Smoker Detection

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***Abstract*—Given the increasing health issues related to the human respiratory system in contact with heavy smoking, we have grown to analyze the necessity of efficiently relating these two and understand more about their harm. In this context, we, the authors, try to understand the relation between a human's smoking pattern and their chest X-rays, which we assume would contribute to a future with reduced smoking-induced sicknesses. After searching for a related dataset, we found the POLCOVID dataset, which consists of chest X-rays containing information about the smoking status of the patients, but poorly labeled for this task, on which we tried multiple strategies to achieve a model that performs well on the task on recognizing the smoker profile of a person. We used supervised learning on the existing data, semi-supervised on the unlabeled data too, and self-supervised on all of the data in an attempt to solve the task we proposed and scored a 74% accuracy using Fix-Match and 47% F1-score and 69% accuracy with SimCLR and 43% F1-score. However, given that these are the best results so far, there is still work to do which could be related to finding a new dataset or changing the model and the techniques used in future research.**

***Index Terms*—Smoker Detection, X-Rays, Resnet-18, MobileNet, EfficientNet, FixMatch, Pseudo-Labeling, SimCLR**

I. Introduction

We live in a constantly evolving world, where urbanization has taken over, and thus stress levels have been increasing in the past decades overall [29]. With great stress come coping habits, of which we could mention excessive alcohol consumption, overeating, or smoking, the last being of interest for our article. The bad effects of it have raised awareness all around the world, trying to reduce it.

According to the British Medical Bulletin [30], over 3 million people die each year in developed countries because of cigarette consumption. In an attempt to reduce its risks or to better track its impacts on human health, there are multiple problems, as smoking affects not only the persons directly involved in the act but also the ones around them. One of them would be the detection of a smoker using technologies, to increase consciousness for those smoking in non-allowed spaces, or from patient data, given that sometimes medical staff must recognize such a characteristic about a person.

As stated by a study in 2020, there were at least 12 smoking detection systems, encouraging us to develop something in this field that could benefit the cause [6]. Still, no valuable X-ray smoking detection techniques could be found, as the smoking detection systems stated above are either on signals or on images, which led us to the idea that we want to investigate whether this should be researched further or not, as it could be helpful in the human health system.

In other words, we try to find a method in order to help medical staff detect whether a person is a smoker or not given its chest X-rays, as they are the most common type of X-rays and it would be of great aid. We focus on image classification deep learning models as they are the most effective in this type of task- especially when it comes to medical image recognition - as of today.

II. Related Work

A. *Significant advancements within the domain*

In recent years, a lot of research has been done to detect cigarette use. There are mainly two approaches to this problem, analyzing image-based or sensor-based data.

The sensor-based methods gather various inputs, speech recognition [15], respiratory inductive plethysmography [26], or different types of sensors available in our day-to-day use, such as smartphones or smartwatches [6], which are used in combination with different types of CNN-s for extracting features or patterns.

After reviewing the literature, the image-based approach has been explored and developed much more. Aditya et al. [5] utilized a deep learning model that helps to identify key regions, along with a detection framework based on YOLOv5 on cigarette images.

On the same topic, Pandey and Pati [17] proposed a custom version of YOLO-NAS to determine if a driver of a car is smoking from a video feed. Jiang et al. [24] proposed a few variations of the YOLOv5 network such as YOLOv5s-VR that utilizes a vertical rotation enhancement method, YOLOv5s-SE that has an additional self-attention module, YOLOv5s-STD contains an extra small target detection layer and YOLOv5-RST which implements all the features of the previously mentioned models. Also, Nakayiza and Ggaliwango [19] presented a framework for detecting smoking behavior using a VGG-16 pre-trained model and a Layer-wise Propagation for backpropagation.

A comparative analysis between different models in search of a superior one that could predict cigarette use in an image was done by Atmajaua et al. [1]. Comparing CNN-s, such as VGG, AlexNet, and ResNet34 with Vision Transformers. After identifying the optimal learning rates for each model, and comparing the performance, the transformer approach was superior.

