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Study and Survey Available Identification technique of COVID-19 Infection using their X-Ray Image

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Abstract – Few in the contemporary period foresaw the outbreak of pneumonia produced by the coronavirus that causes severe acute respiratory syndrome (SARS CoV-2) or coronavirus illness 2019, which began at year's end (COVID-19). Medical professionals' worldwide struggle to keep up with the fast global spread of the COVID-19 pandemic. The disease was first detected in Wuhan, China, but has now spread to every continent. Due to the time required for diagnosis and the high cost of test kits, deep learning and artificial intelligence research and apps have been developed to help doctors treat patients battling illnesses. There is a substantial obstacle to success presented by the high cost of diagnostic laboratory kits, especially in less developed countries. Using X-ray images for automatic detection might be helpful for hospitals and governments without access to a CT scanner or a laboratory kit for detecting COVID-19. A proper diagnosis is crucial since there is currently no effective therapy available. Deep learning approaches have been used for analyzing COVID-19 CXR images. In addition, we have classified the many studies in this field into three distinct groups: COVID-19 studies in the medical field, DL works in CAD connected to COVID-19, and CAD studies related to COVID-19 via deep transfer learning. The results, proposed procedures, datasets, data preparation, and evaluation techniques have all been covered.

Keywords – COVID-19 Infection, X-Ray Image, COVIDX-Net, MobileNetV2, Xception, InceptionV3, ResNetV2, DenseNet121, VGG19

I. RELEVANT INVESTIGATIONS

For COVID-19 patients is proposed by Fang et al. [28]. Fifty-one adults (mean age 45) with recent travel or residency in Wuhan with fever or acute respiratory illness symptoms were selected for this study. Initially, the RT-PCR test for COVID-19 was positive in 36 out of 50 samples. There were 12 positive results from the second round of RT-PCR testing. Patients were positive on the third RT-PCR test (2-5 days later), and one patient was positive on the fourth (7 days). Testing revealed that 98% of the 51 individuals had viral pneumonia by the end of the first day. Based on these findings, chest CT is preferred over RT-PCR because of its higher sensitivity (98% vs. 71%).

A study by Bernheim et al. [29] compared the results of the first chest CT scans conducted on 121 symptomatic positive COVID-19 patients according to how long it had been since the beginning of symptoms (0-2 days for 36 patients, 3-5 days for 36 patients, and 6-12 days for 25 patients).

Analyzing data from 1014 patients in Wuhan between January 6 and February 6, the authors (Tao et al.) [11] conclude with 888 of 1014 patients testing positive for the condition. In addition, the authors analyze the time it takes for RT-PCR findings to shift from negative to positive and discover that, on average, this occurs after 6.9 2.3 days.

To evaluate the efficacy of chest CT and CXR in managing COVID-19, Rubin et al. [30] convened a multidisciplinary panel of radiologists and pulmonologists with experience treating patients with COVID-19 from 10 different countries. The author provides fourteen vital questions and eleven choice points on three tiers—risk factors, community circumstances, and resource constraints. The authors offer five primaries and three additional recommendations for using CXR and CT in the treatment of COVID-19 based on the available evidence.

II. RELATED DL WORKS IN CAD OF COVID-19

Add compiles a database of CXR pictures that researchers may use at any time. After using a pre-trained ResNet, three iterations of fine-tuning are done. Input images are continuously resized from 128 by 128, 224 by 128, and 229 by 229 during the three-stage refining process. Their proposed procedure uses six thousand and nine images (including sixty-nine COVID-19 examples). When sorting items into four distinct classes, they attained a 96.23 percent accuracy rate.

Binary categorization of CXR pictures using the Capsule Network architecture is proposed by Afshar et al. [32] to discover COVID-19 occurrences; they call it COVID-CAPS. Most (90%) of the dataset is used for training, whereas only 10% is used for validation. The improved framework obtains a 95.7% accuracy, while the pre-trained one gets a 98.3% accuracy.

Somewhere about 13,800 CXR pictures are utilized to train the network. Three hundred and eighty-three of them have been identified as having COVID. As for how well the model performs in a three-class classification scenario, it gets 92.6% correct.

