COVID-19 CXR image detection

Literature Review

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“Covid, we’ll code it”

Problem Definition - Background

COVID-19

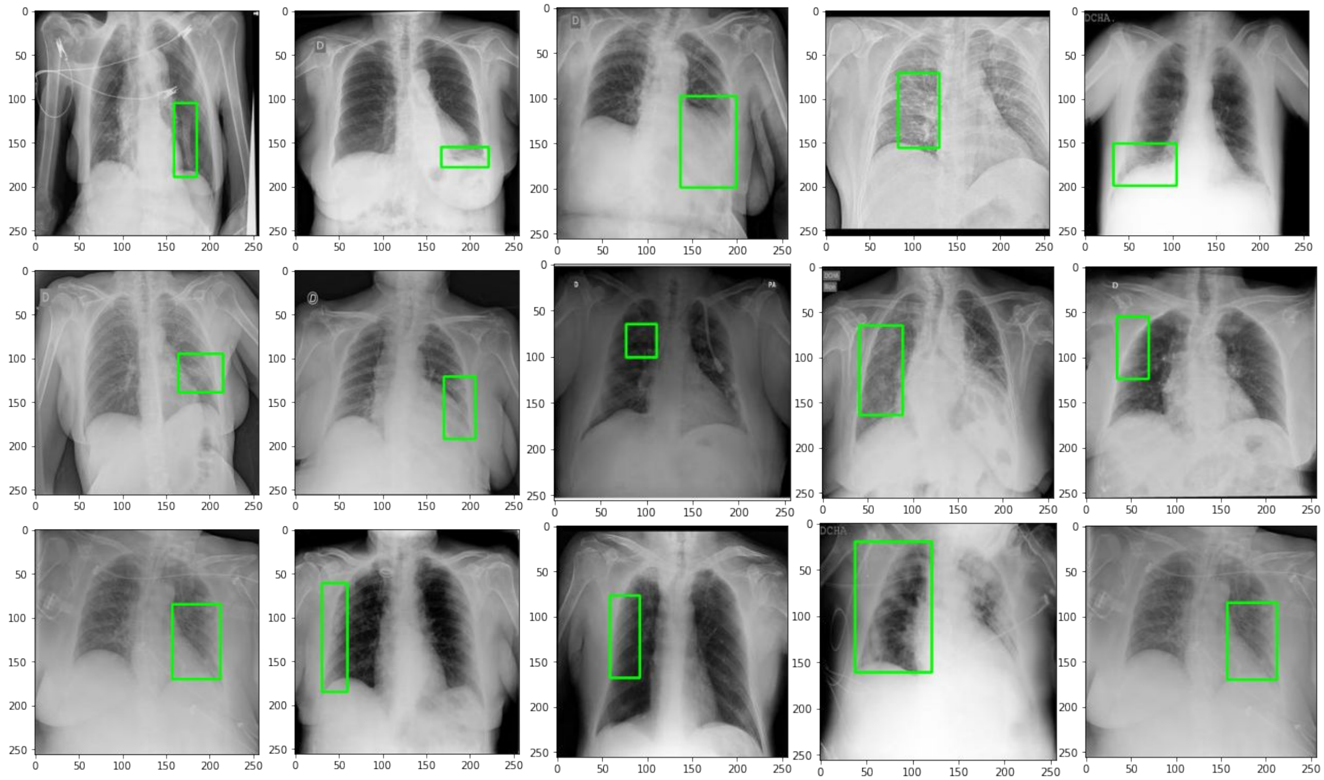
- Worldwide pandemic starts from Dec. 2019.
- Can be reflected on chest radiography images.
- Challenging for diagnosis by visual inspections.

Problem Definition - CXR Image Examples

Atypical

Indeterminate

Typical



Problem Definition - Project Aim

- Lung opacity detection (negative for pneumonia or not)
- Diagnoses classification (Typical, Indeterminate, Atypical)
- Both tasks are based on chest X-ray images

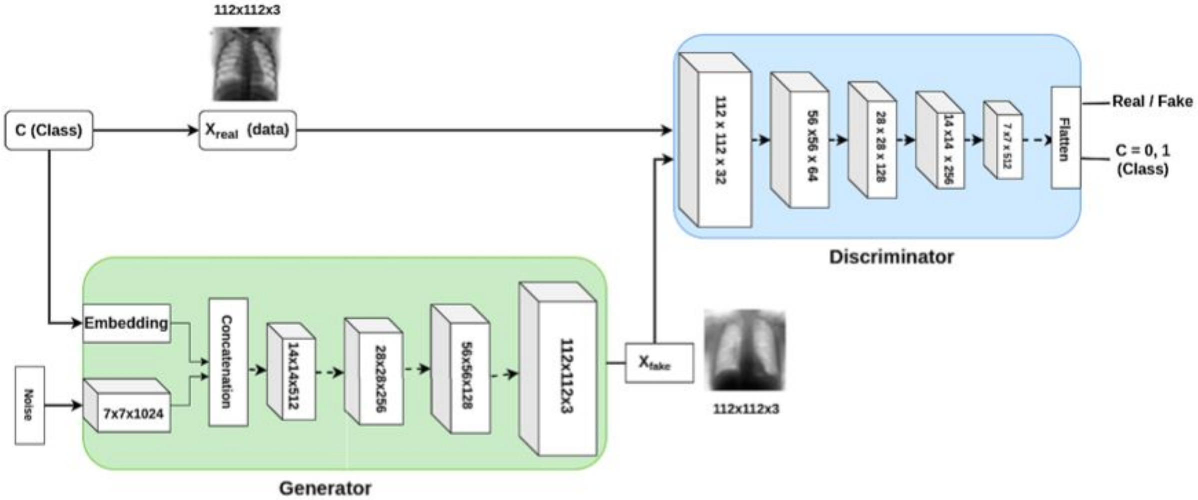
Current SOTA Approaches —preprocessing

CovidGAN

- Background: Scarcity and limited variety of data samples
- Aim: Data augmentation by generating synthetic images for training dataset.
- Backbone Model: ACGAN (Auxiliary Classifier Generative Adversarial Network)

