chain reaction (RT-PCR) for diagnosis of SARS-CoV-2 infection and to evaluate its role in screening programs. Lumipulse® SARS-CoV-2 antigen assay was compared with the gold standard RT-PCR test in a selected cohort of 226 subjects with suspected SARS-CoV-2 infection, and its accuracy was evaluated. Subsequently, the test was administered to a real-life screening cohort of 1738 cases. ROC analysis was performed to explore test features and cutoffs. All tests were performed in the regional reference laboratory in Umbria, Italy. The Lumipulse® SARS-CoV-2 antigen assay can be safely employed in the screening strategies in small and large communities and in the general population.

Lippi, G et al (2022),they provide here a pooled analysis of accuracy of FujirebioLumipulse SARS-CoV-2 Antigen chemiluminescent immunoassay for diagnosing acute SARS-CoV-2 infections. An electronic search was conducted in Scopus and Medline with the keywords "Lumipulse" AND "antigen" AND "SARS-CoV-2" or "COVID-19", up to January 21, 2022, for identifying clinical investigations (minimum sample size ≥100) where diagnostic accuracy of Lumipulse G SARS-CoV-2 Ag was tested against reference molecular techniques. All studies which allowed to construct a 2 × 2 table were included in a pooled analysis. A final number of 21 studies, totalling 17,648 nasopharyngeal and 8538 saliva specimens, were finally included. The pooled diagnostic sensitivity and specificity in nasopharyngeal swabs were 0.80 (95%CI, 0.78-0.81) and 0.98 (95%CI, 0.97-0.98), respectively, whilst the area under the curve and agreement were 0.980 (95%CI, 0.973-0.986) and 94.9%, respectively.

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Thongpradit, S et al,(2022), The SARS-CoV-2 virus, which is driving the current COVID-19 epidemic, has been detected in wastewater and is being utilized as a surveillance tool to establish an early warning system to aid in the management and prevention of future pandemics. qPCR is the method usually used to detect SARS-CoV-2 in wastewater. There has been no study using an immunoassay that is less laboratory-intensive than qPCR with a shorter turnaround time. Therefore, we aimed to evaluate the performance of an automated chemiluminescence enzyme immunoassay (CLEIA) for SARS-CoV-2 antigen in wastewater. The CLEIA assay achieved 100% sensitivity and 66.7% specificity in a field-captured wastewater sample compared to the gold standard RT-qPCR. Our early findings suggest that the SARS-CoV-2 antigen can be identified in wastewater samples using an automated CLEIA, reducing the turnaround time and improving the performance of SARS-CoV-2 wastewater monitoring during the pandemic.

Huang, Chaolinet al.(2020) they discuss in this paper about the Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China All patients with suspected 2019-nCoV were admitted to a designated hospital in Wuhan. We prospectively collected and analyzed data on patients with laboratory-confirmed 2019-nCoV infection by real-time RT-PCR and next-generation sequencing. Data were obtained with standardized data collection forms shared by WHO and the International Severe Acute Respiratory and Emerging Infection Consortium from electronic medical records. Researchers also directly communicated with patients or their families to ascertain epidemiological and symptom data. Outcomes were also compared between patients who had been admitted to the intensive care unit (ICU) and those who had not..

Xing Wu et al. [2020] introduced a model named COVID-AL for diagnosing COVID-19 using CT images. This approach incorporated a pre-trained 2D U-Net architecture specifically for 22 lung region segmentation. COVID-AL achieved an impressive accuracy of 95%, notably using only 30% of labeled data from the dataset. By leveraging active learning within the model, they significantly minimized the manual labeling workload, making the approach both effective and resource-efficient.

Hayden Gunraj et al. [2020] developed a deep CNN called COVIDNet-CT to identify COVID-19 on CT scans. COVIDNet-CT employs a unique machine-powered approach exploration strategy, which autonomously recognizes the optimal network architecture for the CNN. This innovative approach enabled the model to achieve an impressive accuracy of 99.1% while maintaining low computational complexity, making it both efficient and highly accurate.

Tanvir Mahmud et al. (2020) introduced a hybrid neural network called CovTANet for the initial identification and severity forecasting of COVID-19 from CT images. CovTANet integrates a specialized segmentation network, TA-SegNet, designed for accurate lesion segmentation, which enhances the model's ability to differentiate varying stages of COVID-19 severity. CovTANet achieved an accuracy of 96% in severity prediction, demonstrating high reliability for clinical applications. In a study [51], a model was developed using an integrated approach that combines two 3D-ResNets in order to divide pneumonia cases from CT photos. One of the 3D-ResNets functions as a binary classifier to differentiate between COVID-19-related pneumonia and Interstitial Lung Disease (ILD). The model incorporates Prior-Attention Residual Learning (PARL) blocks, which enhance its capacity to focus on relevant features in the CT scans. This design enables the model to train effectively in an end-to-end manner, achieving a classification accuracy of 93.3%.

Xinggang Wang et al. (2020) proposed a deep learning model called DeCovNet aimed at localizing lesions and identifying COVID-19 in 3D CT scans. A notable feature of DeCovNet is its ability to achieve high accuracy (90.1%) in COVID-19 detection without requiring annotated lesions in the CT images. This model’s approach minimizes the reliance on extensive labeled data, which is often challenging to obtain, especially for new or evolving diseases like COVID-19. 23

A. A. Ardakani et al In the study (2021) researchers evaluated ten CNN models that are widely used and pre trained within an artificial intelligence-based computer-aided detection (CAD) system to identify COVID-19 in CT scan images. Among the models tested, ResNet-101 achieved the highest performance, delivering an accuracy of

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99.45%. This result underscores the effectiveness of ResNet-101 in accurately recognizingCOVID-19 from CT images when integrated into the CAD system.

