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Automated Detection of Covid-19 from Chest X-ray Images Based on FlexMatch with ResNet50

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Abstract— *In this research, we aim to come up with a system that is reliable and bias-free in detecting Covid-19 from chest X-ray images. We proposed a combination of two datasets using a semi-supervised learning approach based on the FlexMatch algorithm, which can help leverage unlabeled data efficiently, boosting the accuracy and convergence performance. The method utilizes the ResNet50 architecture trained from end-to-end on two datasets (labeled and unlabeled) for multi-class classification. The proposed model has been trained and evaluated on the prepared dataset, and it achieved an overall accuracy of 94.14%, having Precision, Recall, F1-score, and AUC of 0.9559, 0.9311, 0.9428, and 0.9909, respectively. For the class-wise accuracy in classifying Covid-19 from other lung conditions, we achieved an accuracy of 96.0%. This research proves that the proposed method can accurately diagnose whether chest X-ray images belong to the positive or negative diagnoses of Covid-19 and could help doctors diagnose Covid-19 patients rapidly.*

Keywords— *Chest X-ray,* Computer-aided diagnosis, *Covid-19, Data bias, Flexmatch, Semi-supervised learning.*

I. INTRODUCTION

Covid-19 is a deadly respiratory virus that has caused unprecedented challenges for public health systems worldwide. RT-PCR testing is the most widely used tool to diagnose the virus, but it is expensive, has high rates of false negatives, and takes a long time to get results. It also puts frontline health workers at risk of infection, and its increased demand leads to overwork of medical personnel.

Artificial Intelligence is changing the healthcare sector, where it's being implemented in medical specialties such as radiology, dermatology, oncology, and cardiology. Inspired by the success of deep learning in computer vision, researchers have proposed various machine learning techniques to automatically detect Covid-19 using multiple kinds of data, which proved to be fast and reliable. Cough sound and the three biomedical imaging sources, namely: chest X-ray images, computed tomography (CT), and ultrasound are used with these techniques for screening and diagnosing Covid-19. Motivated by the experimental results in [1], which show that Chest X-ray images produce better generalization results in Covid-19 detection than CT scan images, this research focuses solely on Chest X-ray images. In addition to that, radiologists advise not to use CT for broad screening of Covid-19.

Despite the efforts made in developing automatic Covid-19 detection systems, there are a few issues of concern limiting the full potential of such systems. These issues are related to data and techniques being used, which is paramount to focus on when developing Covid-19 automatic detection from X-ray Images systems.

The first issue is related to data bias due to the Chest X-ray datasets used by many researchers in developing such systems, which need to be verified by medical practitioners. Most of their works are based on small self-collected open-source datasets. Racheal *et al*. [2] made a huge discovery as they exposed issues related to bias on systems developed using open-source datasets, such as the widely used COVIDx dataset, which was introduced by Wang *et al*. [3] that has inflated results on testing proving that the data is not being representative of the actual clinical problem. Using biased datasets is a lurking danger in current Covid-19 machine learning-based detection systems.

In addition to data bias, there is an issue of class bias due to the number of lung-related diseases researchers are considering, as noted in [4]. Many researchers have ignored the probability of other viral illnesses, such as influenza, that show characteristics close to Covid-19 on Chest X-ray images. Many have approached it as a binary classification (Covid and Normal) and some as a multi-class classification problem (Covid, No Covid, and Normal). There is a need to distinguish Covid-19 pneumonia from other viral pneumonia such as influenza. These systems are expected to be bias-free since diagnosis errors may harm people. Another problem is overfitting issues in existing deep learning models, resulting in high accuracies obtained by many questionable works that need to be revised.

The need for more data to be used to train the models is another problem faced in developing AI systems for Covid-19 detection. To achieve better results, vast data samples are required to train deep learning models. For quick and easy access, patients' data is usually stored in a centralized database which makes data sharing with those who are not among the medical practitioners challenging. Also, due to various reasons, the data is not freely available to the public. Researchers are putting more effort into creating valid datasets such as the frequently used dataset [5], made available by Dr. Joseph Cohen, which is accessible to the public that can be used in developing Covid-19 detecting systems. The images were collected from reliable journal websites like the Italian Society of Medical and Interventional Radiology. Despite the effort, lack of data remains a significant challenge in developing machine learning systems for Covid-19 detection.