Hemdan et al. [34] propose a novel deep learning-based system, COVIDX-Net, for autonomously diagnosing COVID-19 from CXR images. The network's nodes include MobileNetV2, Xception, InceptionV3, ResNetV2, DenseNet121, VGG19, and Inception Re-convolutional Network Version 2. The suggested technique is analyzed using fifty computed tomography (CXR) images, 25 of which are positive COVID-19 images. The remaining 20% of images are used for research and analysis. Every picture has been shrunk down to a perfect 224 by 224. VGG19 and DenseNet201 have a 90% success rate.

Shetty et al. [35] suggest using deep learning to recognize COVID-19 in CXR images. The proposed method involves feeding the outputs of several CNN models into a support vector machine to perform classification. Fifty control shots and fifty COVID-19-infected photos are used in the study. We use 60% of the photos to train the model, 20% to validate it, and 20% to test it. In terms of classification accuracy, ResNet50 achieves a maximum of 95.38 percent.

This network is based on a modified version of a standard AlexNet that has already been trained. The model is based on data from 170 CXRs and 361 CT images. The whole dataset is split in half: half is used for training, while the other half is used for validation. Pre-trained networks reach 98% accuracy in binary classification, whereas modified CNN achieves 94.11% accuracy.

Using 3905 X-Ray pictures labeled with one of six classes, Apostolopoulos et al. [37] train a state-of-the-art CNN model dubbed MobileNet. In addition, 455 COVID-19 CXR photos are included. During this processing phase, we do the augmentation work and resize the photos to 200 by 200 pixels. In binary classification tests, they attained a 99.18% success rate, whereas, in seven-class classification tasks, they only managed an accuracy of 87.66%.

If you're looking to spot COVID-19 in CXR pictures, Loey et al. [38] recommend using a Generative Adversarial Network (GAN) with deep transfer learning. Given the scarcity of available COVID-19 CXR images, they resort to GAN to create new ones. There were 307 photos gathered, split across four categories: viral pneumonia bacterial pneumonia, normal, and COVID-19. With GAN, 90% of the dataset is used for training and validation, while 10% is preserved for testing. Transfer learning is performed using a pretrained version of the AlexNet, GoogleNet, or Resnet18. On a four-class (GoogleNet) issue, they got an accuracy of 80%; on a three-class (AlexNet) problem, they got 85.3%; and on a two-class (GoogleNet) problem, they got 100%.

CXR with transfer learning, along with several deep learning models (most notably CNN), have shown good results in identifying COVID-19, as shown above. However, it is not obvious how various CNN transfer learning methods compare in terms of performance. To identify CXR COVID-19, this thesis compares the efficiency of fifteen different CNN models trained using transfer learning.

III. RELATED DEEP TRANSFER LEARNING WORKS IN CAD FIELDS

Zhang et al. [39] present a deep transfer learning-based classification strategy for dividing cervical cells into healthy and cancerous tissue. To measure the efficacy of the suggested approach, we consider the HEMLBC private dataset and the Herlev public dataset. In the preliminary processing, they carry out patch extraction and augmentation procedures. On the Herlev and HEMLBC datasets, they both reach 98.3% accuracy.

In [40], Chen et al. provide a deep transfer learning system for identifying cervical immunohistochemistry pictures using the Inception-V3 network. In the preparation phase, the data augmentation job is done. On average, they succeed with a precision of 77.3%.

Breast histopathology photos are classified using a convolutional neural network (CNN) pre-trained on the ImageNet dataset by Song et al. [41]. The FV-encoding is used to first represent the pictures. After then, a layer of adaptation is created for fine-tuning. In the end, with just 30% of the data being tested, an accuracy of 87% was achieved.

To differentiate COVID-19 CXR photographs from regular CXR shots, Zhang et al. propose a deep learning approach [43]. The core of the network is a pretrained ResNet. For training, 50 out of 100 COVID-19 and 1430 Normal CXR pictures are used, while the remaining images are used for testing. In terms of COVID-19 detection, this approach is 96% accurate, whereas for non-COVID-19 it is 70.65% accurate.

Abbas et al. [44] propose using pre-trained ResNet-50 as transfer learning in their previously created CNN, Compose network (DeTraC-Net), the Decompose, Transfer, and categorizing COVID-19 chest X-ray pictures into mild and severe instances of the acute respiratory syndrome. Using their suggested approach to analyze the performance of 50 standard COVID-19 pictures, they found an accuracy of 95.12%.