TABLE I
MODELS AVERAGE ACCURACY DETAILS [1]

Model	*Avg Acc-Val*	*Best Acc-Val*
Vanilla Alex	0.589	0.677
Vanilla VGG-16	0.627	0.761
Vanilla ResNet34	0.675	0.727
Pretrained Alex	0.663	0.738
Pretrained VGG	0.683	0.738
Pretrained ResNet	0.750	0.838
SWIN-VIT	0.651	0.916

A different approach that is lacking, mainly because of limited data, focuses on determining the smoking status of a person based on medical files such as CT scans, MRIs, or health records. When it comes to health records, Ali Ebrahimi et al. developed an NLP pipeline that would be effective in detecting the smoking status of a patient by considering only Electronic Health Records (EHR) based on Danish medical data. It consists of data pre-processing, using different feature extraction techniques such as BERT, Word2Vec, and others, as well as a Stacking-Based Ensemble model and a CNN-LSTM, pioneering the use of an Explainable AI (XAI) approach to explain the output of the model regarding the patient's status [2]. A similar approach was already investigated by Suraj Rajendran et al. on English EHRs, without the use of XAI [3].

As for MRI, Shuangkun Wang et al. proposed a method that uses the HAED MRI-3DT1WI images of smokers and non-smokers, which were proportionally distributed, and employed two architectures: the first being an RNN with ConvLSTM, and the second a Conv3D, in order to detect the smoking status. They achieved an accuracy higher than 80% for both models, which is a significant improvement for the field [25].

Moumita Chanda et al. proposed a machine learning algorithm for smoker detection using X-ray images generated by themselves, which were divided into smokers and non-smokers, and an InceptionMobileNetV2 model to create an accurate system that detects the potential patient's status [13]. Still, the methods of acquiring the dataset were not clear, nor were they approved by medical workers, and thus, this method needs more examination.

Certain research papers are more unique, employing different approaches, such as analyzing retinal images of a patient to determine smoking status [8], identifying whether an environment present in a picture is associated with smoking [22], or creating a multimodal deep learning architecture that works with limited data and yields good results [12].

B. Areas of the field for potential improvement

After a thorough examination, we concluded that there are little to no annotated MRIs, CT scans, or X-rays for determining if a patient is or not, which may be subject to additional analysis or data mining. A study from 2017 [4] stated that EHRs had inconsistent data about patients' smoking status, which was poorly collected or not collected at all, and we have not found any other such study, which is concerning and suggests that the issue is still relevant today, but needs more research in order to reach a conclusion.

As such, we have concluded that there is not much research on the topic of detecting people smoking using X-rays, CT scans, and MRIs, particularly in the context of developing diseases, and thus trying to learn more about the impact of smoking on human health.

Therefore, we came up with the idea of exploring the connection between illnesses and the toll smoking takes on them. For this purpose, we will use the POLCOVID dataset [16], which consists of lung X-rays in DICOM format for people with pneumonia and COVID-19 that are annotated and include indications of their smoking status, and create a supervised model that aims to describe the influence of cigarette usage on the severity of these two diseases.

III. METHODOLOGY

As a starting point, we proposed a baseline model based on the Resnet-18 architecture that uses a cross-entropy as the loss function and Adm as the optimizer.

Our research proposes a different innovative approach to reach a solution that aims to solve the proposed problem.

Beginning from pre-trained popular models such as Mobilenetv3, Resnet-18, and EffiecientNet, and tuning the hyper-parameters in order to find the most suited model for our task, to using different techniques in combination with these models.

We tried all the learning types when it comes to a few labeled data - supervised, semisupervised, and self-supervised.

- Supervised - as mentioned above, we tried multiple models and hyper-tuning them on the labeled data in an attempt to find at least a better fit for our data. We tried both cross entropy and Focal Loss for the criterion, Adam and SGD for the optimizer, 64 and 32 batch sizes, and different combinations of augmentations.
- Semi-supervised (using Mobilenetv3 an Focal Loss):
  - Pseudo-labeling - we experimented with a lot of ideas, such as pseudo-labeling only the under-sampled class, both classes, and both classes but with different confidence thresholds for each.
  - FixMatch - consisted of using the unlabeled data as well, and classifying the weak and strongly augmented unlabeled data in order to have access to an unlabeled loss and influence - as such - the labeled one and the whole model to better learn from data.
- Self-supervised - we tried SimCLR in combination with a pre-trained model (Resnet-18)