We propose using ResNet50 and FlexMatch for the semi-supervised task, leveraging unlabeled data for covid detection from chest X-ray images. We proposed using two open-source datasets from different sources after analyzing how they were built to deal with the problem of data bias. We addressed the class imbalance problem by applying various data augmentation techniques to the training data. We performed extensive experiments, and our proposed method outperformed other methods taking into consideration the overall model performance and Covid-19 class-wise accuracy.

II. Literature Review

Recently, researchers have proposed various deep-learning techniques in the medical domain to help diagnose Covid-19 from chest X-rays automatically. Studies have taken different approaches to developing state-of-the-art systems for detecting Covid-19, such as supervised learning, unsupervised learning, and semi-supervised learning (SSL) approaches.

Ozturk *et al*. [6] presented DarkCovidNet, a modified DarkNet model for automatic Covid-19 detection using Chest X-ray images for binary and multi-class classification. The proposed achieved an accuracy of 98.08 for binary classification and 87.02 for multi-class classification. Hamid and Seyyed [7] proposed a novel framework based on deep learning and the ANOVA feature selection method for diagnosing Covid-19 cases from X-ray images. A pre-trained network DenseNet169 was used to extract features from the images chosen by a feature selection method ANOVA to reduce computations and time complexity while overcoming the curse of dimensionality to improve predictive accuracy. XGBoost classified the selected features, and the model had 98.72 and 92.00 in binary and multi-class classification, respectively. Nasiri and Hasani [8] employed DenseNet169 to extract features from X-ray images without employing the feature selection method and used XGBoost for classification; they gained 98.24 and 89.70 in binary, and multi-class classification, respectively. Apostolopoulos and Mpesiana [9] assessed various deep architectures on chest X-ray images using transfer learning. In their experiments, they used a dataset created by Dr. Cohen that contained 224 Covid-19, 504 normal, and 700 images of pneumonia. Their best model, VGG19, achieved an accuracy of 98.75 and 93.48 for 2-class and 3-class classification tasks, respectively. Khan *et al*. [10] presented CoroNet, a deep learning model based on pre-trained Xception architecture, which is used for transfer learning. Chest X-ray dataset images were used to train the model for binary (Covid-19 and Normal), 3-class, and 4-class classification (Covid-19, viral pneumonia, bacterial pneumonia, and non-Covid). The proposed model achieved an accuracy of 99, 95, and 89.6 for 2-class, 3-class, and 4-class, respectively. Mahmud *et al*. [11] proposed a CovXNet deep neural network for identifying Covid-19 and other pneumonia types with different localization from chest X-rays using two datasets. The model was created from a fundamental structural unit by incorporating local and global features from various receptive fields using depth-wise convolutions with different dilation rates. The model attained a 97.4 accuracy for 2-class (Covid and Normal), 94.7 for 2-class (Covid/Bacterial pneumonia), and 90.2 for multi-class classification. In [12], the authors proposed the COVID-CAPS, a modeling framework for Covid-19 identification utilizing chest X-ray images based on Capsule Networks. Even though the model had fewer trainable parameters than its competitors, it achieved an accuracy score of 95.7, a sensitivity score of 90, a specificity score of 95.8, and an AUC of 0.97. Using CNN and deep convolutional generative adversarial networks (DCGANs), the authors in [13] proposed a new model for classifying chest X-ray images into three classes. To circumvent the difficulties of an unbalanced dataset, the suggested model DCGAN generates fake images and extracts deep features from each image in the dataset. They used four different publicly available datasets of chest X-ray images for their experimental research. Prior works based on a supervised learning approach face a stumbling block limiting their full potential in classifying chest x-ray images. The technique requires many labeled data to achieve better classification performance. Similar to this paper, there exist works that take the semi-supervised learning approach to overcome the mentioned limitations of other methods by utilizing both labeled and unlabeled data to develop systems that can meet the expected clinical standard performance. Sahoo *et al*. [14] proposed a semi-supervised learning approach using a MultiCon algorithm to detect Covid-19 from chest X-ray and CT scans. MultiCon was evaluated by comparing its performance against other state-of-the-art semi-supervised learning methods, including Virtual Adversarial Training (VAT), MixMatch, Mean Teacher, ICT, pseudo-label, and FixMatch; it performed better than the other ones in classification with average class prediction accuracy of 97.07.

Considering these findings, we can do more to improve the performance of deep learning models in detecting Covid-19. This paper proposes a semi-supervised learning approach based on deep learning to automate Covid-19 detection from Chest X-ray images.