To identify patients with coronavirus pneumonia on CXR, Narin et al. [45] offer a CNN-based method. In this setup, InceptionV3, Inception-ResNetV2, and ResNet50, are used as the pre-trained network models. There are control CXR utilized to evaluate the proposed model. Most (80%) of the data is used for training purposes, while a smaller percentage (20%) is used for testing. They found that, compared to other models, ResNet50 has the greatest accuracy (98%) in binary classification.

IV. LITERATURE REVIEW

To automate COVID-19 identification from chest X-ray pictures, numerous recent research has presented Deep Learning techniques [22, 25] with great performance. Using a variant of DarkNet et al. [26] showed its utility for both binary (COVID-19 vs. Normal) and multiclass classification. A dataset including 114 COVID-19 CXRs reported a sensitivity of 90.65% for the binary scheme and 85.35% for the multiclass technique. High discriminating performance with 98.7 percent sensitivity when MobileNetV2 was tested on a dataset containing 224 COVID-19 instances by Apostolopoulos et al. [27]. Chowdhury et al. [30] explored using six deep CNNs on a dataset consisting of 423 COVID-19 CXR pictures, testing them with both binary and multiclass methods. DenseNet201 has the highest binary and multiclass systems sensitivity scores at 99.7% and 97.9%, respectively. CheXNet was used as a feature extractor by Yamac et al. [31], and Convolution Support Estimation Network (CSEN) was suggested as a classifier to differentiate between normal CXRs, bacterial pneumonia, viral pneumonia, and COVID-19. On the QaTa-COV19 dataset, which consists of 462 COVID-19 CXR pictures, the network performed well, achieving a sensitivity of 98%.

Recognition of COVID-19 was suggested using a patch-based deep CNN architecture by Oh et al. [33]. At first, we used a fully connected (FC)-DenseNet103 to extract lung regions; next, we used a patch-based classification using ResNet50 and majority voting to determine the outcome. The suggested pipeline has a sensitivity of 96.9% on the COVID-19 identification challenge and an IoU of 95.5% on the lung segmentation task. It is a difficult challenge for clinicians to distinguish between members of the Coronavirus family using CXR pictures, hence we recently looked at the potential of deep networks to do so [34]. Lung areas are segmented using the U-Net model and then categorized with a deep CNN classifier in a suggested cascaded system. For the segmentation test, our suggested pipeline produced a 93.1 percent IoU and a 96.4 percent Dice Similarity Coefficient (DSC), while for the recognition task, it achieved a 96.7 percent sensitivity. A sensitivity of 57% and a specificity of 80% were attained in this classification task, which is a very poor result. As a result, the introduced pipeline may be very helpful in the first phases of a particular disease's or pandemic's onset, when annotated data are few. However, supervised techniques are preferred when enough annotated data are provided to train the deep CNN models. Recent studies have shown great classification performance but have also pointed out several problems and limitations. The first problem is that even the biggest of these studies only includes a few hundred CXR samples. This makes it difficult to generalize their conclusions in practice and casts doubt on how well they are evaluated. Second, they didn't try to evaluate and pinpoint the situation beyond identifying COVID-19 and other sorts. These problems reduce its usefulness, especially in a realistic clinical environment.

Contrarily, just a few researchers [36, 37] put lung segmentation at the forefront of their detection process. This protects the network from irrelevant features from places other than the text, backdrop, bones, heart, or lungs, and provides accurate classification decisions. To counter this, earlier segmentation methods largely used the Montgomery [38] and Shenzhen [39] CXR lung mask datasets to train on a total of 704 X-ray pictures for Normal and TB patients. Due to this, segmentation fails in novel settings, such as with severe COVID-19 situations or low-quality photos with low signal-to-noise ratios.

When assessing a patient's condition and determining an appropriate course of therapy, COVID-19 detection is only one part of the puzzle [40]. Perhaps COVID-19 can leave a signature in those specific areas. However, the scope of their suggested method is restricted to determining the precise location of COVID-19 infections. As a result, there is undoubtedly potential for development, notably in identifying and quantifying infection locations via calculating the total percentage of infected areas in the lungs. This may help clinicians gauge the extent of COVID-19 pneumonia and monitor its development over time.