IV. Experiments

A. The Dataset

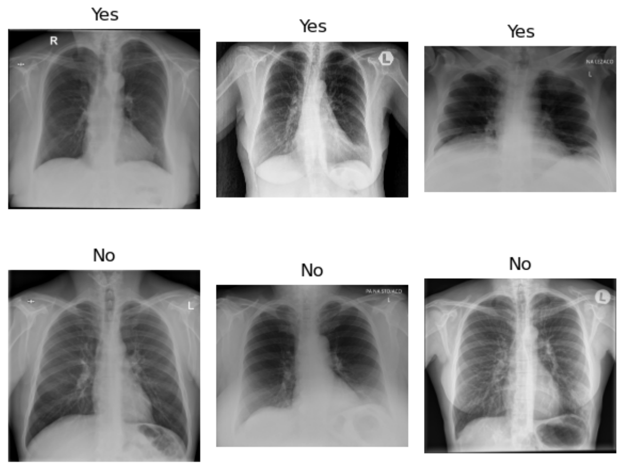

Fig. 1. Examples of lung X-Ray from POLCOVID dataset, where annotated with yes are smokers, and No - non-smokers.

Of open-source datasets, we have chosen POLCOVID [16], which is a dataset that consists of lung X-rays in dicom, jpg, and tiff formats (Fig. 1). It is supposed that the X-rays of a smoker would be a bit different than the ones of a non-smoker one, and should show some scarring, markings, some white margins that could represent air trapping and others, but as these can be caused by other diseases, it is hard yet to tell if there are some real correlations to the effect of the cigarette on the chest X-rays.

As we can see in the figure, it is a bit blurry whether or not we can do so even with a human - non-specialized in the medical field - eye, and thus, maybe for future tasks a medical worker would be suited for collaboration in the development of this project.

The dataset is divided into 3 classes - **normal**, **covid** and **pneumonia**, including metadata such as sex, age, but most importantly - smoker status labeled as ”Yes” or ”No”. It also contains a corresponding csv with all the metadata.

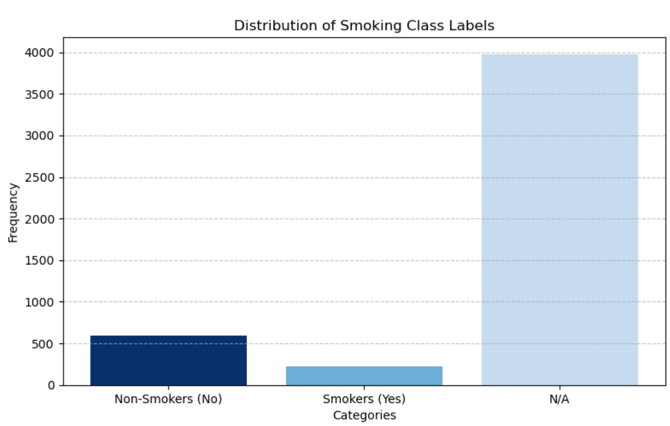

Fig. 2. Distribution of smokers class in the whole dataset

Before diving into analysis and preprocessing, we had to clean up the dataset and fix several issues. The CSV file containing the metadata was poorly formatted, so we had to correct it in order to make it ready for further use. On top of that, some images had corrupted or invalid metadata that couldn’t be parsed with the environment we had, so we had to remove those from the dataset to ensure everything was ready for processing.

We’re focusing on smoking status, which adds complexity to the task. Out of 4803 images, only 823 have valid descriptors, while the rest are labeled as ”N/A.” This means we’re starting with approximately 20% of the dataset. (Fig. 2)

Even with this limited amount of data, we’re taking on the challenge of building a model to find a connection between a person’s smoking history and their lung X-ray.

B. Preprocessing

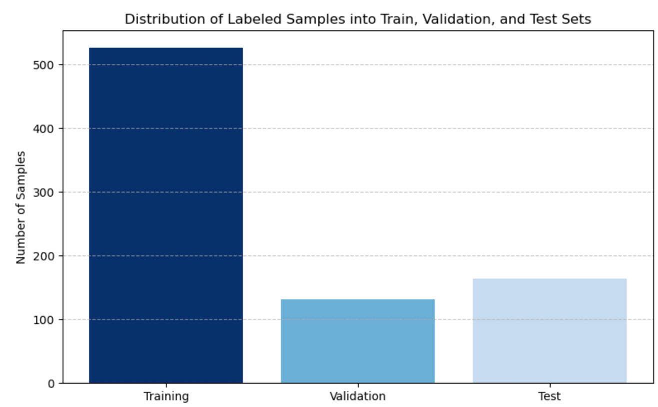

Fig. 3. Distribution of smokers class in the dataset after the splits were performed.