III. Methods And Materials

The overall framework of our method is shown in Fig. 1, in which a small number of labeled samples and a large number of unlabeled samples are used to generate new samples through pseudo-labeling by semi-supervised learning. The new model is then trained with mixed chest X-ray images to get a final diagnosis

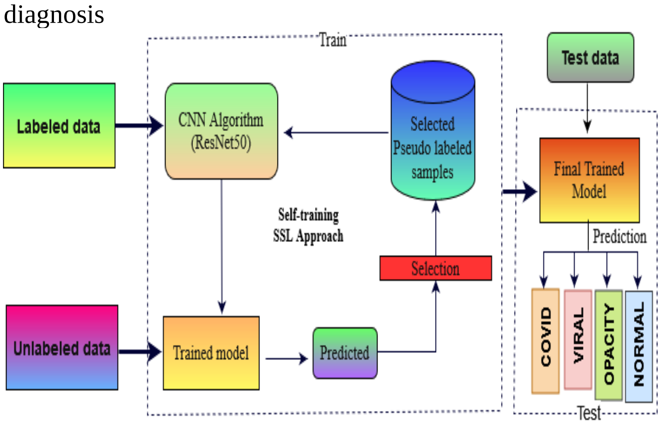

Fig. 1. Overview of the proposed approach

A. Dataset Description

A system to classify X-ray images into Covid-19 and other lung conditions (normal, lung opacity, and viral pneumonia) is presented in this work. We used an existing dataset that has been verified to be bias-free and added the usage of a new one with questionable validity. The following existing datasets were

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used in this work:

- *Covid-19 Radiography database*: The dataset [15] is an open-source dataset made available by a group of researchers working in collaboration with medical doctors. The dataset consists of 3,616 Covid-19 positive, 10192 Normal, 6,012 Lung Opacity, and 1345 Viral Pneumonia images, which were collected from various approved accessible datasets such as PadChest [16], RSNA [17], and other external sources [5]. The dataset won the Covid-19 dataset award on the Kaggle community, which also gives credibility to its reliability and usefulness in tackling the Covid pandemic.

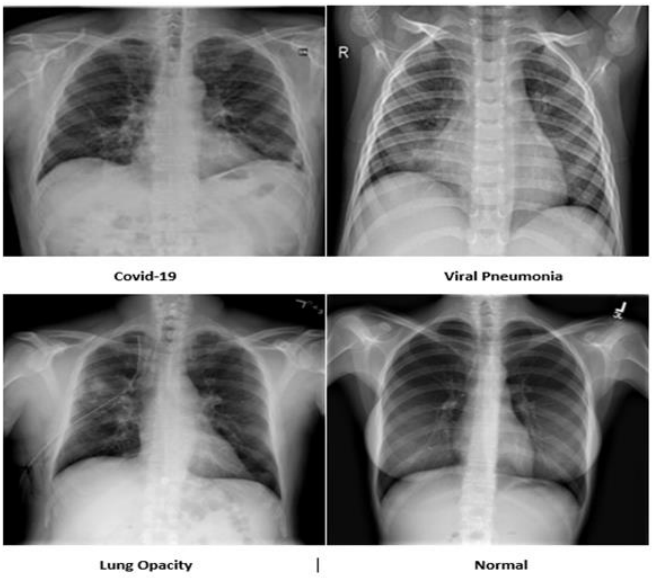

Fig. 2. Data samples

- *COVID-QU-Ex:* Supplementary data was collected from this dataset [18], which researchers of Qatar University compiled. It is considered the largest Covid-19 dataset with 33920 chest X-ray images of 11956 Covid-19 positive, 11263 non-Covid (viral or bacterial Pneumonia), and 10701 normal case observations. The dataset was created by numerous publicly available datasets and repositories with different formats. How the dataset was created has raised questions about the authenticity of the data and whether it is usable and perfect to be considered as close to clinical data. Thus, the data will be used as extra data that facilitates the SSL technique.

B. *Data Preprocessing*

The labeled dataset was randomly divided into training and validation sets using a ratio of 80:20, respectively. After slitting, we resized our chest X-ray images into 224 x 224, putting into consideration our proposed model ResNet-50 input size. The proposed labeled dataset suffers from class imbalance and is also small; hence, we applied data augmentation for the training set. It increases the robustness of the model by creating many versions from one image, which increases the variety of visual features for the model. This resolves class imbalance, overfitting and insufficient data to train the deep learning model. We treated the COVID-QU-Ex dataset as the unlabeled set to increase the training data. After the split, the dataset summary, which consists of the labeled and unlabeled set, is shown in TABLE I.