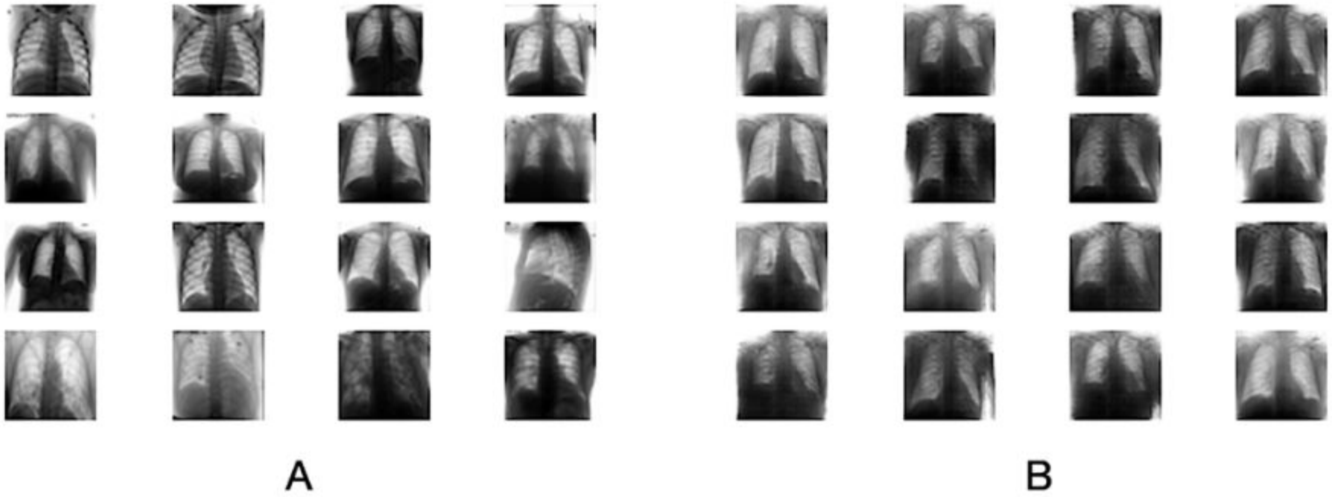
Current SOTA Approaches —preprocessing

CovidGAN - Architecture



Current SOTA Approaches —preprocessing

CovidGAN - Results (Synthetic Images)



Real Images

Synthetic Images

Current SOTA Approaches —preprocessing

CovidGAN - Results (Quantitative Evaluation)

Dataset	Classification Model	Sensitivity(%)	Specificity(%)	Accuracy(%)
Actual Data	VGG16	69	95	85
Actual + Synthetic Data		90	97	95

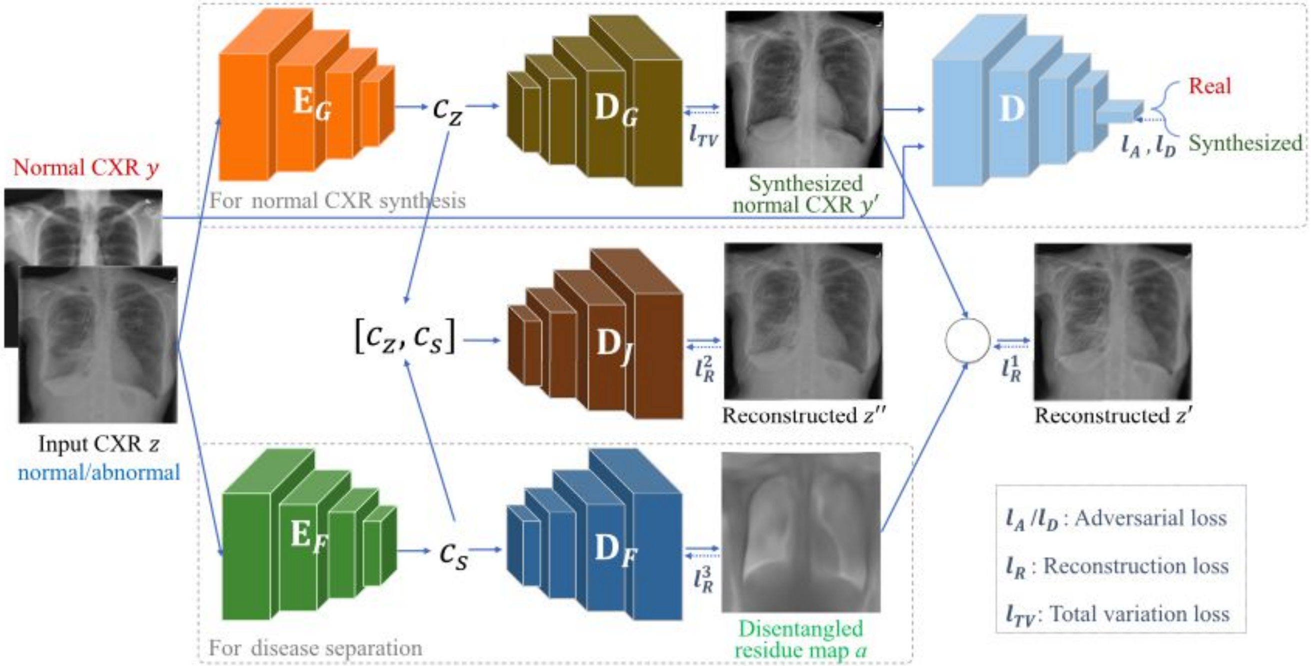
Current SOTA Approaches —preprocessing

DGM (Deep Disentangled Generative Model)

- Background: Lack of Interpretability of current models on CXR images
- Aim: Augment opacities by decomposing images into synthetic normal images and disentangled residue map.
- Method:
    1. Learn a mapping from all types of images to normal images
    2. Disentangle a residue map from original images

