An Ensemble Learning Framework for Multi-class COVID-19 Lesion Segmentation from Chest CT Images

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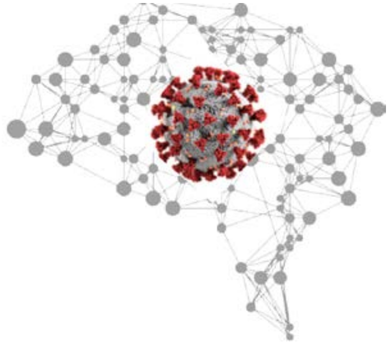
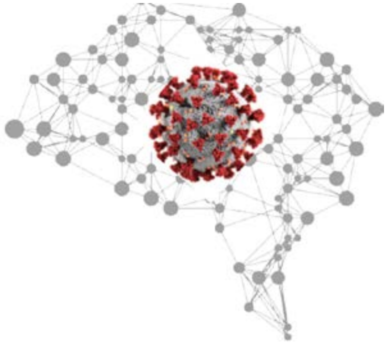


Introduction:



- The novel Coronavirus disease (COVID-19), appeared in December 2019 in Wuhan, China, and was characterized as a pandemic, in March 2020 by WHO.
- More than **185 million** cases and **4 million** deaths globally.
- Emerging new variants of COVID-19, making the situation more threatening.
- Over the past decades: Pandemics/epidemics such as Ebola, H1N1 Flu, and SARS.

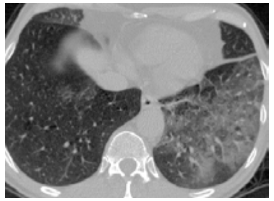
✓ **Manage the COVID-19 pandemic with minimum loss/cost.**

✓ **Learn lessons and be well-prepared for the potential future ones.**

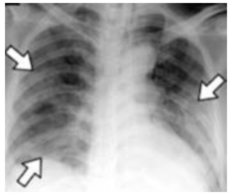
Introduction:

- **The gold standard for COVID-19 testing: R**everse-**T**ranscription **P**olymerase **C**hain **R**eaction (RT-PCR) test.

- **Problems with RT-PCR test**: high false-negative rate, delayed results, access to testing kits.



Mohammadi. A.,et al. 2020



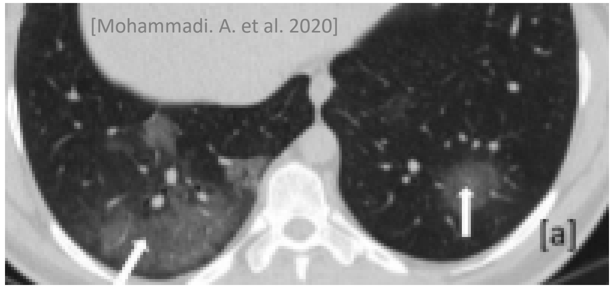
[Jacobi, A. et al. 2020]

- Chest medical images as a complementary source for COVID-19 diagnosis/prognosis.

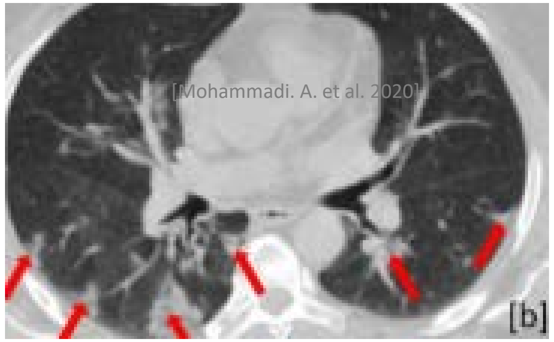
- Medical imaging demonstrates informative features of the COVID-19 disease and can play an essential role in pandemic management.

Mohammadi. A., et al. (2020). Diagnosis/Prognosis of COVID-19 Images: Challenges, Opportunities, and Applications. arXiv preprint arXiv:2012.14106.
Jacobi, A., et al. (2020). Portable chest X-ray in coronavirus disease-19 (COVID-19): A pictorial review. Clinical imaging.

Radiological Characteristics of COVID-19:



Ground Glass Opacity (GGO)



Consolidation

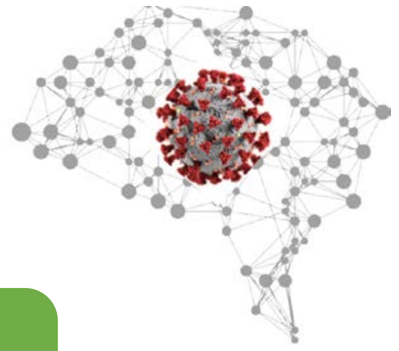
Pure GGO: more frequently appeared in the early stages of the COVID-19 disease [Z. Sun. et al].

