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PRE-PROCESSING OF CT SCAN IMAGES FOR COVID-19 DETECTION

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Abstract: In December 2019, the first covid case was reported in China province. It has achieved a status as pandemic. This pandemic with continuously evolving transmission. Tracing the people who was a close contact with positive people and then quarantining them by some measures like seal-down. So, some other reliable measures have to be taken in order to control the cases of positivity.

Covid-19 is a larger epidemic, it covers several countries or spreads from one continent to another. The early detection of this disease is censorious to control the positivity cases unfurl and impermanence.

The speed and pace and of the transmission of severe acute respiratory syndrome coronavirus 2 also referred as Covid-19 have resulted in a global pandemic, with significant health, financial and other implications.

The global outbreak of novel coronavirus 2019 was declared by the World Health Organization on 30 January 2020. The clinical symptoms of covid-19 are predominantly pulmonary, although serious cardiovascular side effects were also observed in a number of patients.

Existing preventative solutions, include frequent hand wash using soap and water, hydro-alcoholic solution and digital technologies to detect and limit the spread of the virus and track the movement of quarantined peoples. Impact- millions of deaths, lockdown in cities, restricted movements, business losses, global economy slowdown.

Keywords - CT, CNN, VGG16, Mobile net, Densenet121, Xception, Efficient net, NAS Net.

1. INTRODUCTION

The coronavirus disease 2019 (Covid-19), which is caused by the coronavirus Z2 (SARS-CoV-2) that causes severe acute respiratory syndrome, is part of a broader epidemic. The number of people infected with the virus is growing swiftly. The genuine head diagnosis Reverse transcriptase polymerase chain reaction test. The solution time and cost of this test are excessive, so further swift and reachable diagnostic instruments are needed.

The rapid increase in covid infection peoples is enormous. The healthcare system across world-wide with having only limited testing kits, so it is impossible for every covid patient with respiratory illness to test using normal techniques.

Those tests are also have long turn over time and very limited sensitivity. So, X-ray machines are already in use it may help to quarantine high risk covid affected patients stint test results are awaited.

The image-based diagnosis sequence for COVID-19, using a thoracic CT scan as an example. A technician instructs and assists each individual in posing on the patient bed, after which CT scan images are collected in a single breath-hold. The scans are performed using optimum settings determined by the radiologists based on the patient's body shape from the upper thoracic inlet to the inferior level of the costophrenic angle. CT images are reconstructed from the obtained data and then communicated via picture archiving and communication systems (PACS) for later viewing and diagnosis.

Artificial intelligence (AI), a new technique in the field of medical imaging, has made a significant contribution to the fight against COVID-19. In comparison to the traditional imaging workflow, which depends mainly on human labour, AI allows for more secure, accurate, and efficient imaging solutions. The dedicated imaging platform, lung infection region segmentation, clinical assessment and diagnosis, as well as basic and clinical research, are among the AI-powered applications in COVID-19Z. Furthermore, various commercial solutions have been created that successfully integrate AI into ZcombatZCOVID-19 and clearly demonstrate the technology's capabilities.

Due to the importance of AI in all aspects of COVID-19 image-based analysis, this review will focus on the function of medical imaging, which is aided by AI, in combating the disease. First, we'll go through intelligent imaging platforms for COVID-19, then we'll go over prominent machine learning methods in the imaging workflow, such as segmentation, diagnosis, and prognosis. A number of publicly accessible datasets are also discussed.

The increased likelihood of occupational virus exposure makes healthcare practitioners particularly vulnerable. Imaging specialists and technicians are given top priority so that any potential viral interaction can be avoided. In addition to personal protective equipment (PPE), dedicated imaging facilities and procedures may be considered, which are critical in reducing hazards and saving lives.

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2. PRE-PROCESSING METHODS

2.1 Deep Learning Methodologies
Machine learning techniques are akin to artificial intelligence techniques that mirror how people acquire knowledge. Deep learning is a fundamental component of data science, which includes statistics and predictive modelling. A convolutional neural network is a type of deep neural network that is used to analyse visual information. CNN is a deep learning method that takes an input image and assigns weight to distinct items in the image so that it can distinguish between them. CNN is used to classify and identify photos because of its high accuracy.