TABLE I. Data distribution summary

Dataset	**labeled**		**unlabeled**
Classes	**Train**	**Validation**	**Train**
Covid-19	2892	724	11956
Healthy	8153	2039	10701
Viral	1076	269	11263
Opacity	4809	1203	

C. *FlexMatch Algorithm*

Semi-supervised learning is a machine learning technique that takes the middle ground between supervised and unsupervised learning by combining both labeled and unlabeled data [19]. The unlabeled data will be driven from a similar distribution as the labeled data. The method is adopted to solve the issue of the need for medical datasets with labels since labeled data is expensive and hard to obtain (requires experts or special devices). In this work, we use the FlexMatch method, which is a combination of the FixMatch [20], and the Curriculum Pseudo Labeling (CPL) [21] method, to perform pseudo-labeling.

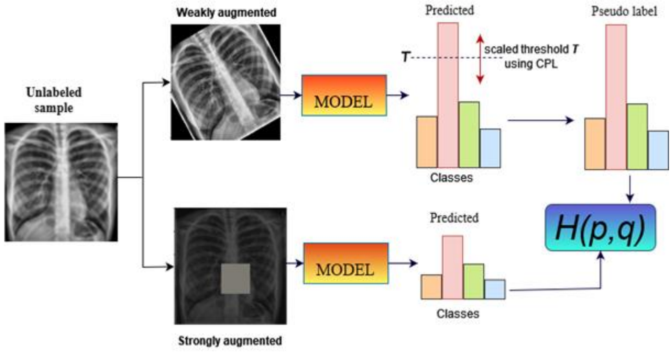

Fig. 3. FlexMatch framework

- *FixMatch*

In FixMatch, two techniques, consistency regularization, and pseudo-labeling, are used to generate artificial labels, making it possible to utilize unlabeled data. This paper deals with a classification problem; hence on the proposed method, for the supervised learning part, the ResNet-50 model is trained on the labeled data using a cross-entropy loss, and the result is a partially trained model. The average of the cross-entropy loss for each labeled image in an assigned batch is used to calculate the supervised total loss for a batch.

On the unlabeled data, two types of augmentations: “strong” and “weak,” are applied to each image resulting in two different versions of the same image. Weak augmentation is performed using techniques such as random flip and cropping. In contrast, strong augmentation involves argumentation techniques such as RandAugment and Cutout, which add noise to an image to reduce overfitting and improve the model performance.

First, the weakly-augmented samples are presented to the model, which outputs predictions. The predicted class with the probability above a predefined fixed threshold is converted to a one-hot pseudo label. Then to capture the essence of

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consistency regularization, the output of the strongly-augmented image is compared to the computed pseudo label to obtain the cross-entropy loss, thus obtaining the total batch loss of unlabeled data. The computed two losses obtained from labeled and unlabeled data are combined to obtain the total loss that will be optimized to improve the model.

However, the method does not consider the difference in learning difficulties of each class as it handles them equally, which results in only high-quality unlabeled data being fed to the model for training while ignoring the vast amount of the remaining data with prediction confidence below the assigned threshold.

- *Curriculum Pseudo Labeling*

To address the stated limitations of the FixMatch algorithm, Curriculum Pseudo Labeling (CPL) is applied directly to FixMatch, resulting in an improved algorithm called FlexMatch [22]. CPL considers each class's learning status by flexibly adjusting each class's thresholds based on their classification difficulty at each time step. The method significantly boosts the convergence speed and improves the model's performance.

The central assumption of the technique is that it considers the learning effect of a class based on the predicted number of samples belonging to that particular class whose prediction is above the threshold. The estimated learning effect is a count of samples; thus, its size varies according to the number of samples in the dataset. Hence there is a need to normalize it to a range of 0 to 1, making it possible to scale the fixed threshold. The normalization approach is characterized by the idea that the best class learns to have a learning effect of equal to 1. The probability threshold is lowered for classes that are difficult to learn, and it's adjusted higher for classes that are easier to learn, which in turn helps to improve the data utilization ratio as compared to having a fixed threshold. A non-linear mapping function is added to the fixed threshold to add sensitivity, which ensures that in the initial stages of training, all the estimated learning effects constantly rise from 0 until all the unselected data is no longer dominant. The obtained scaled threshold after adjustments is used for calculating the unsupervised loss.