GGOs with consolidation: more common during progressive stages [Z. Sun. et al].

Consolidation rate: a severity measure for COVID-19 patients [S. Chaganti, et al., 2020].

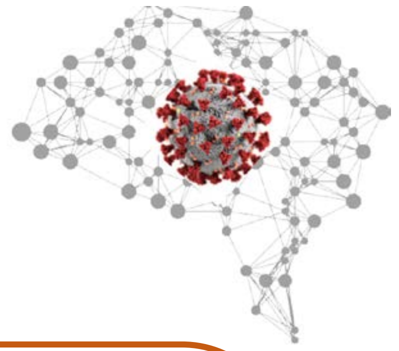
Segmenting COVID-19 infection regions and distinguishing the infection types: identifying the disease severity/stage.

Z. Sun, et al., “A systematic review of chest imaging findings in covid-19,”Quantitative imaging in medicine and surgery, vol. 10, no. 5, p. 1058, 2020.
S. Chaganti, et al., “Automated quantification of ct patterns associated with covid-19 from chest ct,”Radiology: Artificial Intelligence, vol. 2, no. 4, p. e200048, 2020.



High contingency & increasing number of critically-ill patients → Severity assessment & Outcome prediction of COVID-19 patients → Efficient allocation of limited medical resources, Making informed treatment decisions, Saving more lives

- Visual interpretation of medical images by radiologists is time-consuming and subjective.
- Developing automatic segmentation models for COVID-19 prognosis to speed up the severity assessment process.

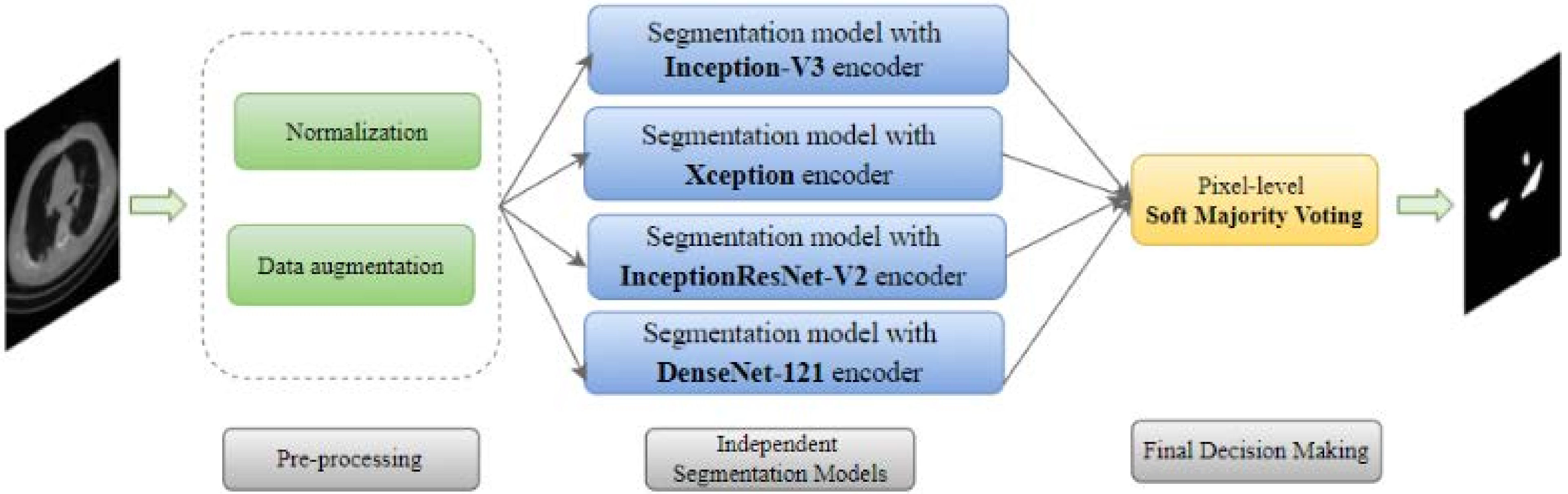


Motivation

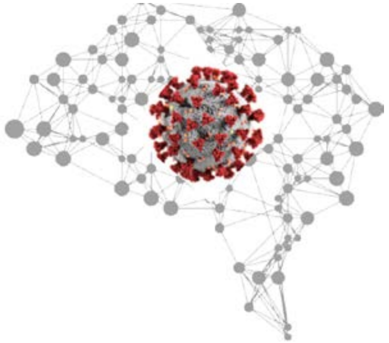
- Automated quantification of lung involvement: accelerating the COVID-19 severity assessment.
- Identifying different types of infection patterns from CT images: determining the stage/severity of COVID-19 patients more accurately.

