Tackling Class Imbalance in Radiomics: the COVID-19 Use Case

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ABSTRACT

Since the start of the COVID-19 pandemic, much research has been published highlighting how artificial intelligence models can be used to diagnose a COVID-19 infection based on medical images. Given the scarcity of published images, heterogeneous sources, formats, and labels, generative models can be a promising solution for data augmentation. We propose performing data augmentation on the embeddings space, saving computation power and storage. Moreover, we compare different class imbalance mitigation strategies and machine learning models. We find CTGAN data augmentation shows promising results. The best overall performance was obtained with a GBM model trained with focal loss.

CCS CONCEPTS

• **Information systems → Data mining**; • **Computing methodologies → Computer vision problems**; • **Applied computing**;

KEYWORDS

COVID-19, CT Scans, Imbalanced Dataset, Data Augmentation, Computer-Aided Diagnosis, Radiomics, Artificial Intelligence, Machine Learning

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1 INTRODUCTION

In December 2019, an outbreak of the coronavirus SARS-CoV-2 infection (a.k.a COVID-19) began in Wuhan, China. The disease rapidly spread across the world, and on January 30$^{\text{th}}$ 2020, the World Health Organization (WHO) declared a global health emergency. The most common COVID-19 symptoms are dry cough, sore throat, fever, loss of taste or smell, diarrhea, myalgia, and dyspnea[5]. In addition, older people, or people with previous medical problems (e.g., diabetes, obesity, or hypertension), are more likely to develop a severe form of the disease[12, 42], which can derive into multiple organ failure, acute respiratory distress syndrome, fulminant pneumonia, heart failure, arrhythmias, or renal failure, among others[37, 40].

Expert radiologists have observed that the impact of the COVID-19 infection on the respiratory system can be discriminated from other viral pneumonia in computed tomography (CT) scans[7, 39]. Most frequent radiological signs include irregular ground-glass opacities and consolidations, observed mostly in the peripheral and basal sites[31]. While such opacities were observed up to a maximum of seven days before the symptoms onset[25], they progress rapidly and remain a long time after the symptoms onset[35, 38]. While such opacities can be observed on chest radiography, they have low sensitivity, which can lead to misleading diagnoses in early COVID-19 stages, and thus a CT scan is preferred[38].

Scientific studies have shown Artificial Intelligence (AI) is a promising technology transforming healthcare and medical practice helping on some clinicians' tasks (e.g., decision support, or providing disease diagnosis)[45]. In particular, the field of radiomics studies how to mine medical imaging data to create models that support or execute such tasks. Given that distinct patterns can be observed on chest radiographies and CT scans, clinicians and researchers sought to use AI for COVID-19 diagnostics[31].

There are multiple challenges associated with radiomics, and in particular, with the COVID-19 diagnosis use case. Despite the limitations that can exist regarding privacy concerns[26, 44], many datasets have been made publicly available. From those datasets, many are limited to a few cases[35]; were collected from different sources and image protocols, and thus cannot be merged (e.g., the gray-levels across images can have different meanings[7]); or were labeled at different granularity levels (e.g., patient-level, or slice-level)[2]. Therefore, models developed from these datasets cannot always be ported to a specific environment. Finally, limitations can exist regarding data collection, further limiting available data to develop working models to diagnose the disease.

The main contributions of this research are (i) a comparative study between four data-augmentation strategies used to deal with class imbalance, (ii) across eight frequently cited machine learning algorithms, based on a real-world dataset of chest CT scans annotated with their COVID-19 diagnosis. We developed the machine learning models with images provided by the Medical Physics

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Research Group at the University of Ljubljana and made them available as part of the RIS competition[1].

We report the models' discrimination power in terms of the area under the receiver operating characteristic curve (AUC ROC). The AUC ROC is a widely adopted classification metric that quantifies the sensitivity and specificity of the model while is invariant to *a priori* class probabilities.

This paper is organized as follows. Section 2 outlines related scientific works, Section 3 provides an overview of the use case, and Section 4 details the methodology. Finally, section 5 presents and discusses the results obtained, while Section 6 concludes and describes future work.