Current SOTA Approaches —preprocessing

DGM - Architecture

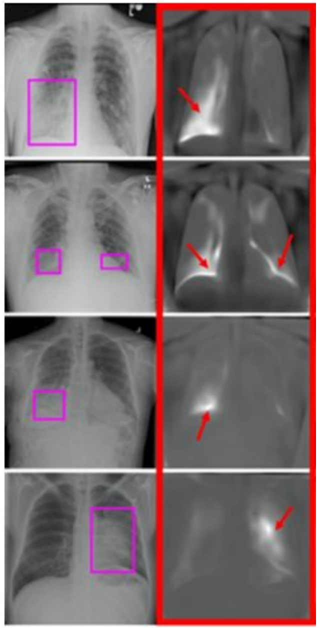


Current SOTA Approaches —preprocessing

DGM - Results

synthetic normal images

residue maps



Current SOTA Approaches —Classification

COIVD-Net

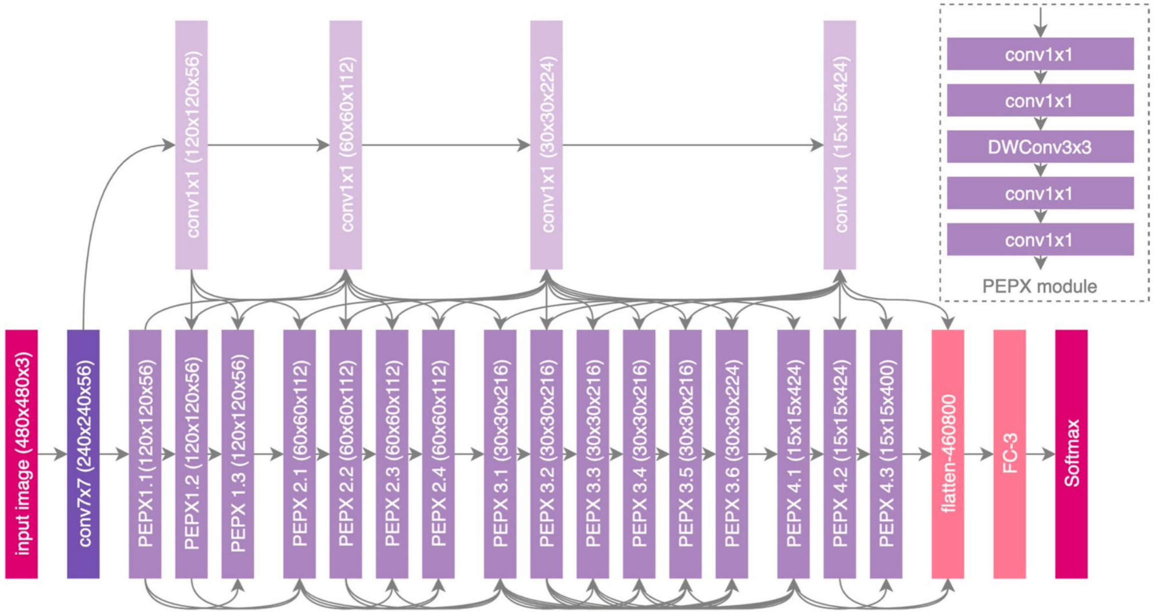


Figure 5. COVID-Net architecture. High architectural diversity and selective long-range connectivity can be observed as it is tailored for COVID-19 case detection from CXR images. The heavy use of a projection-expansion-projection design pattern in the COVID-Net architecture can also be observed, which provides enhanced representational capacity while maintaining computational efficiency.

Current SOTA Approaches —Classification

COIVD-Net

Architecture	Params (M)	MACs (G)	Acc. (%)
VGG-19	20.37	89.63	83.0
ResNet-50	24.97	17.75	90.6
COVID-Net	**11.75**	**7.50**	**93.3**

Table 1. Performance of tested deep neural network architectures on COVIDx test dataset. Best results highlighted in bold.

Current SOTA Approaches —Classification

COIVD-Net

Architecture	Normal	Non-COVID19	COVID-19
Sensitivity (%)			
VGG-19	**98.0**	90.0	58.7
ResNet-50	97.0	92.0	83.0
COVID-Net	95.0	**94.0**	**91.0**

Table 2. Sensitivity for each infection type. Best results highlighted in bold.

Architecture	Normal	Non-COVID19	COVID-19
Positive predictive value (%)			
VGG-19	83.1	75.0	98.4
ResNet-50	88.2	86.8	98.8
COVID-Net	**90.5**	**91.3**	**98.9**

Table 3. Positive predictive value (PPV) for each infection type. Best results highlighted in bold.

Current SOTA Approaches —Classification

COIVD-Net

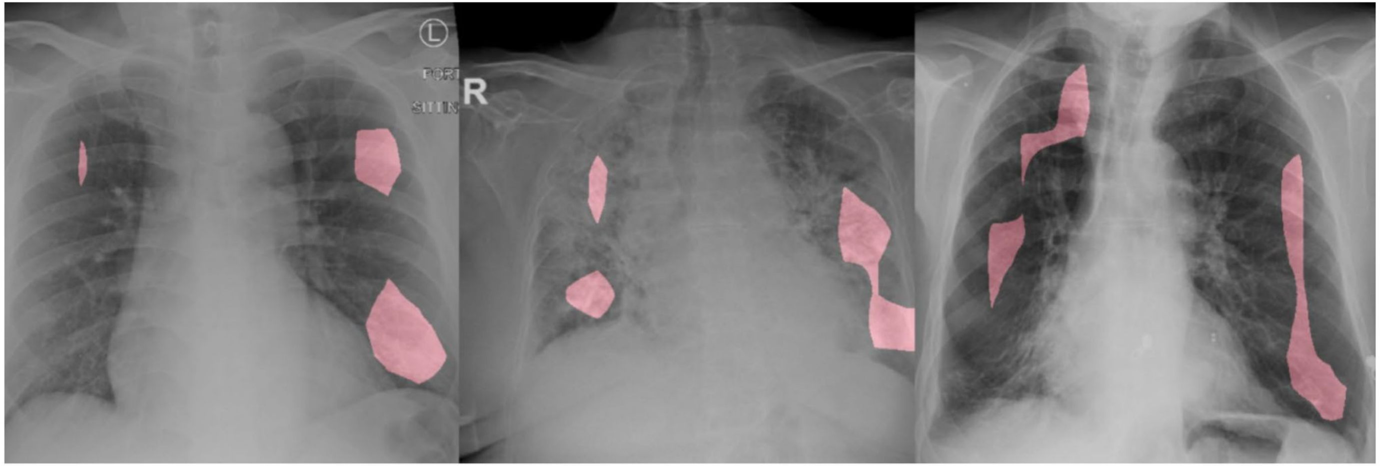


Figure 7. Example CXR images of COVID-19 cases from several different patients and their associated critical factors (highlighted in red) as identified by GSInquire[44].