Objective

DL-based framework for multi-class segmentation of COVID-19 lesions from chest CT scans, identifying GGOs and consolidation.



- Each segmentation network contains:
  - ✓ Encoding path for extracting high-resolution features from CT images
  - ✓ Decoding path for localizing the extracted features and constructing the infection masks.

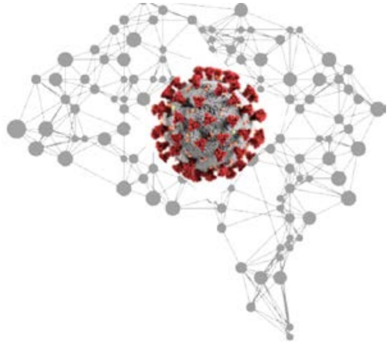


Encoding Path

- **Inception-V3**, **InceptionResNet-V2**, **Xception**, and **DenseNet-121**, available in Keras Applications alongside their pre-trained weights on the ImageNet dataset.
- The pre-trained weights on the ImageNet: the network's initial weights, all the layers are unfrozen to be trained on our dataset.
- The fully connected layers from each pre-trained CNN model are eliminated and replaced with the decoder path.
- Adoption of state-of-the-art CNN models in encoding path: learning the contextual information more accurately

Decoding Path

- Four decoding blocks, each consisting of a 2×2 up-sampling layer, following by a 3×3 convolution layer, ReLU activation function, and Batch-Normalization (BN) layer.
- ReLU activation function helps the model learn nonlinear patterns from images
- BN speeds up the training process by normalizing the inputs of the layers.
- Softmax activation function predicts the probability of each pixel belongs to GGO, consolidation, or background class.



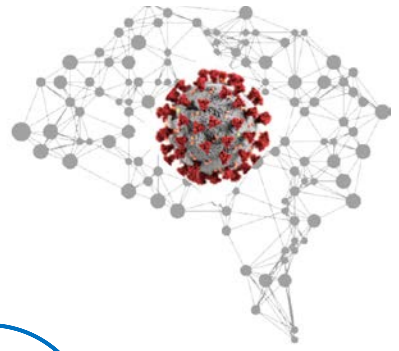
Voting technique

- Hard voting: The class obtained the majority of the votes from individual models
- Soft voting: The class with the maximum predicted probability by individual models

Considering the individual models' uncertainty in ultimate decision-making

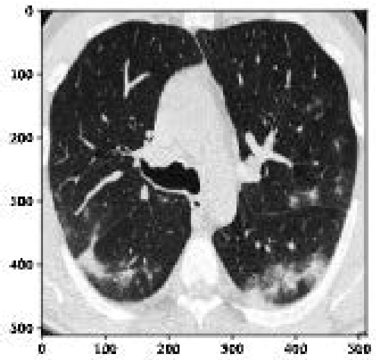
For segmentation tasks: soft voting is computationally less expensive

Pixel-level soft voting for aggregating the results of the segmentation networks

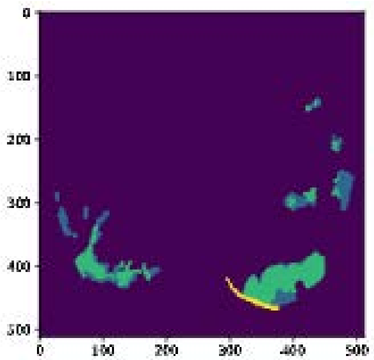


Implementation

- Loss function: categorical cross-entropy.
- Early-stopping method to avoid overfitting: training process is stopped whenever the loss function on the validation set is not decreased over ten epochs.
- Real-time data augmentation strategies, including zooming, shifting, and shearing, to mitigate overfitting.
- The training-testing process is performed in a 2-fold cross-validation approach.