Against this background, we try to conquer the hurdles mentioned above and the study's restrictions. Key contributions made by this thesis include:

With 10,701 normal (healthy) images, 11263 non-COVID (but sick) images, and 11956 COVID-19 photos, COVID-QU-Ex [65] is the biggest COVID-19 benchmark dataset to date. COVID-QU-Ex is the go-to standard by which all other COVID-19 quantifications, localization, detection, and models are measured, especially those based on cutting-edge deep network architectures.

To decrease the manual work required to annotate the photos in the COVID-QU-Ex dataset, we have created ground-truth lung segmentation masks using a sophisticated human-machine collaboration technique. This is the first effort of its kind to create such comprehensive ground-truth lung segmentation masks. Along with the results of this research, both the dataset and the associated ground-truth demonstrations will be made available as a benchmarking resource. We anticipate that the major benchmark COVID-19 CXR pictures and associated ground-truth lung masks will be invaluable to researchers, physicians, and engineers worldwide who are working to develop new methods for the early identification of COVID-19.

In addition, we have conducted experiments to determine which model is best suited for each segmentation job by using three image architectures FPN) [44], U-Net++ [43], and U-Net [42] with varying backbone encoder topologies. We used InceptionV4 [47], DenseNet161 [47], DenseNet121 [46], ResNet50 [46], and ResNet18 [45]. This is a monumental achievement since it allows for the most precise diagnosis and evaluation of the condition.

Since there is now no vaccination available, isolating those who have been cured is the best action to control the outbreak. However, differentiating positive patients from negative ones quickly becomes a challenge. Several papers described their methods for spotting abnormalities on chest X-rays and CT scans. Indeed, Gozes et al. (2020) presented a model that could distinguish between those with and without coronavirus. Lung abnormality mapping and measurement were also accomplished using the suggested approach. Two distinct parts made up the whole: Subsystem A: Nodules and tiny opacities were identified with the help of a 3D analysis performed using off-the-shelf software. Metrics and pinpointing were then supplied. In the first stage of subsystem B, lung Crop, the lung ROI was harvested using a lung segmentation module (U-net architecture). The second phase involves utilizing the deep convolutional neural network model ResNet50 to detect irregularities in coronaviruses. The third stage included determining the precise location of the anomaly. Grad-cam was used to extract network-activation maps whenever a fresh slice tested positive.

Narin et al. suggested a fully automated deep learning-based technique that uses X-ray images to predict Covid19 (2020). Three distinct Deep Convolution Neural Network topologies were employed in the suggested technique. All the pictures were scaled to 224 by 224 pixels and were taken from a dataset that included 50 X-rays taken of covid19 patients and 50 regular X-rays. The authors employed transfer learning models to get around the difficulty of the small dataset. They also used a transfer learning strategy and a cross-validation procedure where k was set to 5. Pre-training the model ResNet50 yielded satisfactory results (an accuracy score of 98.0%).

To aid radiologists in the automated identification of Covid19, Hemdan et al. (2020) introduced a deep learning classifier architecture called COVIDX-Net. Thanks to the established framework, X-ray pictures of Covid19 may be sorted into positive and negative categories. The authors used seven distinct recurrent neural networks (RNN) designs (MobileNetV2, Xception, InceptionResNetV2, InceptionV3, ResNetV2, DenseNet121, and VGG19). They employed 50 X-ray pictures, divided equally between normal and Covid19 positive patients, as part of a dataset (25 X-ray images for each). All the pictures have been shrunk down to 224x224 dimensions. We trained using 80% of the photos and evaluated with 20%.

Hafeez (2020) CNN architecture for differentiating instances of Covid19 from other Pneumonia (Bacteria and viruses) and usual problems. Wang and Wong's COVDIX dataset was utilized (2020). There are 5941 chest radiographs in this data collection, taken from 2839 different individuals. A subset of the COVIDX dataset was employed for this study; specifically, Viral (931), Bacterial (660), the Covid19 (48 pictures), and Normal sets (1203 images). The Cyclical Learning Rate was utilized to aid in selecting the best learning rate at each stage of the training procedure, which consisted of three distinct phases. Compared to Covid-83.5% Net's accuracy, the suggested Covid-ResNes achieved 96.23%.