2 RELATED WORK

The field of radiomics is concerned with extracting high-dimensional data from medical images, which can be mined to provide diagnoses and prognoses, assuming the image features reflect an underlying pathophysiology[16, 27, 28]. While the research on the field is experiencing exponential growth, multiple authors have warned about common issues affecting the quality and reproducibility of radiomics research and proposed several criteria that should be met to mitigate them (e.g., RQS, CLAIM, or TRIPOD)[10, 27, 32]. It has also been observed that the translation into clinical use has been slow[13].

Since the start of the COVID-19 pandemic, much research has been published highlighting how AI models could be used to issue COVID-19 diagnoses based on medical images. While much research was invested into transfer learning leveraging pre-trained deep learning models, or the use of deep learning models as feature extractors[24], some authors also experimented with handcrafted features[7]. Most common machine learning approaches involved the use of deep learning (end-to-end models, or pre-trained models for feature extraction)[14, 23, 34, 36, 43], Support Vector Machine (SVM)[4, 7, 14, 22, 23, 34, 36, 38, 43], k-Nearest Neighbors (kNN)[14, 22, 23, 38, 43], Random Forest (RF)[22, 23, 36], CART[22, 23, 36], Näive Bayes[22, 23], and Gradient Boosted Machines (GBM)[6, 22].

Two commonly faced challenges regarding COVID-19 diagnoses based on medical images are images scarcity and class imbalance. Given the heterogeneity of the datasets, it is not always possible to merge them[2, 7, 35]. Thus, some researchers successfully experimented using generative adversarial networks (GANs) to generate new images that comply with the existing patterns in the dataset[1, 34]. GANs provide means to learn deep representations from labeled data and generate new data samples based on a competition involving two models: a *generator*, learns to generate new images only from its interaction with the *discriminator*; and the *discriminator*, who has access to the real and synthetic data instances, and tries to tell the difference between them[3, 11]. While this method was first applied on images[17], new approaches were developed to adapt it for tabular data[41].

The fact that the classification categories are not approximately equally represented in a dataset can affect how the machine learning algorithms learn and their performance on unseen data, where the distribution can be different from the one observed in training data[8]. Due to these reasons, care must be taken to select metrics not sensitive to such imbalance. Among common strategies to deal with class imbalance, we find oversampling data methods, which aim to increase the number of data instances of the minority class to balance the dataset. Oversampling methods can add data instances from existing ones by replicating them (e.g., using a näive random sampler that draws new samples by randomly sampling with replacement from the available train samples), or by creating synthetic data instances (e.g., through SMOTE[9], ADASYN[19], or GANs). In addition to data oversampling, the *Focal Loss*[29] can be used on specific algorithms. The *Focal Loss* reshapes the cross-entropy loss to down-weight well-classified examples while focusing on the misclassified ones, achieving better discrimination. Finally, while the techniques mentioned above are useful for classification, we can reframe the problem as an anomaly detection problem, attempting to detect which data instances correspond to the minority class (anomaly).

Through the research we reviewed, we found a paper describing the use of SMOTE[14], and two papers using GANs[1, 34] for data augmentation at the image level. We found no paper performing a more extensive assessment of the class imbalance influence nor compared class imbalance strategies towards the COVID-19 detection models' outcomes. We propose utilizing data augmentation techniques, generating new embeddings instead of full images. Such an approach provides similar information in the embedding space as would be obtained from synthetic images while enabling widely used techniques for tabular data oversampling. Furthermore, in GANs, new data instances are cheaper to compute and store than would be if creating new images.

3 USE CASE

The research reported in this paper is done with images provided by the Medical Physics Research Group at the University of Ljubljana and made available as part of the RIS competition. The dataset was built from computed tomography (CT) scans obtained from three datasets reported in[18, 25, 33], that correspond to 289 healthy persons and 66 COVID-19 patients. Healthy persons are determined with a CT score between zero and five, while COVID-19 patients are considered those with a CT score equal to or higher than ten[15]. Each CT scan was segmented into twenty slices, resulting in 7.100 images with an axial view of the lungs, and annotated into two classes: COVID-19 and non-COVID-19. The visual inspection of CT scans aims to determine if the person was infected with the COVID-19 disease. Automating this task reduces manual work and speeds up the diagnosis.

4 METHODOLOGY

We propose using artificial intelligence for an automated COVID-19 diagnosis based on images obtained from CT scan segmentation, posing it as a binary classification problem. The discrimination capability of the models is measured with the AUC ROC metric with a cut threshold of 0.5.