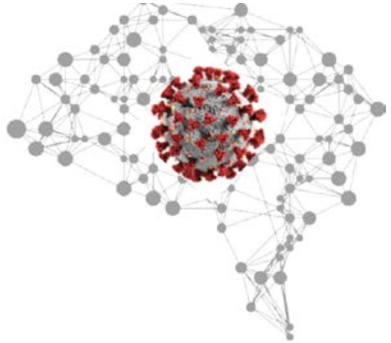


(a) CT image



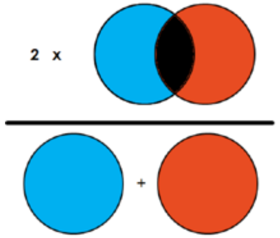
(b) Ground-truth mask

- An open-access dataset provided by the Italian Society of Medical and Interventional Radiology, to the best of our knowledge, **the only publicly available CT dataset for multi-class segmentation of COVID-19 pneumonia**.
- **100** axial CT scans with the size of 512×512 pixels from **60** COVID-19 patients.
- The images are normalized using min-max normalization.
- Randomly split the dataset into 40, 10, and 50 images for training, validation, and testing.



Evaluation metrics

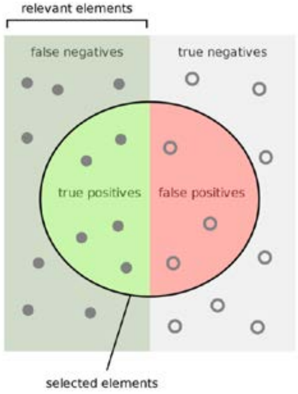
Dice Similarity Coefficient (DSC): $\frac{2(|Pr| \cap |GT|)}{|Pr| + |GT|}$



https://towardsdatascience.com/metrics-to-evaluate-your-semantic-segmentation-model-6bcb99639aa2

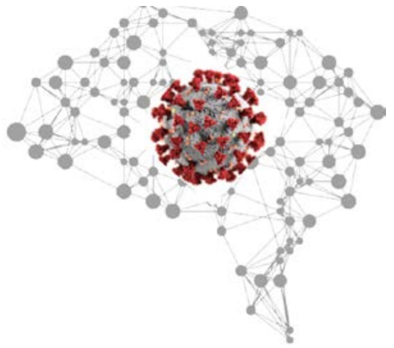
Sensitivity (SEN): $\frac{TP}{TP + FN}$

Specificity (SPEC): $\frac{TN}{TN + FP}$



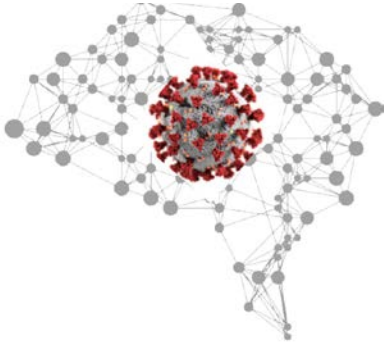
https://en.wikipedia.org/wiki/Sensitivity_and_specificity

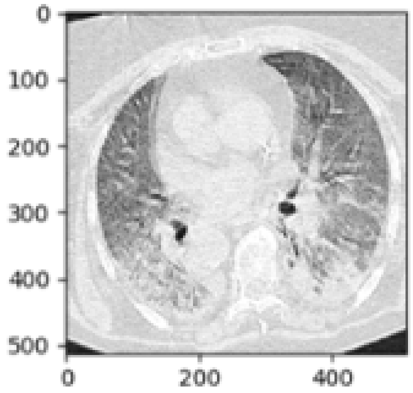
Model Overall Performance (MOP): $\sum_{i}^{n} \alpha_i M_i,$ $\alpha_i = \{0.4, 0.4, 0.2\}$: For DSC, SEN, and SPEC



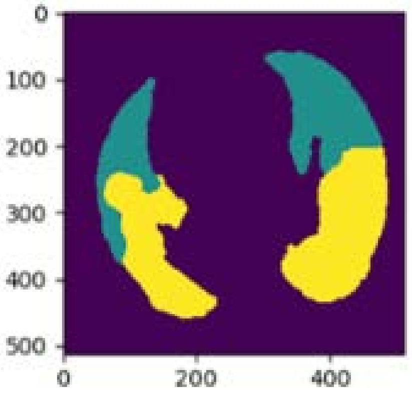
Methods	GGO				Consolidation				Average			
	DSC	SEN	SPEC	MOP	DSC	SEN	SPEC	MOP	DSC	SEN	SPEC	MOP
1 Semi-Inf-Net & MC	0.624	0.618	0.966	0.69	0.458	0.509	0.967	0.5802	0.541	0.564	0.967	0.635
Inception-V3-Seg	0.536	0.573	0.978	0.639	0.511	0.603	0.982	0.642	0.523	0.588	0.980	0.640
Xception-Seg	0.618	0.652	0.981	0.704	0.524	0.451	0.994	0.589	0.571	0.552	0.987	0.647
InceptionResNet-V2-Seg	0.576	0.558	0.984	0.650	0.565	0.582	0.989	0.656	0.570	0.570	0.987	0.653
DenseNet-121-Seg	0.605	0.624	0.982	0.688	0.571	0.549	0.991	0.646	0.588	0.586	0.987	0.667
ensemble-model	0.627	0.679	0.980	0.718	0.592	0.593	0.990	0.672	0.609	0.636	0.985	0.695