Chun Li et al.(2022)] introduced a method using a TL approach to effectively train a model on a restricted quantity of COVID-19 CT images. This method employed ChexNet, a pre trained network, to predict COVID-19 severity levels, achieving an accuracy of 87% in severity evaluation. By leveraging ChexNet's pre-trained capabilities, the model could generalize well from fewer labeled CT images, making it efficient for scenarios with restricted data availability. In the study [55], a Deep Convolutional Neural Network (DCNN) model, named ReCOV-1-1, is introduced to aid in the identification of COVID-19 from CT scan images. The model leverages ResNet-101 as its backbone architecture, chosen for its depth and proven efficacy in feature extraction across complex image datasets. To improve performance and generalization, data augmentation tools are used to expand the diversity of the datasets, and transfer learning is implemented, allowing the model to benefit from pre-trained knowledge.

Shuai Wang et al(2022). examined the efficacy of a deep learning system tailored for COVID-19 detection from CT images. Their approach utilizes a modified version of the pre-trained InceptionV3 Convolutional Neural Network (CNN) model, referred to as M-Inception. This modification was specifically designed to enhance model performance for COVID-19 screening applications. In study [57], a novel method for COVID-19 detection from CT scans is presented, featuring the CHFS method alongside an integrated SHC. This approach enhances the accuracy of COVID-19 classification through a multi-step process.

The study by Tulinet al.(2022)Presents a robust approach to covid-19 detection applying lung X-ray pictures through an automated model integrated with the YOLO real-time object detection mechanism. Researcher utilized a DarkNet-based classifier with 17 convolutional layers, achieving a great degree of precision in distinguishing between different conditions, in Binary Classification the model obtained an impressive accuracy of 98.08% and for Multi-Class Classification the model scored an accuracy of 87.02%.

Khan (2022) et al introduced CoroNet, CNN tailored for covid-19 diagnosis using chest radiography images. The Xception architecture serves as the foundation for CoroNet, originally pre-trained on the ImageNet dataset, and further fine-tuned with a comprehensive dataset from various publicly available sources. CoroNet obtained an average accuracy of 89.6%, with a recall rate of 93% and a high precision rate of 98.2%, specifically for COVID-19 cases.

Elharrouss et al. (2020) introduced a multi-class COVID-19 chest infection segmentation model that uses a multi-task learning methodology. To distinguish between the ROI and the infections, it uses two encoder-decoder systems. The primary encoder-decoder network receives the structure and texture components as input after they have been extracted from a CT slice using structure-texture decomposition. The subsequent network is trained to separate the infections using the structural component and the ROI segregated by this network. CNNs and UNets perform better than other segmentation models, according to a survey conducted on deep learning 29 algorithms for chest lesson recognition and classification. The combined residual blocks are used in a residual attention UNet for segmenting numerous infection areas from CT images. With a Dice value of 0.94, this model outperforms the baseline architectures and the conventional UNet by almost 10%.

Ma et al. (2020)have created three benchmarks to validate novel deep learning models for the segmentation of lungs and COVID-19 infections from CT scans in order to encourage the advancement of deep learning models for the quantitative care of patients. These standards are intended to assess classification models created using the domain generalization, exchange of information, and Few Shot Learning (FSL) paradigms.

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Table 1 Comparison of COVID-19 diagnostic models utilizing CT and X-ray images and several deep learning networks

Authors	Imaging modalities CT/CXR	Deep learning Techniques	Total Data samples	Number of Classes	Splitting ratio (Training: Validation :Testing)	Results
Wu et al.[70]	CT	ResNet50	495	2(Covid19, Noncovid19)	80:10:10	A=76% Se=81.1% Sp=61.5% AUC=81.9%
L. et al[71]	CT	ResNet50	4536	3(Covid19, CAP, Normal person)	90:00:10	Se=90% Sp=96% AUC=96%
Yousefzadeh et al[72]	CT	Dense Net, ResNet50, Xception , Efficient NetB0	2124	2(Covid19, Noncovid19)	80:20:00	A=96.4% Se=92.4% Sp=98.3% AUC=98.9% F1score=95.3%
Jin et al[73]	CT	ResNet152	1881	2(Covid19, Noncovid19)	Random Splitting	A=94.98% Se=94.06% Sp=95.47% AUC=97.91% F1score=92.7%
Jin et al[74]	CT	DPN-92 Inceptionv3 ResNet50	1391	2(Covid19, Noncovid19)	Random Splitting	Se=97.04% Sp=92.2% AUC=99.1%
Chen et al [75]	CT	UNet++	35,355	2(Covid19, Noncovid19)	Random Splitting	A=98.85% Se=94.34% Sp=99.16% AUC=99.4% Precision=88.37
Wang et al[76]	X-Ray	Covid Net (CNN)	13,800	2(Covid19, Noncovid19)	90:00:10	A=92.4% Se=80% Precision=88.9

III. RESEARCH GAP

It is observed that the majority of the datasets utilized in binary or multiclass classification for the diagnosis of COVID-19 exhibit significant imbalances. The effectiveness of an established model may be influenced due to the deviation of the dataset. Such irregular datasets offer a major hurdle for AI researchers, as it was challenging to get an adequate number of reliable photos, especially in the early stages of the epidemic. This thorough literature review delves into the realm of deep learning applications for COVID-19 management, illustrating the diverse strategies and techniques employed in this domain. It brings to light pivotal challenges such as data heterogeneity, quality, feature selection, model interpretability, and temporal dynamics. By shedding light on the current state of deep learning models in COVID-19 management, the review emphasizes the necessity of continuous research to overcome existing challenges and fill research gaps. The insights gained from this review will steer the advancement of inventive deep learning models and methodologies, ultimately contributing to more effective COVID-19 management and enhanced patient care.

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