CoV-TI-Net: Transferred Initialization with Modified End Layer for COVID-19 Diagnosis

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Abstract—This paper proposes transferred initialization with modified fully connected layers for COVID-19 diagnosis. Convolutional neural networks (CNN) achieved a remarkable result in image classification. However, training a high-performing model is a very complicated and time-consuming process because of the complexity of image recognition applications. On the other hand, transfer learning is a relatively new learning method that has been employed in many sectors to achieve good performance with fewer computations. In this research, the PyTorch pre-trained models (VGG19_bn and WideResNet -101) are applied in the MNIST dataset for the first time as initialization and with modified fully connected layers. The employed PyTorch pre-trained models were previously trained in ImageNet. The proposed model is developed and verified in the Kaggle notebook, and it reached the outstanding accuracy of 99.77% without taking a huge computational time during the training process of the model. We also applied the same methodology to the SIM-FISABIO-RSNA COVID-19 Detection dataset and achieved 80.01% accuracy. In contrast, the previous methods need a huge computational time during the training process to reach a high-performing model. Codes are available at the following link: github.com/dipuk0506/SpinalNet

Index Terms—Transfer learning, MNIST, COVID, VGG, PyTorch, WideResNet, SpinalNet.

I. INTRODUCTION

The classification and categorization of the complex data including text, image, video, and document are great challenges in science-related sectors because it depends on various components [1]–[3]. Deep learning architecture such as deep neural network (DNN), conventional neural network (CNN), and recurrent neural network (RNN) are recently applied in classification to address this challenging issue [4]–[6]. The supervised learning-based model is used for classification to practically label the data. Naïve Bayes Classifier (NBC) is a simple technique in a supervised learning-based classification problem that is proposed by Rish [7] and Murphy [8]. It has been used in information retrieval and text recognition applications. NBC normally employs a bunch of words for feature extraction, then the order of the sequence cannot be reported on the results. Support Vector Machines (SVM) [9], [10] is a quite popular classifier that has been used in dealing with a wide range of data. Yu and Joachims [11] proposed a new SVM structure using a latent variable to increase the performance of the model in three main sectors, including coreference resolution, motif-finding, and optimization. Tong et al. [12] introduce a new approach by combining SVM and active learning. SVM has an extreme computational load during the training process that reduces the applicability of the model. Kabir et al. [13] proposed the Stochastic Gradient Descent (SGD) classifier to reduce the computational burden of the system. CireAan et al. [14] proposed the multi-column DNN for classification purposes. Jindal et al. [15] proposed an efficient text classification model via a nonlinear processing layer during the training process. Krizhevsky et al. [16] employed 2-dimensional conventional layers with the addition of 2-dimensional space features of the image for classification purposes. Also, Hassan [17] used CNN in text classification with the ability to reach convincing accuracy. RNN is employed in language processing and document classification applications by Mikolov [18] and Yang et al. [19], respectively. SpinalNet architecture is a powerful classifier that is inspired via the biological network of the human spine [2], [20], which is proposed by Kabir et al. [2]. The Spinal structure has achieved state-of-the-art (SOTA) performance in several handwritten digit datasets.

The idea of transfer learning is used to ease the complicated training process of the deep learning method. It used a strong knowledge of the main problem and applied it to a bit differently related topics [21]–[24]. The transformation of the knowledge from the previous task improves the performance of the new task. Transfer learning is used in different fields such as entertainment [25], image processing [26], filtering [27], and etc. Transfer learning by freezing weights of initial layers often directs optimization to a local minimum. Transfer learning without freezing weight is similar to traditional learning [28]. Only the initial weights are transferred. Multiple
training with transferred initialization can potentially lead the optimization to the global minima.

Contributions of this paper are as follows:

1) Applying transferred initialization for handwritten digit classification.
2) We apply Spinal fully connected layer with the random initialization, and transfer learned weights of initial layers.
3) Compared transferred initialization with transfer learning, and results indicate superior performance.
4) We also discuss transfer learning, data augmentation, and SpinalNet structure.

