

Conditional Synthetic Data Generation for Robust ML Applications with Limited Pandemic Data

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Introduction

Original

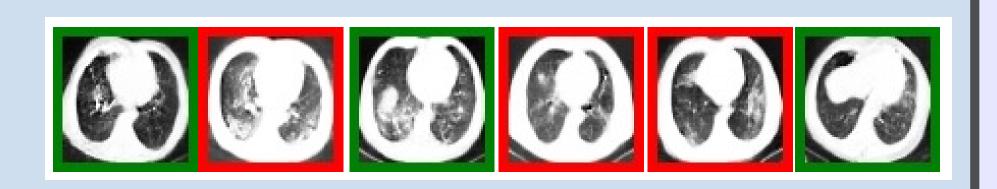
COVID

Non-COVID

- At the onset of a pandemic, such as COVID-19, data with proper labeling/attributes corresponding to the new disease might be unavailable or sparse.
- At the same time, ML algorithms designed to fight pandemics must have good performance and be developed in a time-sensitive manner.

Conditional Feature Representation (Z)

Feature Extractors



Synthetic CT scans generated by our model. Red border: COVID, Green: Non-COVID.

To tackle the challenges of limited pandemic data, we propose generating conditional synthetic data, to be used alongside real data for robust ML. We conduct experiments on chest CT scans corresponding to normal, COVID-19 and pneumonia afflicted patients.

Model Training and Synthetic Sample Generation Training Step 1: Classifier Training Step 2: Conditional flow Conditional Generative Flow **Forward Flow (Inference)** $\nu = f_{\theta}(x,z)$ Local Conditional Feature Representation (Z) Representation Classifier (ν) Classifier COVID **COVID** COVID Non- COVID Conditional Final Fully-**Conditional Non- COVID** Non- COVID **Feature** Connected **Feature** Representation Representation Softmax (Z) (\mathbf{Z}) **Feature Extractors Feature Extractors Training Step 1:** Train a COVID/Non-COVID classifier to decouple the Sample Generation feature representations (z) for COVID, where, $\dim(z) \ll \dim(\text{input data})$. Conditional Generative Flow Generated $\mathbf{x} = \mathbf{f}_{\boldsymbol{\theta}}^{-1}(\boldsymbol{\nu}, \mathbf{z})$ **Backward Flow (Generation)**

Sample a Local

Representation

 $\nu \sim N(0, I)$

Classifier

Conditional

Feature

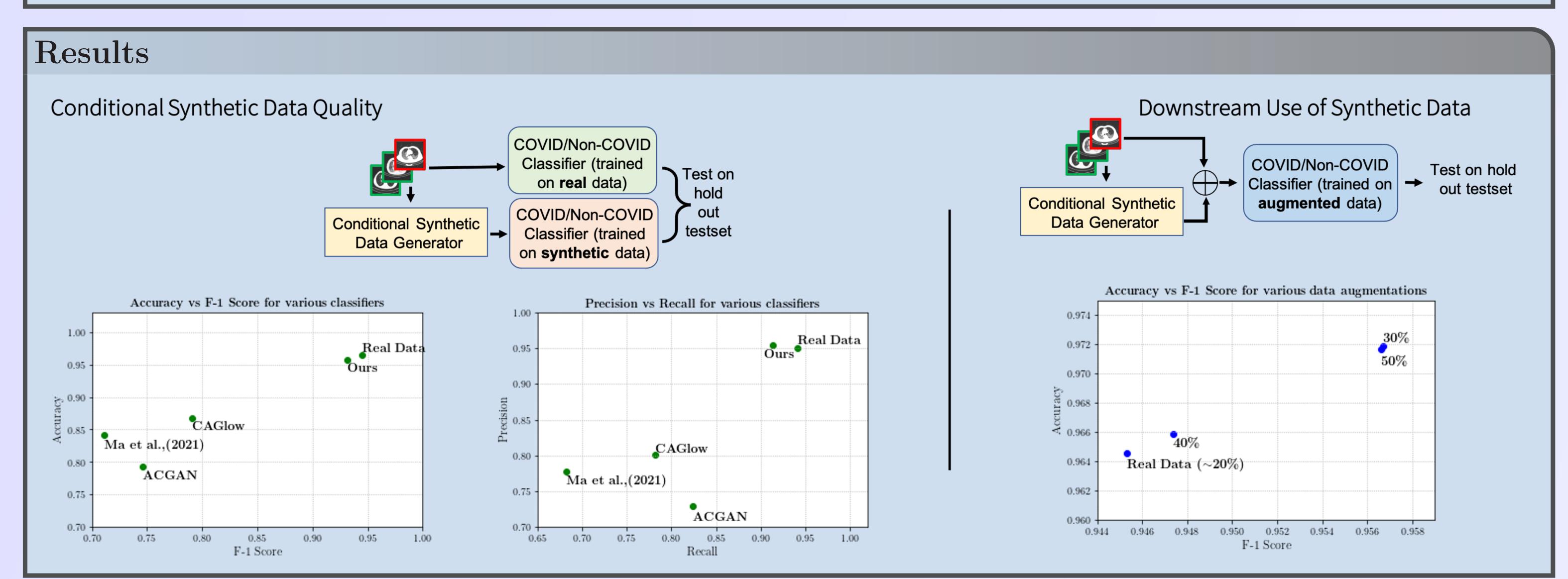
Representation

(z)

Training Step 2: Train a conditional generative flow [1], which takes the input data x and conditional representation z, and gives local representation ν , $f_{\theta}(x,z) = \nu \sim \mathcal{N}(0,I)$.

Sample Generation: Take an input sample x, keeping the conditional feature representation the same (z), sample a new local representation $\tilde{\nu}$, to generate a synthetic sample $\tilde{x} = f_{\theta}^{-1}(\tilde{\nu}, z)$.

Data Source and Pre-processing: We use chest CT scan dataset from [2], and combine Normal and Pneumonia classes into "Non-COVID" class ($\sim 80\%$ samples) and kept the "COVID" class as it is ($\sim 20\%$ samples).



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Key References

- Gunraj et al., "COVIDNet-CT: A tailored deep convolutional neural network design for detection of COVID-19 cases from chest CT images." Frontiers in medicine (2020).
 - Ma et al., "Decoupling global and local representations via invertible generative flows." In ICLR 2021.