We selected only 823 labeled samples, of which 596 are non-smokers, and 227 are smokers. Then, we split the data into training and test sets by taking 20% of the entire dataset for testing. After that, we further split the training data, taking 20% of it to create a validation set. (Fig. 3) and then we normalized the images and applied augmentations such as Gaussian blur and others.

C. The Baseline Model

1) Proposed model: For the baseline model, we used Resnet18. This model type has been used to classify X-ray images, making it a perfect baseline. A ResNet [31], also known as a residual neural network, introduces a residual connection between layers that proposes a good solution for the vanishing gradient problem in deep neural networks.

ResNet-18 contains eighteen computational layers, seventeen convolution layers with additional residual connections every two layers starting after the first convolution, a fully connected layer, and a softmax layer that performs the classification task.

2) Hyper-parameters: The baseline model was initialized with random weights and the images used as input were rescaled down to 128 x 128, separated in batches of 64, and trained for a total of twenty epochs.

Cross-entropy was used as the loss function for the model, along with the Adam optimizer, with a learning rate of 0.001.

3) Performance and results: The performance metrics that we used to evaluate our model and will be used in the future to compare with different models consist of precision, recall, f1-score, and accuracy. The results of the baseline model can be observed in the table below (Table 1).

TABLE II
METRICS FOR BASELINE MODEL

Baseline Model	***Metric***	***Value***
No (Non-Smokers)	Precision	70%
	Recall	85%
	F1-Score	77%
Yes (Smokers)	Precision	35%
	Recall	18%
	F1-Score	24%
Overall	Accuracy	**65%**
	Avg F1-Score	**50%**

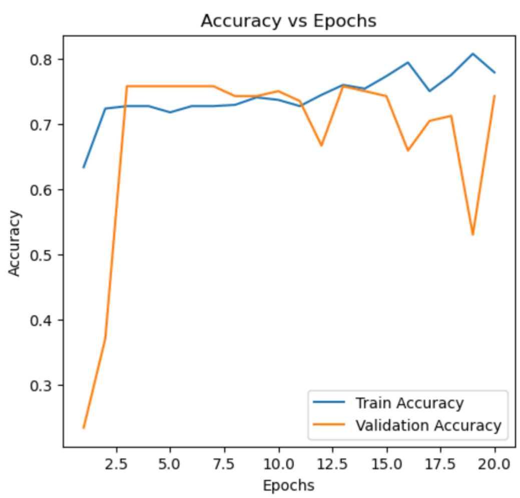

Fig. 4. Training and validation accuracy evolution.

The loss curve (Fig. 4) shows a normal error decrease as it starts to learn and improve its performance, converging around 0.2. But, when looking at the accuracy curve (Fig. 5) we observe that the model tends to overfit on the training dataset slightly.

The confusion matrix (Fig. 6) indicates that the baseline model can efficiently classify True Negatives, but struggles with correctly identifying True Positives, this observation is based on the low recall for the True class. A key factor in misclassifying is, for sure, the imbalance present in the dataset.

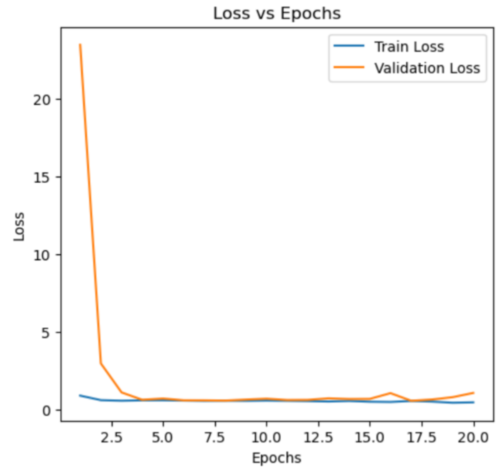

Fig. 5. Training and validation loss evolution.