The final loss is the weighted sum of the supervised and unsupervised losses with an added hyperparameter to scale the unsupervised loss. The obtained total loss will be optimized during training to improve the model for classifying our chest X-ray images.

D. *Classification*

This paper proposes a multi-class classification problem for classifying Covid-19, healthy lungs, viral pneumonia, and other lung opacity. We use the ResNet-50 as the backbone model whereby we fine-tuned the last layer to make our classifier network with four units representing the number of classes in our dataset. The model was selected because it is small in size and simple at the same time, able to produce state-of-the-art results. The model can also tackle the mentioned problem in very deep neural networks of vanishing gradients since it uses skip connections. We obtain the prediction classes in the output layer. The network transmits the data, and the prediction error is determined. The system then propagates the error to enhance the prediction. A softmax activation function was added on the last layer to normalize the output. Because softmax activation spreads the probability distribution throughout all output nodes, we employ it with the cross-entropy loss. The classifier is assisted in making the right choice by the hidden distribution of information acquired from the model, leading to increased generalization and accuracy.

IV. IMPLEMENTATION

In this section, we introduce our hyper-parameters and experiment design. The ResNet-50 architecture is utilized for feature extraction as we train it from end to end after fine-tuning. Standard stochastic gradient descent (SGD) with a momentum of 0.9 serves as the optimizer for our experiment. We employ a cosine learning rate decay schedule to an initial learning rate of 0.03 for our dataset. We set the total number of training steps to 500000, and the model will be evaluated on every 5000 distinct iterations in which the best model will be saved during training. Our suggested network can be trained entirely, from the beginning to the end, using SGD in conjunction with backpropagation. During the training process, we also employ an exponential moving average with a momentum of 0.999. The batch size was set to 32, and despite the fact that smaller batches are often noisier, this choice was made since they contribute to the formation of a regularization effect and lower the generalization error. We used five different assessment measures to evaluate the classification performance of the approach that was suggested in this research. These metrics are as follows: Accuracy, Precision, Recall, AUC (Area Under Curve), and F1-score. We used the PyTorch framework to build our model, which we trained on a GPU.

V. RESULTS

In this section, we describe our experimental results for the proposed approach of Covid-19 detection from chest X-ray images. We present the detailed results of the model's performance and demonstrate the effectiveness of our proposed approach by comparing it with other existing methods.

A. *Model Performance*

Regarding the results of training loss, Fig. 2 shows the total loss on labeled and unlabeled data using the FlexMatch method on our dataset. The deep learning method aims to find the best possible way to minimize a loss function. This loss function assesses the amount the prediction deviates from the ground truth provided.

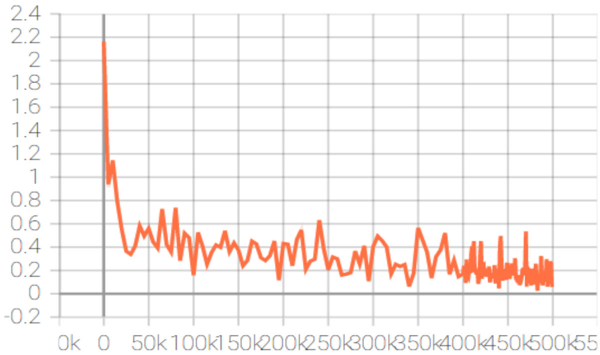

Fig. 2. Total training loss

The overall model's effectiveness was evaluated on the evaluation set, as shown in Fig. 3. Using 489000 iterations, the best accuracy of 94.14 was achieved, and the model was saved; more iterations did not improve accuracy.

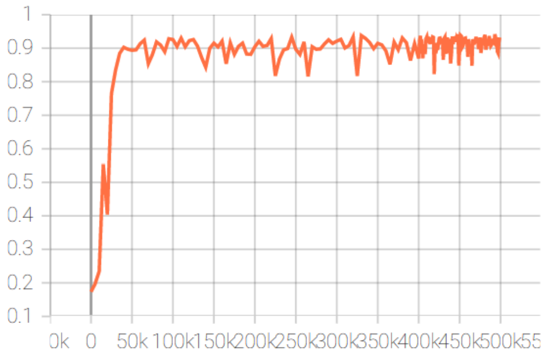

Fig. 3. Evaluation accuracy

The confusion matrix in **Error! Reference source not found.** demonstrates that the proposed approach greatly lowers the error of model judgments and enhances the model's accuracy for the Covid-19 diagnostic.