Current SOTA Approaches —Classification

Few shot learning using Siamese Network

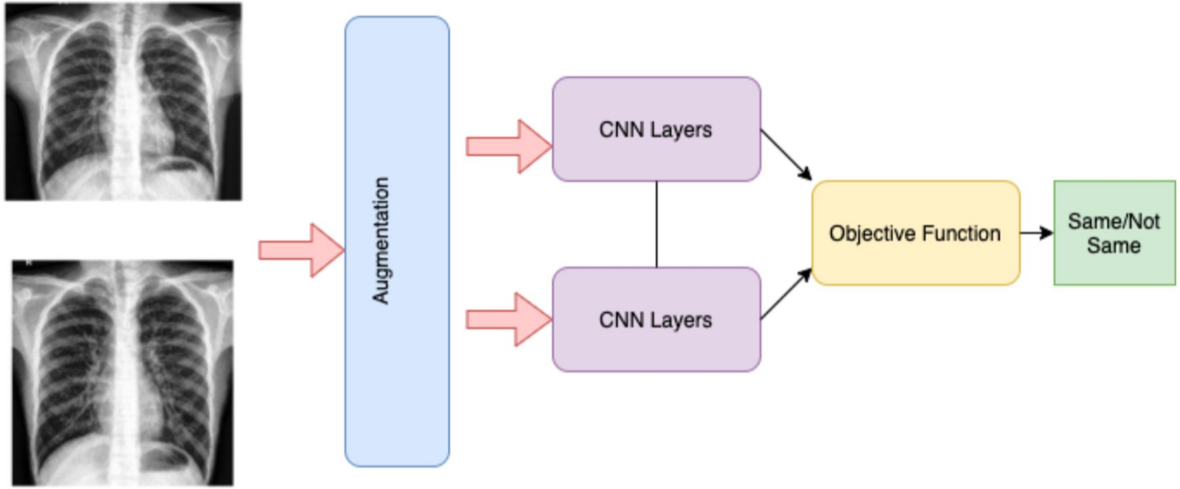


Figure 4. An architectural representation of Siamese Networks with case of two different class input.

Current SOTA Approaches —Classification

Few shot learning using Siamese Network

Table 1. Accuracy, Precision, Recall and F1-Score using mentioned classification based modeling approaches trained and tested on combined datset-1 and dataset-2.

Model Name	Accuracy	Precision	Recall	F1-score
Logistic Regression	82.4%	0.822	0.828	0.828
Convolutional Neural Network	90.2%	0.912	0.901	0.904
Transfer Learning(VGG16)	93.3%	0.931	0.932	0.928
Siamese Networks	94.6%	0.945	0.941	0.947
Siamese Networks(Transfer Learning)	**96.4%**	**0.965**	**0.962**	**0.959**

Table 2. Analysis of Clusters formed by K-Means and GMM algorithms with Silhouette Score using input as extracted embeddings of mentioned classification approaches.

Model Name / Clustering Approach	K-Means	Gaussian Mixture Models
Logistic Regression	0.156	0.158
Convolutional Neural Network	0.165	0.171
Transfer Learning	0.189	0.185
PCA+TSNE	*0.578*	*0.575*
Siamese Networks	0.490	0.487
Siamese Networks (Transfer Learning)	**0.592**	**0.583**

Current SOTA Approaches —Classification

Fusing convolutional neural network features with hand-crafted features for osteoporosis diagnosis

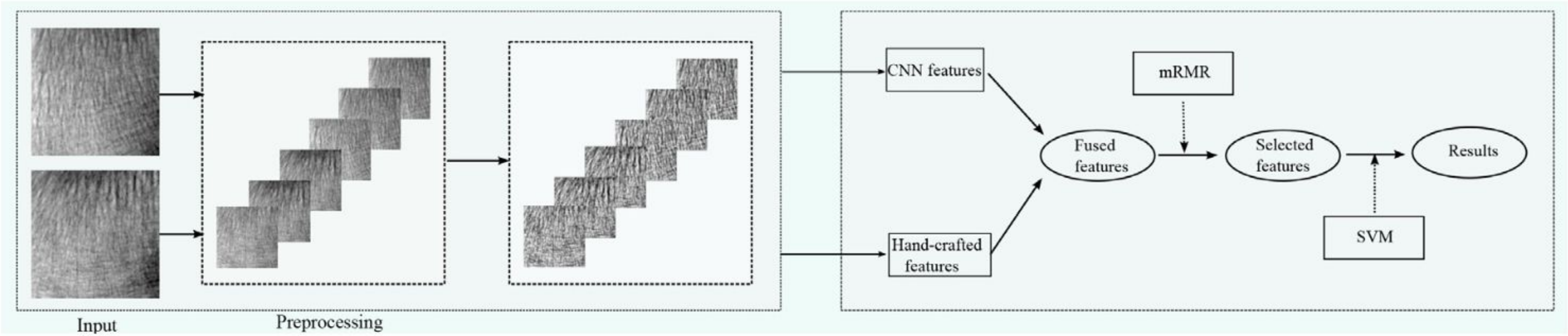


Fig. 4. The framework of the proposed hybrid model.