2.2 Classification
The data is classified using deep learning architectures such as VGG16, DenseNet, MobileNet, Xception, EfficientNet, and NASNet. These models are trained via transfer learning. A total of 50 epochs were used to train each model.

2.3 Xception
The Inception network has been phased out in favour of the Xception network. Xception is a term used to describe extreme inception. The Xception network employs depth-wise separable convolution layers rather than traditional convolution layers. Xception includes mapping spatial and cross-channel correlations, which can be totally separated in CNN feature maps. Inception's fundamental design has outlasted Xception. The Xception model's 36 convolution layers can be divided into 14 discrete modules. Every layer has a continuous residual link surrounding it after the first and last layers are eliminated. To acquire cross-channel correlations in an input image, the input image is translated into spatial correlations within each output channel. The depth-wise 11 convolution approach is then applied. Relationships can be shown instead of 3D maps.

2.4 VGG16
VGG16 is a CNN model developed at Oxford University by the VGG. AlexNet, the network's replacement, was launched in 2012. As shown in Figure 2, VGG16 contains eight layers, three entirely connected layers, five max-pooling layers, and one softmax layer. The architecture was created as part of the ImageNet competition. The width of the convolution blocks is set to a small integer. After each max-pooling operation, the width parameter is increased by two until it reaches 512. The picture size for the VGG16 is 224 224 pixels. To keep the image's spatial resolution, spatial padding was applied. Similar operations can now be carried out using the VGG16 network, which has been made open-source. Because of this, the model can also be utilised for transfer learning.

2.5 MobileNet
Depthwise separable convolutions are used by MobileNet. When compared to a network with regular convolutions of the same depth in the nets, the number of parameters is significantly reduced. Lightweight deep neural networks are constructed as a result. MobileNets are built using depthwise separable convolution layers. A depth-wise convolution layer and a pointwise convolution layer make up each depth-wise detachable convolution layer. When depthwise and pointwise convolutions are counted individually, a MobileNet has 28 layers, as shown in Figure 3. A typical MobileNet's number of parameters can be reduced to 4.2 million by adjusting the width multiplier hyperparameter. The size of the input image is 224 x 224 pixels.

2.6 NASNet
The NAS Network was established by the Google Machine Learning team. The network architecture is built using reinforcement learning. The network is adjusted based on the success of the kid block changing. The effectiveness of the children's block is assessed by the parental block. The network's components are RNN and CNN. Weights, regularisation methods, layers, and optimizer functions were all changed in the architecture to get the most performance from the web. Using several NASNet variations such as A, B, and C algorithms, reinforced evolutionary processes choose the best candidates and chose the best cells.

The cells with the worst performance are eliminated using tournament selection approaches. The cell structure's performance is improved by increasing the child's objective functions and implementing reinforcement mutations. A block is the smallest element, while a cell is made up of multiple blocks. The network's search space is divided into cells, which are then divided into blocks. The number of cells and blocks is determined by the dataset type, which is not fixed. Within a block, convolutions, pooling, mapping, and other operations are performed. Because of its transferrable learning methodology, NASNet was one of the technologies utilised to detect infected and non-infected patients. It provides more options due to its simple network design.