The rest of the paper is organized as follows. Section II presents several closely related works. Section III presents theoretical details. This section presents the dataset, augmentation, training, SpinalNet, performance parameters. Section IV presents the result. Section V is the concluding section.

II. RELATED WORKS

There exist numerous works in both deep learning-based COVID-19 diagnosis. COVID-19 was first identified as an outbreak in December 2019. Most of the datasets and competitions related to COVID-19 is published since 2020. Papers in early stages of COVID-19 has received tremendous attentions and citations. Most of the deep learning based COVID-19 diagnosis takes X-ray images as inputs. Diagnosis from X-ray images has received great attention due to convenience. The conventional technique of taking samples from nose for COVID-19 diagnosis seems troublesome to many patients and health personals.

Several popular deep learning models has proposed for fine-tuned X-ray classification for the diagnosis of coronavirus disease. Several popular models are Covidx-net [29], CovidNet [30], COVIDiagnosis-Net [31], CoV2-Detect-Net [32], SpinalXNet [33], Covid-net cxr-s [34], Corona-net [35], etc.

Hemdan et al. has proposed Covidx-net [29]. Their proposed Covidx-net demonstrated seven different DNN architectures. All of those architectures are previously proposed, and very popular architectures. They applied those DNNs for coronavirus diagnosis.

Wang et al. proposed COVID-Net [30]. They customized a conventional DNN for COVID-19 and the pneumonia dataset. They did a rigorous performance analysis of their proposed DNN.

Ucar et al. proposed COVIDiagnosis-Net [31]. They demonstrated an ML-based novel structure that outperformed existing models of that time. They selected SqueezeNet and tuned for the coronavirus disease diagnosis with the Bayesian optimization.

Dixit et al. proposed CoV2-Detect-Net [32]. They have applied feature extraction and K-means clustering for pre-processing data. They also proposed a novel feature optimization technique relying on particle swarm optimization and a hybrid differential evolution algorithm. Finally, a support vector machine classifier distinguishes the samples. They applied their model to publicly available data.

Kumar et al. proposed SpinalXNet [33]. They applied transfer learning with a modified fully connected layer for classifying X-ray images. They modified the fully connected layed to a SpinalNet layer and achieved superior performance compared to the traditional counterpart.

Aboutalebi et al. proposed Covid-net cxr-s [34]. They have applied DNNs on chest X-ray (CXR) images. Their DNN was applied for predicting the airspace severity of a coronavirus-positive patient.

Elbishiawli proposed CORONA-Net [35] for COVID-19 diagnosis. Their proposed DNN was divided into two phases: (1) The reinitialization phase and (2) the classification phase. They also applied their proposed DNN on a publicly available dataset.

As different researchers have applied their proposed DNNs in different datasets, their performance is not comparable. We applied our proposed methodology on the dataset provided by Society for Imaging Informatics in Medicine (SIIM) [36]. They launched a competition while they made the dataset publicly available on mid 2021.

III. METHODOLOGY

The MNIST is one of the most popular datasets in image vision. The dataset contains grey-scale images. However, most of the transfer learning models are trained on RGB data. That might be a reason for the limited conducted studies on transfer learning-based hand-written digit recognition. Therefore, we show the transfer learning process in MNIST on a Kaggle notebook. A deep learning model provides a good result depending on several factors. Many datasets require special augmentation to get an eye-catching result. MNIST dataset requires several augmentations.

A. Dataset: MNIST

The MNIST dataset contains ten thousand test images and sixty thousand training images. Images are in the grey-scale format with 28x28 pixel dimensions. There are ten classes of images starting from 0 to 9. Fig. 1 presents the several samples in MNIST dataset.

As the original MNIST dataset has training and test sets, we split the training data into training and validation subsets to avoid overfitting. We keep 90% of the data in the training set, and we move 10% of the data into the validation set.