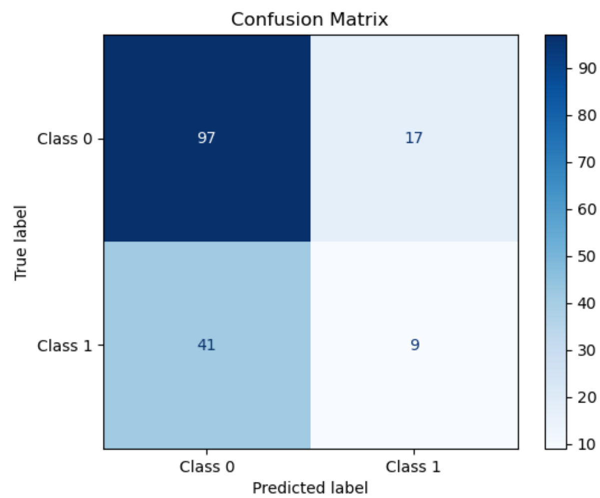

Fig. 6. Confusion matrix on the model's prediction of the test set.

V. Our Contribution

Having as a starting point the POLCOVID dataset [16] and the baseline model mentioned earlier, we tried to obtain a robust and reliable model that could support our claim of identifying the smoking status of a person only from an X-ray image.

So, we present below some techniques in an attempt to exploit the dataset and get better results in the task that we envisioned.

Given that we did not have access to more data than the few the dataset proposed to us, for the upcoming presentation of our approaches we tried keeping the initial split only, in test and train and gave up on the validation setup, as we observed better performances using only this type of split.

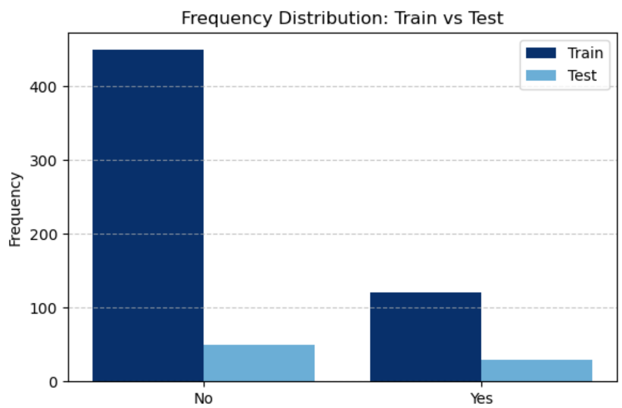

Fig. 7. Class distribution and split for future experiments

A. Supervised Approach

Starting from the baseline, we tried training different models, different class weights for weighted loss, and learning rates in hopes that we would find the best hyper-parameters that fit this task. The best-performing models were trained using 64 batch size, 0.0001 learning rate, Focal Loss with alpha = 0.6 and gamma = 2, Adam optimizer, and some augmentations and we used the IMAGE-NET weights for pre-training.

TABLE III
METRICS FOR MOBILENETV3

	Metric	***Value***
No (Non-Smokers)	Precision	77%
	Recall	71%
	F1-Score	74%
Yes (Smokers)	Precision	43%
	Recall	51%
	F1-Score	47%
Average	Accuracy	**65%**
	F1-Score	**61%**

EfficientNetB0 [34] may seem better in overall accuracy (0.70) and excels at classifying the Non-Smokers class. MobileNetV3 [32] though has the best intuition about the two classes, achieving the highest average F1-score (61%) and Smokers F1-score (47%), making it the best when it comes to our task given that we had an imbalanced dataset. ResNet50 [31] performs well in the Non-Smokers class but does no good when it comes to the Smokers class, given its low F1-score (15%) for this category.

B. Semi-Supervised Approach

Seeing that we did get better results, but not better enough to tell the model is indeed a good one - trying only hyper-parameter tuning and changing models - we chose to try some semi-supervised techniques, given that we still had over 3000 unlabeled images using the best hyper-parameters found:

- **Pseudo-labeling** [36] - we tried training a model on the labeled data, then predicting some labels on the unlabeled data selecting the ones for the under-sampled class with a high confidence (greater than 0.85) and then combining them into the base dataset and train another model on the combined dataset. And so, we got these results:

The pseudo-labeling technique used for this specific task was not giving performances of any kind, especially when it came to the under-sampled class, which meant that maybe the pipeline of the technique was not good enough, or that it indeed did not work so well on this dataset. We also tried re-training the same model but because it was not that good before at pseudo-labeling the data we got it to overfit 100% to the Non-Smokers class.