We use the ResNet-18 model[20] for feature extraction, retrieving the vector produced by the Average Pooling layer. Since the vector consists of 512 features, we perform feature selection computing the features' mutual information and selecting the *top K* to avoid

[1]http://tiziano.fmf.uni-lj.si/

overfitting. To obtain K, we follow the equation $K = \sqrt{N}$ suggested by[21], where N is the number of data instances in the train set.

To evaluate the models' performance across different data augmentation strategies, we apply a stratified ten-fold cross-validation. Data augmentation is performed by introducing additional minority class data samples on the train folds. We consider five imbalance mitigation strategies: NONE (without data augmentation), RANDOM (näive random sampler), SMOTE, ADASYN, and CTGAN (GAN that enables the conditional generation of data instances based on a class label)[41]. No augmentation is performed on the test fold to ensure measurements are comparable. The performance of the data augmentation strategies is measured across eight machine learning algorithms: SVM, kNN, RF, CART, Gaussian Näive Bayes, Multilayer Perceptron (MLP), GBM, and Isolation Forest (IF)[30]. Finally, we compare the performance of the data augmentation scenarios computing the average AUC ROC across the test folds and assess if the difference is statistically significant by using the Wilcoxon signed-rank test, using a p-value of 0.05.

5 RESULTS AND ANALYSIS

When comparing the results across different imbalance mitigation strategies (see Table 1), we observed that data augmentation leads to inferior results in most cases. While this outcome was expected for IF (the minority class is no longer an outlier after data augmentation), we found that only the CART, MLP, and GBM algorithms achieved better performance with CTGAN data augmentation compared to the original dataset. Moreover, six algorithms achieved the best results when augmented with CTGAN compared to other data imbalance strategies (except NONE). We confirmed the AUC ROC differences between imbalanced datasets strategies were statistically significant, with a few exceptions: *SMOTE vs. ADASYN* for CART, MLP, and GBM; *NONE vs. RANDOM* for CART; *NONE vs. SMOTE* for Näive Bayes; *RANDOM vs. SMOTE* for SVM and RF; and *RANDOM and SMOTE vs. CTGAN* for SVM and IF. From the results obtained, we consider the CTGAN success can be attributed to the fact the generative model can learn over time to generate high-quality data instances based on the discriminator's feedback loop, while Näive random sampling reuses existing instances (providing little new information to the dataset), and the SMOTE and ADASYN algorithms generate new samples based on heuristics without learning capabilities.

We observed that GBM models trained with a Focal Loss achieved the best results in all datasets. Even when no data augmentation is performed and the RF achieves the best result, the difference is not statistically significant compared to the GBM model. The overall best performance was obtained with a GBM model trained over a dataset with CTGAN data augmentation. While the reasons behind the performance drop for the kNN, Näive Bayes, RF, and SVM models remain unclear, further investigation is required to clarify them. Nevertheless, we consider the CTGAN data augmentation on the embeddings space approach is promising.

6 CONCLUSION

This research presents a novel approach towards data augmentation in radiomics by generating new data instances in the embedding space rather than generating new images. We demonstrate that this approach leads to the best forecast outcomes with a GBM model trained with a Focal Loss on a dataset enriched with new CTGAN generated instances. Moreover, we compare this approach to other imbalanced data strategies, finding that Näive random oversampling, SMOTE, and ADASYN degrade the resulting models' performance compared to the original dataset. Future work will focus on further understanding the cases where the CTGAN data augmentation leads to poor results and provide an integral explainability model for machine learning classifiers that consume image embeddings.

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Class Imbalance Mitigation Strategies	CART	IF	kNN	MLP	Naive Bayes	RF	SVM	GBM
NONE	0,6429	0,6802	0,8504	0,7879	0,6653	**0,8601**	0,8066	*0,8555*
RANDOM	0,6402	0,5215	0,7846	*0,7993*	0,6464	0,6691	0,6888	**0,8150**
SMOTE	0,6147	0,5607	0,6813	*0,7663*	0,6590	0,6660	0,6817	**0,7826**
ADASYN	0,6020	0,5863	0,6660	*0,7655*	0,6282	0,6435	0,6652	**0,7787**
CTGAN	0,7401	0,5340	0,8118	*0,8419*	0,6395	0,7090	0,6896	**0,8871**

Table 1: Average AUC ROC values obtained across the ten cross-validation folds. Best results are bolded, second-best results are highlighted in italics.

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