B. Dataset: COVID-19 Detection

The Dataset was provided by Society for Imaging Informatics in Medicine (SIIM) [36]. The images were in digital imaging and communications in medicine (DICOM) format. There exist 6334 samples in this dataset. First, we convert DICOM images to RGB images of 512×512 size. Red, Green, and Blue components present magnitude, edge magnitude, and edge angle of DICOM images.
C. Data Augmentation

Most of the PyTorch transfer learning models are pre-trained on $224 \times 224$ sized images [37]. However, the MNIST data contains $28 \times 28$ sized images. Moreover, further augmentations create fewer noises while the image size is larger. We tested several resizing options in our local computers, and $112 \times 112$ is found to be an optimal size for the MNIST dataset. Initially, we also perform random rotation and random perspective to augment the data. The data augmentation varies randomly for different images. As a result, the NN training becomes more robust, and the NN becomes prepared for slightly different test images.

To augment train images of COVID-19 dataset we did a center crop of $470 \times 470$ size. We performed random rotations of ten degrees. We also applied random perspective, random horizontal flip, and random greyscale functions of the PyTorch library. Finally, we did a center crop of $448 \times 448$ size. We did not augment validation and test images. We resized them to $448 \times 448$ size.

D. SpinalNet

The observation of the human spinal cord reached the development of the SpinalNet by Kabir et al. [?]. The SpinalNet is the powerful classifier method that imitates the duty of the human spinal cord. It receives the inputs gradually, similar to the spinal cord. Also, it sends the processed input data to the global output. It tunes the weight parameters of the network during the training process of the network. Fig. 3 shows the schematic structure of the SpinalNet. The network consists of the input rows, multiple hidden layers in the row and the row of outputs. The input of every layer is the input of the previous layer to decrease the number of multiplications without making an underfitting issue. Based on Fig. 3, the input is divided into two rows to be imported to different hidden layers, respectively.

E. Transfer Learning

In real life, the human brain gathers experiences through education and many events. Later humans use the learned skills and strategies for accomplishing a new task [?] by seeing a few examples on that task. Then, it is worth mentioning that the transfer is an integral part of the learning process. In this study, the transfer learning technique is applied for training the network to recognize the hand-writing. There are two main issues with applying this method. Initially, the training process
of the hand-writing using deep learning techniques needs a massive amount of data which is not always available for the home user researchers. Secondly, the computational load of the training process is very expensive and time-consuming. While using transfer learning, the computational load and training time decreases. Then, the model can be run in a shared server in a short period.

The model is designed and developed using VGG19_bn and WideResNet-101 as the base models [7], which are two of the best models in the ImageNet dataset for classifying the data. Fig. 4a-b shows the structure of the proposed transfer learning-based method hand-writing detection using based models including VGG19 and WideResNet-101, respectively. There is a similarity between classifying the image data and handwriting recognition. It should be noted that the employed base model has been trained using a massive amount of data with many layers and millions of trainable indexes. These indexes and layers are kept constant during the training process of the proposed method. The front line of the proposed transfer learning-based model is fed with the handwriting images of the number from 0-9. The SpinalNet is employed in the last layer of a VGG network, which resulted in less trainable parameters to classify the hand-writing characters, and this is explained in the next subsection.

F. Performance Matrices

Popular performance matrices are overall accuracy, cross-entropy loss, confusion matrix, precision, recall, and F1 score. The overall accuracy of test data is the ratio between correctly predicted samples and the total number of samples [38]–[40]. A confusion matrix is a graphical view that represents which classes are frequently wronged by the model. Also, the confusion matrix shows the wrongly predicted class.

The precision of Class-X is the ratio between the number of samples the model predicts correctly as Class-X and the total number of samples the model predicts as Class-X. The recall of Class-X is the ratio between the number of samples the model predicts correctly as Class-X and the total number of samples labeled as Class-X. F1 score is the harmonic mean of recall and precision [41], [42].

IV. RESULTS AND DISCUSSIONS

In this section, the proposed model in Section II is verified and validated in simulation environment, and the results are provided to prove the significant of the proposed method. We download images and pre-trained models with the help of the PyTorch command. Also, we apply a popular PyTorch transfer learning code to train the network. In the code, we first write data loader functions with relevant transformations. We observe augmented images before the training. We declare SpinalNet with a layer width of 1024 while using VGG19_bn. We declare SpinalNet with a layer width of 20 while using WideResNet-101. The number output is equal to the number of classes. The MNIST dataset has ten classes.