Current SOTA Approaches —Classification

Fusing convolutional neural network features with hand-crafted features for osteoporosis diagnosis

SOTA hand-crafted features contains:

1. A group of standard texture features
   a. Local binary pattern(LBP)
   b. Gray level co-occurance matrix (GLCM)
2. A group of encoded features - that have shown impressive discriminative capabilities
   a. encoded LBP
   b. encoded GLCM

Current SOTA Approaches —Classification

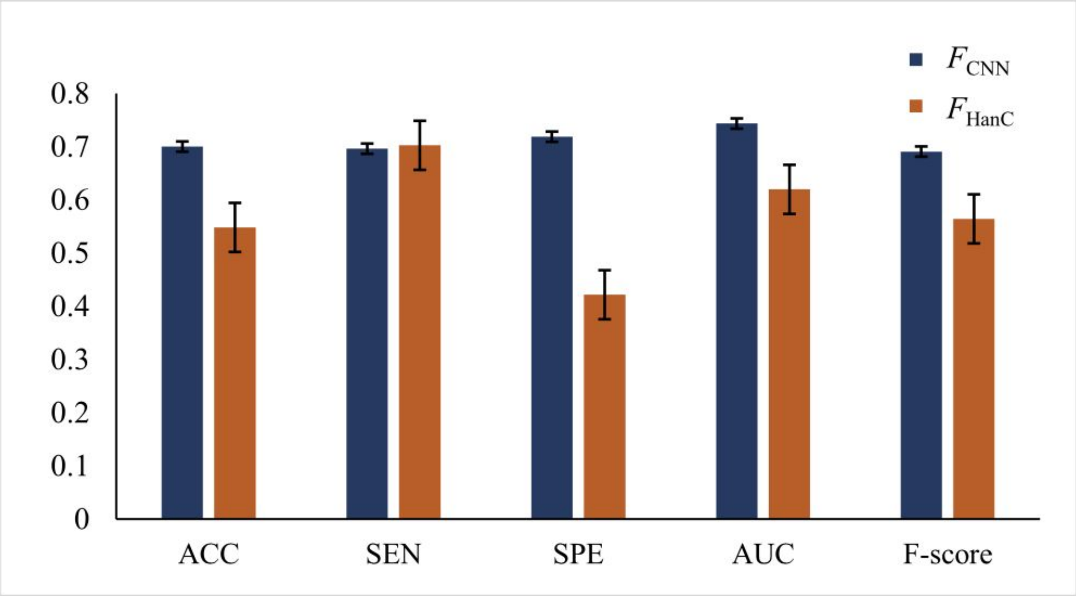
Fusing convolutional neural network features with hand-crafted features for osteoporosis diagnosis

Comparison between CNN features and hand-crafted features.

	Features	ACC (%)	SEN (%)	SPE (%)	AUC (%)	*F*-score (%)
F_{CNN}	$F_{AlexNet}$	72.4	72.9	71.9	73.2	71.8
	F_{VggNet}	68.9	69.5	72.1	74.0	68.4
	F_{ResNet}	67.2	73.9	62.8	73.9	68.6
	$F_{DenseNet}$	71.5	62.0	80.7	76.2	67.5
F_{HanC}	F_{STD}	48.3	64.8	37.4	61.2	54.3
	F_{ECD}	61.3	75.7	46.9	62.7	58.5

Current SOTA Approaches —Classification

Fusing convolutional neural network features with hand-crafted features for osteoporosis diagnosis



Current SOTA Approaches —Classification

Fusing convolutional neural network features with hand-crafted features for osteoporosis diagnosis

The performances for different fusions of features. We divided the 12 fusions into four groups. The performance using CNN features alone was also shown for each category.

	Features	ACC (%)	SEN (%)	SPE (%)	AUC (%)	*F*-score (%)
$F_{AlexNet\_Fus}$	$F_{AlexNet\_HanC}$	73.3	72.9	73.3	73.5	72.5
	$F_{AlexNet\_STD}$	72.4	72.9	71.9	73.2	71.9
	$F_{AlexNet\_ECD}$	73.3	72.9	73.3	73.4	73.2
	$F_{AlexNet}$	72.4	72.9	71.9	73.2	71.8
F_{VggNet_Fus}	F_{VggNet_HanC}	68.1	74.2	64.9	76.1	69.4
	F_{VggNet_STD}	68.9	69.5	72.1	74.1	71.5
	F_{VggNet_ECD}	68.9	69.5	72.1	74.1	71.5
	F_{VggNet}	68.9	69.5	72.1	74.0	68.4
F_{ResNet_Fus}	F_{ResNet_HanC}	67.2	72.3	64.6	73.8	67.9
	F_{ResNet_STD}	67.2	74.0	62.8	74.0	66.6
	F_{ResNet_ECD}	67.2	72.3	64.6	73.8	67.5
	F_{ResNet}	67.2	74.0	62.8	73.9	68.6
$F_{DenseNet\_Fus}$	$F_{DenseNet\_HanC}$	68.9	63.7	73.4	73.2	66.9
	$F_{DenseNet\_STD}$	72.4	63.7	80.7	76.1	77.0
	$F_{DenseNet\_ECD}$	68.9	65.9	72.1	74.2	70.1
	$F_{DenseNet}$	71.5	62.0	80.7	76.2	67.5

Current SOTA Approaches — Single label Detection

Faster R-CNN- Overview

- Backbone Model: DeepConv-DilatedNet
  - deconvolution
  - fully convolution network
- Soft-NMS : filter boxes and ensure sample quality
- K-means++ : determine the aspect ratio suitable for the dataset