Chest X-ray and CT scan pictures of the lungs may be used to detect cancer, and Bhandary et al. (2020) have published a deep-learning framework. Modified AlexNet provided the foundation for the suggested model (MAN). So, they put out a pair of hypotheses: One such solution is to utilize a MAN model in conjunction with a Support Vector Machine (SVM) to differentiate pneumonia photos from generic ones. When compared against the ResNet50, VGG16, AlexNet, VGG19, and MAN Softmax models, the suggested model outperformed them with impressive accuracy (96.8%). Spiral CT scans of the lungs were utilized for this analysis. To boost classification accuracy, the authors combined MAN with the Ensemble-Feature-Technique (EFT). The model was then coupled with a support vector machine (SVM), k-Nearest Neighbors (k-NN), and Random Forest to categorize CT images as Malignant or Benign (RF). These findings demonstrated that when MAN and SVM were used together, they produced high levels of accuracy (97.27 and 86.47, respectively) both with and without EFT.

Using Chest X-ray pictures, they proposed a deep-learning algorithm for detecting Covid19 in healthy individuals. The three pillars on which the model rested were: The first is a residual convolutional neural network with 18 layers, which serves as the backbone. The rule of thumb for this method is to take a chest X-ray and pull out the salient details. The second component is the Pcls categorization score generator head. The characteristics extracted provided the energy, while the backbone network kept everything running smoothly. The anomaly detecting head, the third part, may provide a scalar anomaly score Pano. When making a call, a threshold T was used with the categorization and scalar anomaly calculation results. The findings revealed that the sensitivity also fell when the threshold T was lowered.

For CT image classification, they employed a concatenation of convolutional neural networks (CNN). There are four stages to the method outlined here: 1) The photos were processed beforehand to isolate functional lung areas. 2) Several potential picture cubes were separated using a 3D convolutional neural network. Covid19, Influenza-A, and normal image patches were differentiated using an image classification technique. 4) a full analysis report for a single CT sample was prepared using the noisy-or Bayesian algorithm. Regarding segmentation, we employed the VNET-IR-RPN model, and when it came to classification, we turned to the ResNet-18 and the ResNet-18.

Using a novel deep learning algorithm, Shan et al. could segregate and quantify infection areas in CT scans from COVID-19 patients (2020). Using a HITL strategy and the VB-Net Neural Network, the authors assisted radiologists in providing context for the automated annotations made in each instance. The model's efficacy was then determined using assessment measures. The CT scans were sorted into several groups. To train the segmentation network, it will be fed CT images that radiologists manually contoured. After that, radiologists reviewed and adjusted the segmentation findings by hand, all while considering fresh data to feed the model. The model was built iteratively by repeatedly going through this procedure.

To ensure that no important research was overlooked, we prioritized sensitivity in our study selection process above accuracy. So far, with a few exceptions, all research in this area has focused only on binary categorization. To that end, this study aims to solve the following research issues by contrasting the most up-to-date deep convolutional neural network architectures for automatically classifying X-ray and CT pictures into normal, bacterial, and coronavirus classes:

- Does deep learning provide any method that stands out from the crowd?
- Coronavirus early screening using DL on CT and X-ray images: possible?
- How reliable is DL's diagnosis using CT and X-ray images?
- Can DL help with coronavirus treatment, tracking, and, detection,?

V. DATA AND PATIENTS

Adult patients at four Israeli medical sites were included in retrospective research conducted during and after the first COVID-19 pandemic outbreak. There were 2427 frontal (AP/PA) CXR pictures from 1384 patients (average age 63 years, male to female ratio 832:552) included in this analysis, 360 of which had a positive COVID-19 diagnosis and 1024 of which did not. The X-rays were taken using several portable devices. Every patient with symptoms who tested positive for COVID-19 using RT PCR was routinely admitted to the hospital, regardless of how mild their symptoms were. Standard chest X-rays were taken on the day of admission and again later for follow-up. Photos that tested positive for COVID-19 were interpreted as such regardless of the severity of the lung damage seen. All CXR images in our cohort that did not include COVID-19 were collected from the same X-ray equipment before the outbreak in January 2017 through April 2019. Depending on the patient's medical history, these might range from normal to abnormal radiographs.