We also tried pipelines such as training and pseudo-labeling with a high confidence threshold in the training process and then training on both labeled and pseudo-labeled data, and also strategies such as pseudo-labeling independently with different thresholds for each class depending on their count, but we did not get any better results.

TABLE IV
METRICS FOR PSEUDO LABELING WITH MOBILENETV3

	Metric	***Value***
No (Non-Smokers)	Precision	68%
	Recall	78%
	F1-Score	73%
Yes (Smokers)	Precision	22%
	Recall	14%
	F1-Score	17%
Average	Accuracy	**59%**
	F1-Score	**45%**

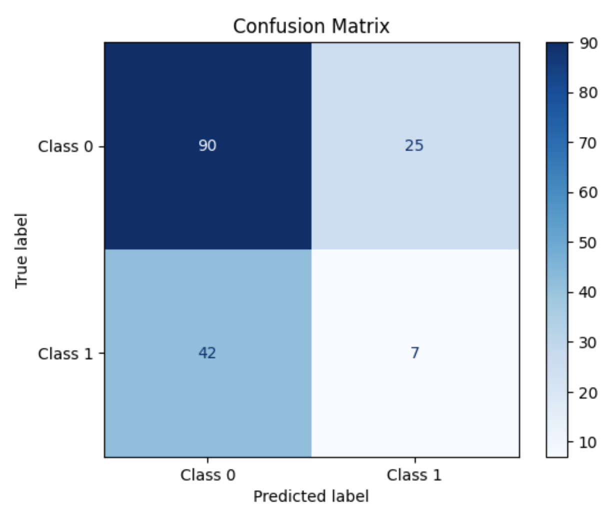

Fig. 8. Confusion matrix for the trained model using Pseudo-Labeling

As we can see in Fig. 8, the model over-fitted and even got worse at predicting the over-sampled class, contrary to the idea that it should perform better, which led us to abandon pseudo-labeling methods and implement other algorithms.

- **FixMatch** [36]- we tried applying strong and weak augmentations on the unlabeled images such that we can generate an unlabeled loss (for the predicted labels with confidence higher than 0.8) and try to train our model guiding it using both losses. We used Random Horizontal Flip and Random Rotation as weak augmentations and for the strong ones we used these two plus Color Jitter and Random Resized Crop.

TABLE V
METRICS FOR FIXMATCH USING MOBILENETV3

	Metric	***Value***
No (Non-Smokers)	Precision	77%
	Recall	89%
	F1-Score	83%
Yes (Smokers)	Precision	59%
	Recall	39%
	F1-Score	47%
Average	Accuracy	**74%**
	F1-Score	**65%**

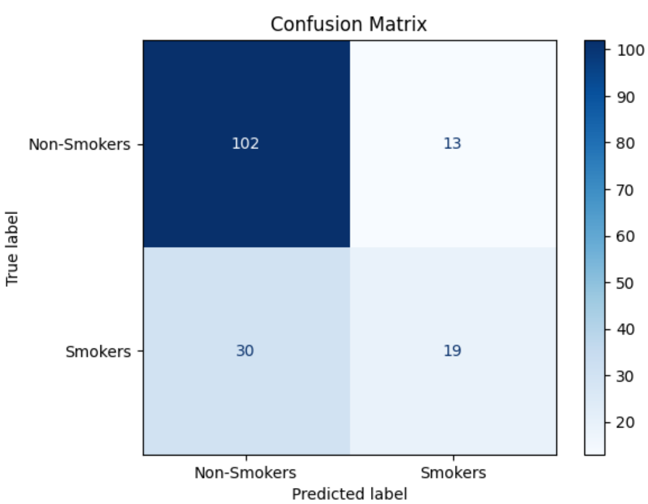

Fig. 9. Confusion matrix for the trained model using FixMatch

We used these augmentations as a result of viewing the samples from the dataset - a lot of them had a cropped aspect and some had different coloring, a bit rotated and so on. We got the best result so far using this technique. As we can see in the table with results, we achieved a 74% accuracy and 65% average F1-score, and the confusion matrix (Fig. 9) looks the best so far.