Current SOTA Approaches — Single label Detection

Faster R-CNN- Architecture

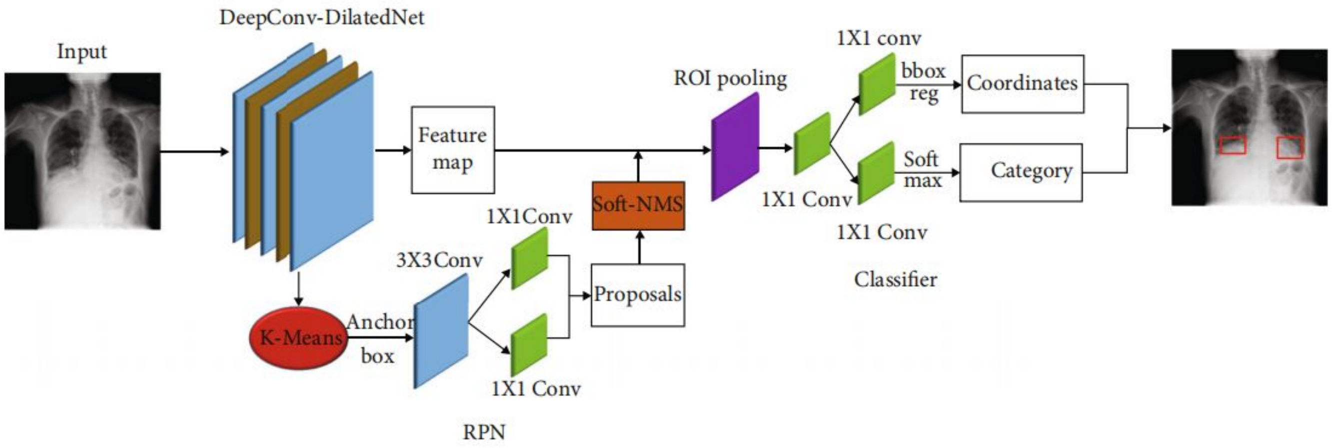
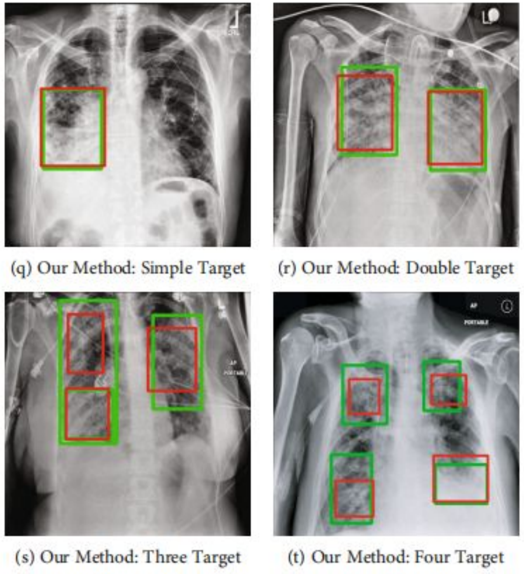


Figure 6: Network structure for pneumonia detection.

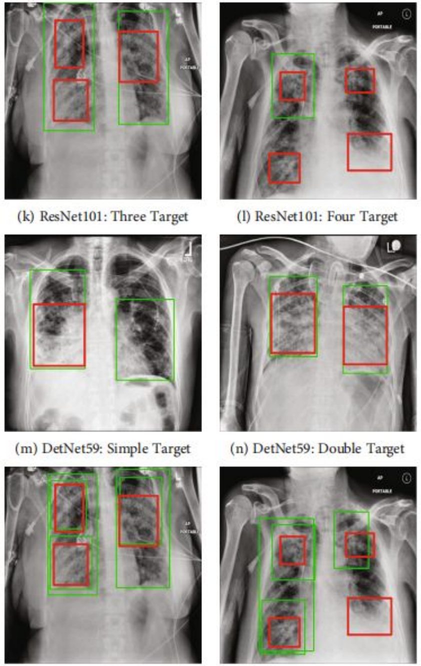
Current SOTA Approaches — Single label Detection

Faster R-CNN- Result

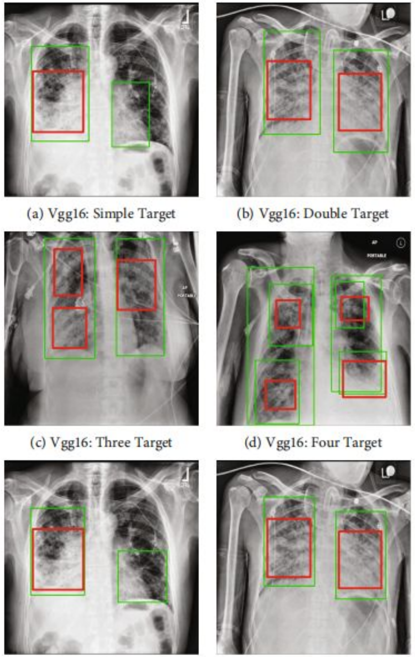


(q) Our Method: Simple Target
(r) Our Method: Double Target
(s) Our Method: Three Target
(t) Our Method: Four Target

FIGURE 11: Comparison of test results of different models.



(k) ResNet101: Three Target
(l) ResNet101: Four Target
(m) DetNet59: Simple Target
(n) DetNet59: Double Target
(o) DetNet59: Three Target
(p) DetNet59: Four Target



(a) Vgg16: Simple Target
(b) Vgg16: Double Target
(c) Vgg16: Three Target
(d) Vgg16: Four Target
(e) ResNet50: Simple Target
(f) ResNet50: Double Target

Current SOTA Approaches — Single label Detection

Faster R-CNN- Result

TABLE 2: Assessment results for different IoU thresholds.

	AP@0.4	AP@0.5	AP@0.6	AP@0.7	mAP
DetNet59	0.6317	0.4201	0.2068	0.0657	0.3311
ResNet50	0.6066	0.3791	0.1863	0.0513	0.3058
ResNet101	0.5539	0.3508	0.1540	0.0406	0.2748
VGG16	0.5506	0.3559	0.1881	0.0660	0.4210
DeepConv-DilatedNet	**0.6419**	**0.4570**	**0.2732**	**0.0746**	**0.3617**

TABLE 4: Comparison of results for different networks.

Network	MS
Mask R-CNN	0.2181
DeepConv-DilatedNet+Soft-NMS	**0.35087**

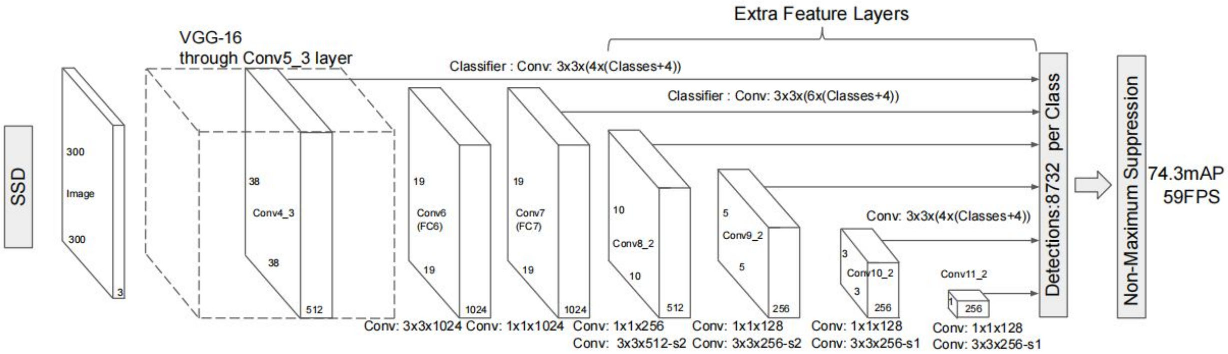
Current SOTA Approaches — Single label Detection