Of the whole CXR dataset, 15% (or 350 CXR) were used for the test, with 179 CXR (51% positive) and 171 CXR (49% negative). Images of patients with more than one were utilized for the test or train set, but never both. This was done so that the model wouldn't automatically attribute the label to patient-specific visual characteristics (such as metal implants) that aren't necessarily there. Patients from all four hospitals are represented in the training and testing sets.

All photographs were utilized at their native resolution with no lossy compression, with just 4% (101/2426) of the total images being omitted because of skewed orientation or other distortions. Ninety-eight of them tested positive for COVID-19. This study did not employ clinical and radiological results as independent exclusion criteria.

VI. IMAGE MANIPULATION

To begin, each picture is processed utilizing augmentation, which is a collection of visual alterations, normalisation, which establishes a uniform scale of image size and color, and segmentation, which highlights the region of the lungs and combines it with the rest of the image. The full collection of images is then loaded into a neural network, which returns a classification conclusion for each picture as either positive or negative for coronavirus illness 2019 (COVID-19). In addition, the network's final layer's embedded features are retrieved to discover other pictures with the same traits as the input image.

Changes in direction and brightness are only two examples of the kinds of alterations that may be made using augmentations. Although they have no bearing on classification accuracy, variations in orientation and pixel values during the picture-collecting process may impact the network's training performance. They help broaden the dataset by generating a variety of pictures, which improves the reliability and generalizability of the model [15, 16]. Importantly, we engaged with radiologists to define the augmentation parameters to guarantee they would match natural variance in CXR acquisition.

The normalization procedure aims to create uniformity in picture size and other attributes. Each picture is cropped to remove unwanted dark areas, the brightness is equalized across the board, and the resolution is scaled using bilinear interpolation to a uniform 1024 by 1024 pixels.

To improve performance, we added a new picture channel trained using lung segmentation data from an external dataset using a U-net, as described in [17]. While training, this network may obtain information from a CXR pixel mask that indicates the likelihood that each pixel is part of the lungs.

VII. OUTPUT AND NETWORK DESIGN SPECIFICATIONS

ResNet34, ResNet152 [18], CheXpert [9], VGG16 [19], ResNet50, and were the five network models we compared. These designs use the method of mapping pictures from a high-dimensional space to a low-dimensional space, where a simple border may separate image classes [9]. An ensemble model that takes the findings from several networks and returns a single result was also used to refine the picture classification process further.

We also present a technique for collecting many CXR pictures comparable to a particular image, adding this functionality to categorization.

Information regarding clinical indications seen in the images should be captured by activating layers of the neural network. We utilized the embeddings generated by the network's last layer to find the images' closest neighbors to look for similarities among the resultant vectors.

VIII. ANALYSIS AND RATING

The ROC and P-R curves were used alongside accuracy, sensitivity, and specificity to assess the models. Ten independent random splits of the data were used to determine confidence intervals (CIs). The CI was calculated by computing the required metrics for each model using 100 bootstrap samples taken from the test set. Each statistic provides two and ninety-five percentile confidence intervals (CIs). We provide the CIs for the first data split in the thesis. We test the model on a collection of 22 CXRs that a radiologist has deemed difficult to diagnose and compare its performance with and without any picture preprocessing. Using t-distributed stochastic neighbor embedding (t-SNE) [20], a technique that translates multi-dimensional data into a two-dimensional space to facilitate visualization, we give further insight into the model's effectiveness by displaying its findings.

IX. CONCLUSION

To stop the new coronavirus from infecting other people, it is crucial to diagnose the virus as soon as possible. Along with this study, we developed a deep transfer learning-based system that combines chest X-ray pictures of patients with COVID-19 and those without the condition to automatically identify the illness. The proposed classification model can identify COVID-19 with an accuracy of greater than 98 percent. Our study's findings indicate that, given its strong overall performance, doctors and other health professionals should naturally rely on it to aid in clinical decision-making. This work has a thorough grasp of the application of deep transfer learning algorithms to find COVID-19 as soon as feasible. COVID-19 kills millions of people worldwide and poses a danger to the healthcare industry.

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