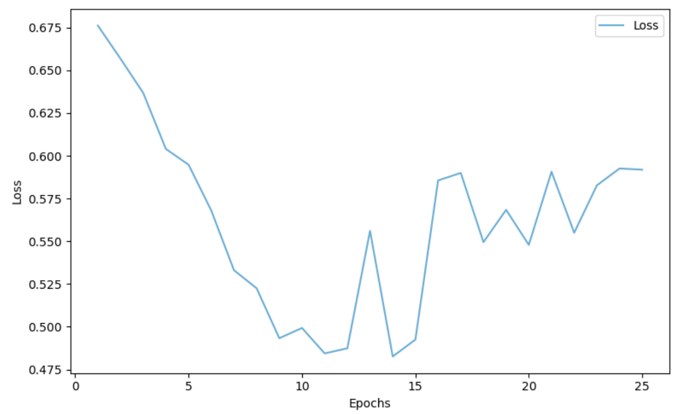

Fig. 10. Overall loss evolution using FixMatch

We have to mention that for this method, by looking at the loss evolution we can state that in early epochs the model learns very well, but even if it does not grow that much in the late epochs, there is an indication that it still learns, but it faces some challenges learning, probably because the unlabeled loss calculation is done using some noisy unlabeled data, which again is telling us that the dataset may not be of the most suited ones for this task.

C. *Self-Supervised Approach*

Having a significant part of the dataset marked as unlabeled for the target label, we considered a self-supervised approach, which consisted of pertaining the network on all 3000 images using contrastive learning, hoping to create a more robust starting model to train on the rest of the labeled data.

We chose SimCLR [33], also known as a simple framework for contrastive learning of visual representations. This technique tries to maximize the agreement between two different augmented views of the same image, it utilizes heavy augmentations, a base encoder framework, which is our initial model, and a projection head, an MLP, that maps the representations obtained from the model to a space where contrastive loss can be applied.

As augmentations, we used color jitter, grayscale, crop, and horizontal flip, each applied with a different probability on a resized (112,112) image due to hardware limitation, for the base encoder, we used the RESNET-18 architecture, a small MPL formed from two convolutional layers with ReLU as the nonlinearity. For training the model using SimCLR we observed that the best results were given for batch size 512, projector size 64, and trained for 8 epochs. Then the RESNET model was trained on the labeled data, filtering all the images that did not have good quality and using weighted loss to account for the imbalance present between the two labels.

Compared to the baseline model we can observe a significant increase in the recall and f1 score for the persons that are labeled as smokers, but a small increase in accuracy, from 61% to 69%.

The improvement when using this method is not that great. This can be due to not using images to the standard resolution of (224,224) that was established when training the base model, the number of unlabeled data which is small in comparison with other datasets, which imposes a small amount of epochs to train the model.

TABLE VI
METRICS FOR RESNET-18 PRE-TRAINED WITH SIMCLR

	Metric	*Value*
No (Non-Smokers)	Precision	80%
	Recall	78%
	F1-Score	79%
Yes (Smokers)	Precision	42%
	Recall	44%
	F1-Score	43%
Average	Accuracy	**69%**
	F1-Score	**61%**

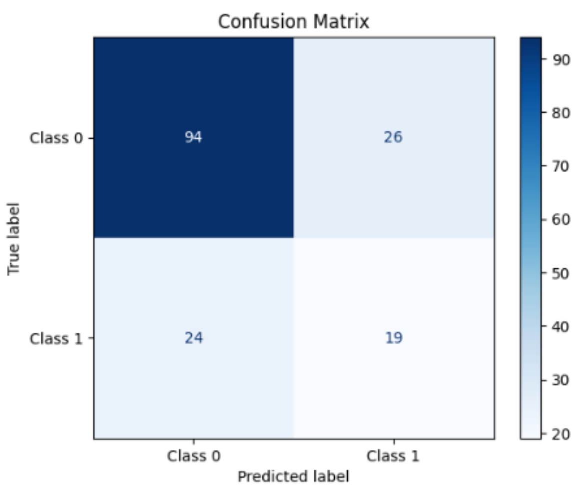

Fig. 11. Confusion matrix self-learning pre-traing.