SSD- Overview

- Backbone Model: VGG-16

- Features
  - multi-scale convolutional bounding box
  - simple relative to methods that require object proposals

- Architecture



Current SOTA Approaches — Single label Detection

SSD- Result

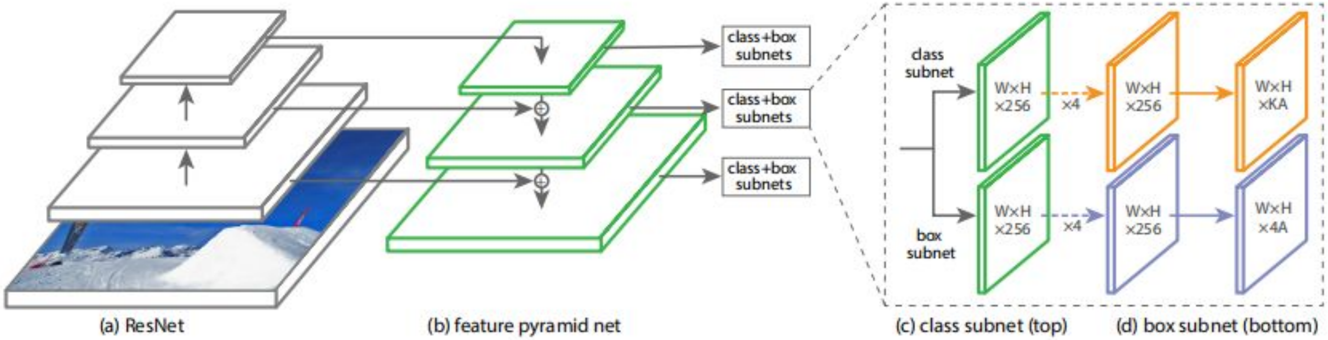
Metric	Operation	Value
Sensibility	842 / (842+45)	0.9492
Specificity	92 / (92+8)	0.9200

Image class	CLAHE	Total images	True detection	Accuracy
Normal	No	887	827	93.24%
Normal	Yes	887	842	**94.92%**
COVID-19	No	100	83	83.00%
COVID-19	Yes	100	92	**92.00%**

Current SOTA Approaches — Single label Detection

RetinaNet- Overview

- Backbone Model: ResNet-101-FPN
- Focal loss function
- Architecture

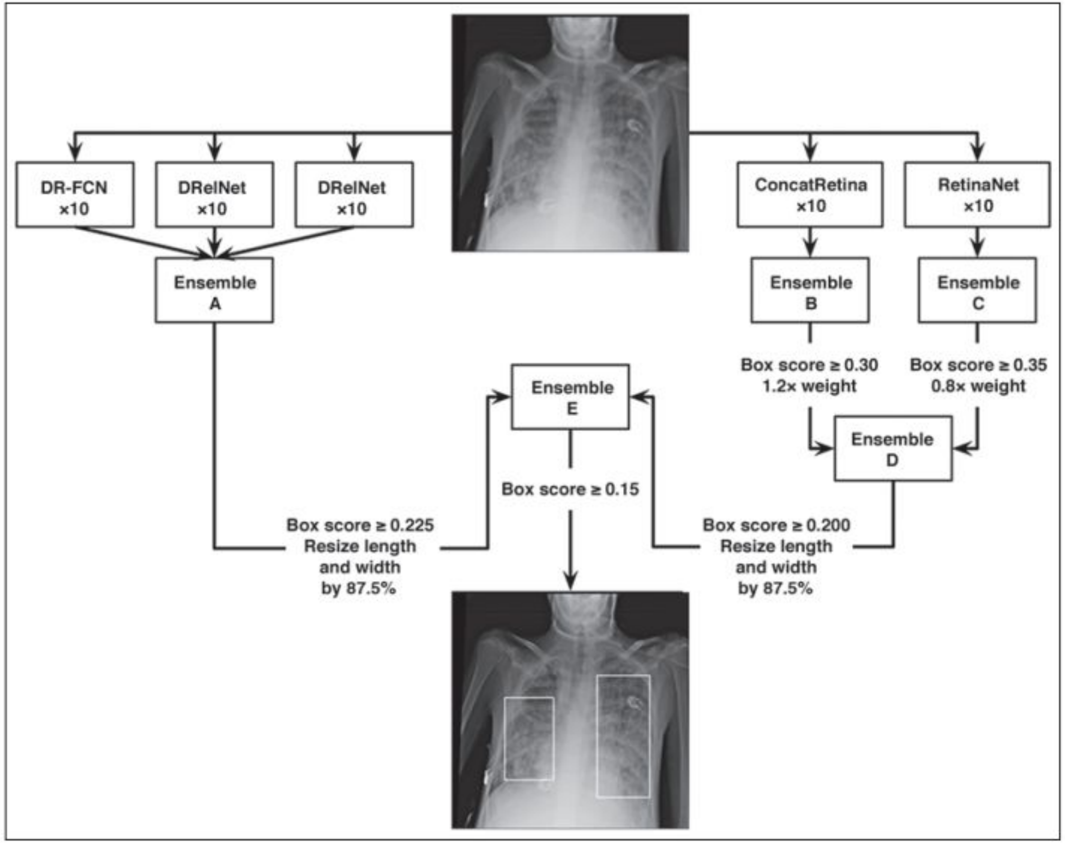


Current SOTA Approaches — Single label Detection

RetinaNet-
Winner Architecture

- weights alloction according to confidence

- average classification scores



Current SOTA Approaches — Single label Detection

RetinaNet- Result

TABLE 2: Final Leaderboard Ranking

Rank	Team Name	RSNA Metric Score
1	Ian Pan and Alexandre Cadrin	0.25475

Summary of all reviewed approaches

No.	Technique	Pros	Cons
1	CovidGAN	Generate synthetic images with GAN to enhance the training set	The small size of training set dose not ensure the robustness of the obtained GAN model.
2	DGM	Enhance opacity area by imposing a saliency map on it; Provide an interpretation of CXR images	Validating on the single-label detection or binary classification only.
3	Covid-net	Introduce a lightweight projection-expansion-projection-extension (PEPX), an open-source, and an explainability approach; Introduce an open access dataset	Dataset is significantly unbalanced as it contains very few (less than 100) COVID-19 samples compared with 16,000 non-COVID ones.
4	Siamese Network	Learn embedding features more effectively by putting a pair of inputs into twin models and analyse their similarities.	The model cannot learn the data distribution well, which can cause biased models. It's likely that general classification models will have poor performance.