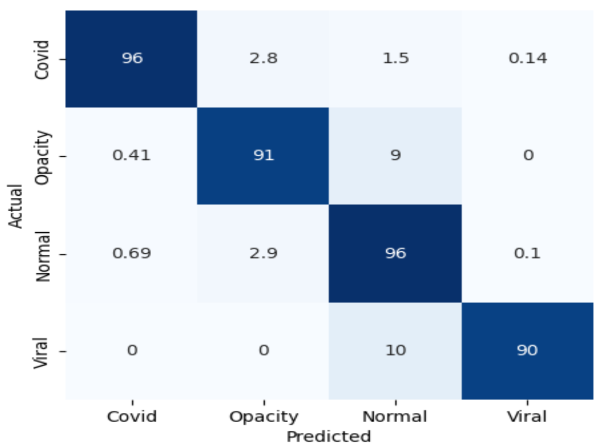

Fig. 6. Confusion matrix

B. *Comparison with Other Methods*

TABLE II compares our approach and other multi-class COVID-19 detection approaches. The effectiveness of our model can be inferred from the table in which it dominates in terms of its AUC, Recall, Precision, and F1-score though its Accuracy is slightly surpassed by the results obtained in [12] and [13].

TABLE II. Performance comparison with other models

Study	Class	Precision	Recall	F1	Accuracy	AUC
[6]	3	89.96	85.35	87.37	87.02	-
[12]	4	-	90	-	95.7	97
[10]	4	-	-	-	89.6	-
[13]	3	-	-	-	**98.5**	95
[11]	3	88.5	90.3	89.4	89.6	90.7
	4	90.8	89.9	90.4	90.2	91.1
[9]	3	-	92.85	-	93.48	-
Ours	**4**	**95.59**	**93.11**	**94.28**	94.14	**99.09**

C. *Class-wise Performance*

Since the main intention of the study is to detect Covid-19 from chest X-ray images, we evaluate the class-wise performance of the proposed approach for the Covid-19 class. Using the multi-class classification confusion matrix of the FlexMatch result, we converted it into a binary classification confusion matrix as presented in **Error! Reference source not found.**, using the Covid-19 class versus the non-Covid-19 class (combination of all the other classes) to capture the notion of True positives and True Negatives. For the Covid-19 class-wise evaluation performance, we achieved an accuracy of 98.62, precision of 95.62, recall of 98.87, and F-score of 97.21. We performed a comparative study with other proposed state-of-the-art methods on Covid-19 detection that also independently evaluated the class-wise performance of their approaches on the Covid-19 class. This was done to show the effectiveness of our proposed approach. Based on the results shown in TABLE III, we can conclude that our model performed better than other methods.

TABLE III. Class-wise comparison

Study	Model	Precision	Recall	F1	Acc
[10]	CoroNet	93.17	98.25	95.61	-
[13]	DCGAN	96	95	-	96.8
[6]	DarkCovidNet	**97.97**	90.65	94.07	98.07
Ours	**ResNet50+SSL**	95.62	**98.87**	**97.21**	**98.62**

VI. CONCLUSION

Our work is focused on a semi-supervised learning approach on chest X-ray images for covid-19 detection. To develop a state-of-the-art model that can classify Covid-19 images accurately in a real clinical setting, there is a need to consider the quality and verified sources that represent clinical data as well as the involvement of radiologists in the dataset creation process. A novel automated detection has been introduced by proposing a framework based on a semi-supervised learning approach that uses the FlexMatch algorithm and Resnet-50 as its backbone model on the proposed dataset. We addressed issues related to data bias by proposing the use of two datasets. Then for the limited data, we followed the FlexMatch rules that ensure better utilization of unlabeled data during pseudo-labeling. We experiment on an independent chest X-ray dataset containing covid-19 images along with other classes to evaluate the feasibility of our method. This research proved that the proposed method could accurately diagnose whether chest X-ray images belong to the positive or negative diagnoses of COVID-19, and can help doctors diagnose rapidly in the early stages of a COVID-19 outbreak. Future work will be aimed at reducing the model size and providing a visible result interpretation that highlights areas of infection on chest X-rays to help doctors clearly understand the diagnosis results.

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