1: Fan, D.P., et al., 2020. Inf-net: Automatic covid-19 lung infection segmentation from ct images. IEEE Transactions on Medical Imaging, 39(8), pp.2626-2637.

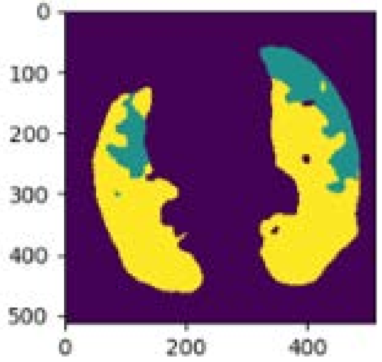




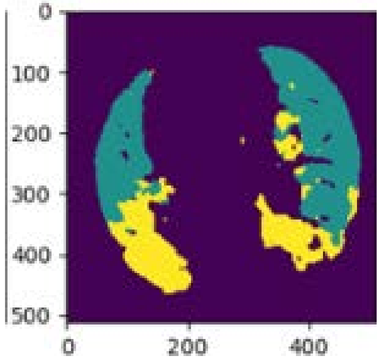
CT image



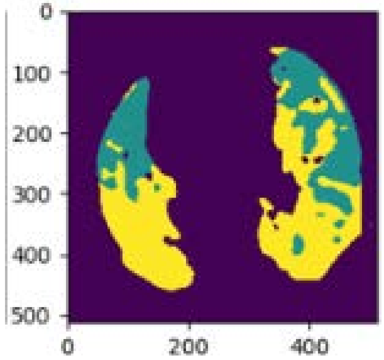
Ground truth Mask
Green: GGO, Yellow: Consolidation



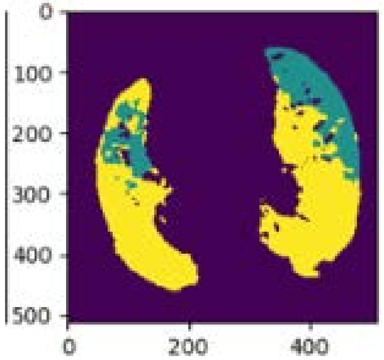
Inception-V3-Seg



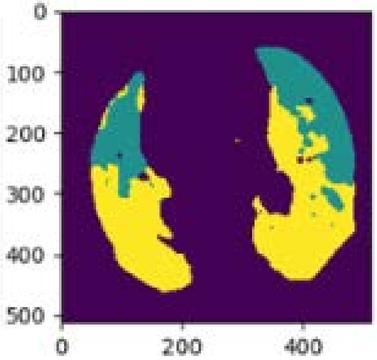
Xception-Seg



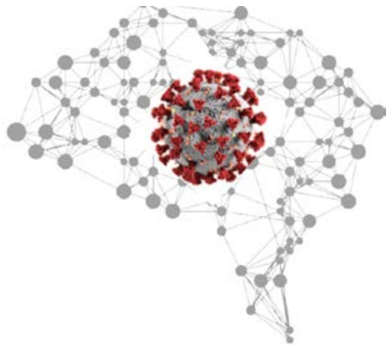
InceptionResNet-V2-Seg



DenseNet-121-Seg



Ensemble Model



- A multi-class segmentation framework for segmenting COVID-19 lesions under two classes, GGOs and consolidation, helping health experts evaluate the disease severity faster and more accurately.

- Containing four individual segmentation networks with top performance pre-trained CNNs as encoder and the pixel-level Soft Majority Voting for combining the results and inferring the final output.

- The experimental results indicate that since each network may have some fails and successes in predicting class labels for a class of infection or a sub-group of pixels, aggregating their results improves the model overall performance.

- The dataset we used is the only open-access CT dataset for multi-class segmentation of COVID-19 lesions, containing only 100 chest CT images. Although we tried to compensate for this problem by keeping more CT images for the test phase, still having a limited dataset is a restriction of our work.

Thank you!