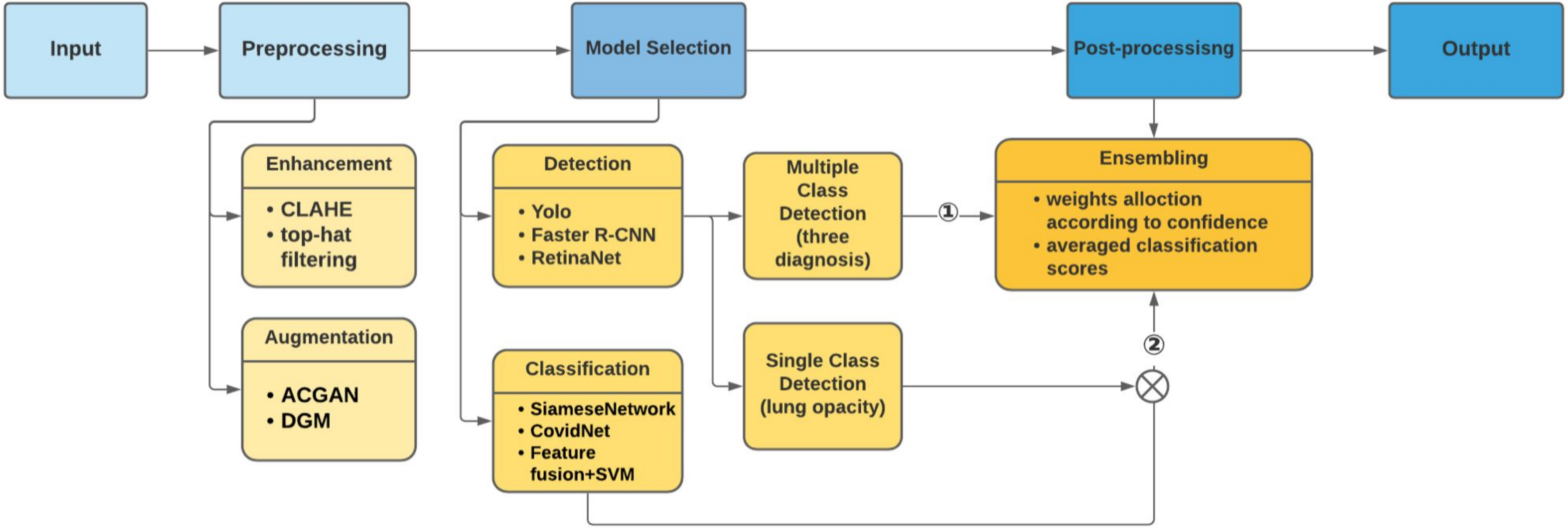
Discussions

Summary of all reviewed approaches

No.	Technique	Pros/Contributions	Cons/Limitations
5	Fusing CNN features with hand-crafted features	Combine deep and hand-crafted features which imrpove classification performance in accuracy, sensitivity, and specificity	Training is not efficient as cascaded classifiers are time-consuming and therefore, the model is hard to applied as a real-time classifier.
6	faster RCNN	Experiment with different backbone structures for Faster-RCNN; Propose a low complexity residual neural network with a dilated bottleneck structure that outperforms the traditional Faster-RCNN structure	Though the detection performance is improved, the mAP is only 0.48 and far from being considered as an effective method.
7	SSD (applied Transfer learning)	Introduce an efficient and accurate model based on SSD; Train and test on a balanced dataset	The model focuses on the detection of entire lungs instead of the opacity area and thus, it might not be applicable to opacity detection.
8	Ensemble method with RetinaNet	Propose an ensemble method which improves the result dramatically; Two independent training processes are adopted to reduce false-positive findings.	Limited generalization ability on different datasets and lack of strict comparative criterion to radiologists against standard data sets, leading to not available in large-scale adoption

Discussions

Primary design of experiments



Discussions

Dataset (CXR images: BIMCV-COVID19 Data & MIDRC-RICORD Data)

Hierarchy	Task	Quantity	Distribution
study-level	Classification of CXR Dignosis	6054	1676(28%) - Negative for Peumonia 2855(47%) - Typical Appearance 1046(17%) - Intermediate Appearance 474 (8%) - Atypical Appearance
image-level	Opacity (Single-class) Detection	6334	2040(32%) - None Opacity 4294(68%) - Opacity
bbox-level	Muti-class Detection	8157	6034(74%) - Typical Appearance 1494(18%) - Intermediate Appearance 629 (8%) - Atypical Appearance

Discussions

Evaluation methods

Pascal VOC 2012 mean Average Precision (IoU > 0.5)

Sensitivity: TP/(TP+FN)

Specificity: TN/(TN+FP)

Individual contributions

MY- Mintao Yi; YM - Yang Ma; LL-Lihuan Li; ZQ-Zhihan Qin

Tasks	Team member	Time estimation
Dataset Cleaning & Preparation	LL; ZQ	10 hours/person
Enhancement	ZQ; YM	5 hours/person
Augmentation	LL; ZQ	30 hours/person
Detection	MY; LL; ZQ	50 hours/person
Classification	YM; MY	40 hours/person
Ensembling	MY; YM; LL; ZQ	20 hours/person
literature review + Presentation	MY; YM; LL; ZQ	30 hours/person
Report	MY; YM; LL; ZQ	20 hours/person
Weekly Meeting	MY; YM; LL; ZQ	2 hours/person

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Thank you ！

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