VI. RESULTS AND DISCUSSION

Starting from the idea that we do not know if there is a clear relation between one's smoking status and chest X-rays, as smoking causes various scars and tissue degrading similar to other diseases, in our attempt to identify this relation and create a model that would detect it, we started from an open-source dataset, which was not intended for this purpose, but contained some of the information about if a patient smokes or not, even if few and over-sampled for the less significant class, we obtained very poor baseline result, even with a pre-trained model (50% F1-score and 65% accuracy) as the data.

We still tried different methods and techniques, such that we could overcome the quality of the dataset with little success, having achieved much better accuracy scores with FixMatch (65% F1-score and 74% accuracy) and with SimCLR (61% F1-score and 69% accuracy).

Still, there was a question of whether or not these results were good given that the pre-trained Mobilenetv3 (61% F1-score and 65% accuracy) had by itself improved results, but

TABLE VII
COMPARISON OF PRECISION, F1 SCORE, AND ACCURACY ACROSS MODELS

Model	***Value***
Precision (Avg)	
Baseline Model	52.5%
Mobilenetv3	60%
Pseudo Labeling Model	45%
Mobilenetv3 with FixMatch	**68%**
RESNET-18 with SimCLR	61%
F1 Score (Avg)	
Baseline Model	50%
Mobilenetv3	61%
Pseudo Labeling Model	45%
Mobilenetv3 with FixMatch	**65%**
RESNET-18 with SimCLR	61%
Accuracy	
Baseline Model	65%
Mobilenetv3	65%
Pseudo Labeling Model	59%
Mobilenetv3 with FixMatch	**74%**
RESNET-18 with SimCLR	69%

given that we trained multiple times this model and the results varied, but for the FixMatch technique and SimCLR the results were constant and better, we did make the observation that these two techniques were the best. We can notice this also by the confusion matrix values of these models (Fig. 9), where FixMatch has the most True Values predicted, even if not near as good as it would be wanted especially for the ”Yes” class, it is still a big improvement.

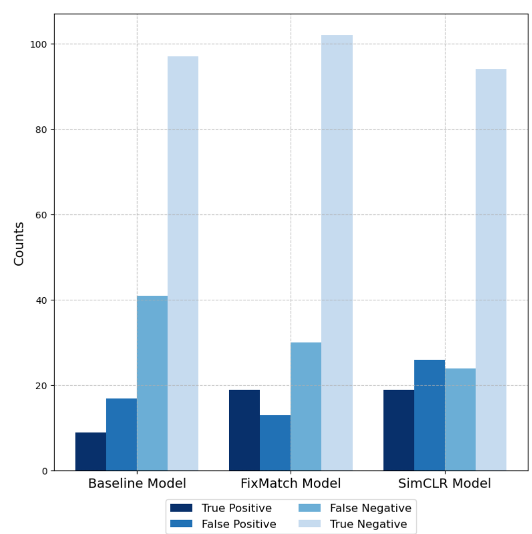

Fig. 12. Confusion matrix self-learning pre-traing.

The poorest of them performed the pseudo-labeling technique (45% F1-score and 59% accuracy), and from the multiple trials, we concluded that the dataset is not suitable at all for this method, as it is under-sampled for the important class to identify ("Yes" for the smoking status) and with few data in general.

VII. Conclusions

Analyzing all the proposed techniques, we determined the most successful one, was the semi-supervised approach that used FixMatch, followed by the self-supervised one. The FixMatch method presented a 10% increase in accuracy from the baseline model proposed initially and a 5% from the SimCLR technique.

Even though we tried different approaches, with different techniques, we did not fully succeed in getting the model to learn how to differentiate the smoking nature of a person from its X-rays, this may also be due to some limitations that we encountered such as limited hardware, not being able to keep the native resolution of the images, might've lead to loss of crucial data in classifying correctly, choosing the right augments to use for this particular task, or just knowing if there is a connection between a X-ray and the smoking status of a patient.

Most probably, the dataset was not good for this particular task, and maybe having another bigger annotated dataset would have given better results. The problem we propose to solve still stands and may be beneficial in trying to advance the limited research in this domain.

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