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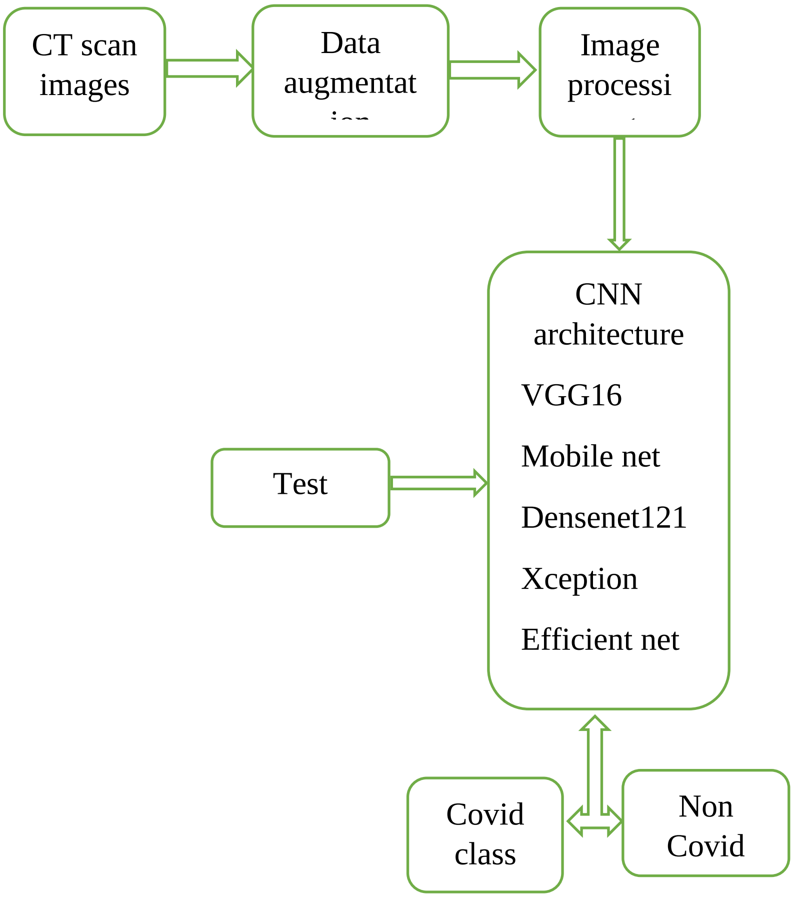
2.7 DenseNet121

DenseNet is a densely linked neural network, a new technique for increasing the size of deep convolutional networks without having to deal with issues like expanding and disappearing gradients. Each layer connects directly to adjacent levels, allowing the most information and gradient flow to get through. The problems are now resolved. Instead than depending on huge, deep, or broad CNN architectures for symbolic power, the goal is to focus on feature reuse. DenseNets require fewer or equal numbers of nodes than traditional CNN. Because DenseNets does not learn feature maps, and the parameters are not required. Several ResNets versions contributed very little, and those layers can be eliminated.

Only a few key characteristics are added by DenseNet layers, and the layers are narrow with only a few extra filters. Because deep neural networks contain information flow and gradients, the problem arises when training the data. DenseNets addresses these concerns by directly accessing the gradients and transfer functions of the actual input. As feature translation from the I 1 th level becomes the intake to the pith layer, the Dense Net network design becomes increasingly hierarchical. Because the input to the breadth layer can come from any level I 1, I 2, or even I n, the DenseNet is a widely applicable network (where n must be less than the num ber of layers total). A batch normalisation step is used to normalise the network, which minimises the real size of the network.

2.8 EfficientNet

When using CNNs, one of the most essential factors is the model's scaling. The performance of the system is improved by increasing the model's depth. Selecting the model's depth, on the other hand, is a difficult task that necessitates a human hit-or-miss approach to selecting a better-performing model. The EfficientNet models' key component is MBConv. This block now includes a squeeze-and-excitation optimization block. In MobileNet V2, the MBConv block works similarly to the inverted residual blocks. 3 depth-wise and pointwise convolutions are used to build a direct link between the start and finish of a convolutional block to reduce the number of channels in the output feature maps to reduce the number of channels in the output feature maps to reduce the number of channels in the output feature maps to reduce the number of channels in the output feature maps to reduce the number of channels in the output feature maps to reduce the number of channels in the output feature maps to reduce the number of channels in the output feature maps to reduce the number of channels Low-level connections connect the small levels.



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CONCLUSION

Assessment of infectiousness of the COVID-19Zcases during their early symptomatic phase is critical in designing preventative strategies for pandemic control. Household contacts of COVID-19 cases are most vulnerable population and needs special attention especially when all the countries have imposed lockdowns and are advocating “stay home”. Asymptomatic cases have lesser chances of spreading the disease. However, immediate isolating of the cases upon development of the symptoms reduces the risk of disease drastically. So, enough measures should be taken to limit the contact.

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