We train the NN in two stages. The initial training has a learning rate of 0.01. We apply ‘SGD’ as an optimizer, ‘lr_scheduler’ as the scheduler, and ‘CrossEntropyLoss’ criterion. The momentum of SGD is set to 0.9. Step size and the multiplicative factor ‘gamma’ are set to 7 and 0.1, respectively. The initial training takes ten epochs. The final training is training with a lower learning rate (0.001). Values of other parameters remain the same as the values obtained from initial training. It should be noted that the proposed methods using the transfer learning technique are coded and implemented in the Kaggle notebook, which is available to be reviewed in the Kaggle notebook.

Table I and Table II present the results using VGG19_bn and WideResNet-101 as a base model with the implementation of traditional and spinal end layers. The average accuracy of the proposed method using VGG19_bn improved 0.17% and 0.04% as compared with those of WideResNet-101 using traditional and spinal end layers as classifiers, respectively. Also, the top accuracy of the proposed method using VGG19_bn improved 0.12% and 0.04% as compared with those of WideResNet-101 using traditional and spinal end layers as classifiers, respectively. It proves the efficiency of the VGG19_bn compared with WideResNet-101 as a base model using the transfer learning technique. Moreover, SpinalNet is able to increase the average accuracy of the model by 0.01% and 0.14% compared with the traditional end layer using VGG19_bn and WideResNet-101, respectively. Also, the top accuracy value increases 0.01% and 0.09% using SpinalNet as compared with those of the traditional end layer using VGG19_bn and WideResNet-101 as a base model, respectively.

Transfer learning(TL) keeps good accuracy on average but transfer initialization (TI) brings better top accuracy. If someone tries about 5 times with both TL and TI, a model with TI will likely give the best accuracy. TL may bring the optimization to a local minimum where TI has a chance of getting the global minima. We achieved both higher top accuracy and average accuracy for the COVID-19 dataset using TI.

Fig. 5 shows the training and validation accuracy of the proposed transfer learning method on the MNIST dataset, including WideResNet-101 as a base model and SpinalNet as a classifier for 20 epochs. The training accuracy at the first epoch was 96% which is increased to reach about 99.8% at the twentieth epoch. Also, the validation accuracy of the WideResNet-101 base model using the SpinalNet classifier was 99.4% at the first epoch, which increases to 99.71% at the twentieth epoch.

Confusion matrix in multiclass classification helps future researchers in understanding the uncertainties in data and models. One AI model may provide good overall accuracy, but the user of the model may not know that where the model might fail. Also, while people are writing digits, they have vibrations in their hands. One person may write f (4), and another person may recognize it as (9). There exist uncertainty and variance in human brains too. Seeing the confusion matrix
of a NN in a dataset, one can understand the strength and weaknesses of the models in different input domains. Seeing the confusion matrix of different NN on the dataset, one can understand closely related classes where NNs may fail. Fig. 6 illustrates the sample confusion matrix of the prediction with VGG19_bn Spinal FC. Based on the presented results, it is obvious that the accuracy of the presented network is 99.74%. It was able to predict the 9974 true results out of ten thousand test samples. In other words, the error rate of the mentioned network is 0.26%. Fig. 6 reveals the sensitivity of the VGG19_bn Spinal FC for different classes. For instance, the recall of the recently developed algorithm for 0, 4, 7, and 9 are 99.80%, 99.80%, 99.71%, and 99.70%, respectively. In addition, the precision of the different classes such as 0, 4, 7, and 9 are 99.90%, 99.49%, 99.71%, and 99.70%, respectively. It should be noted that precision is used to show the true prediction rate of the network for different classes. Lastly, the prevalence of the different classes can be calculated based on the presented results in Fig. 6. It shows the occurrence chance of each class in every trial.

It should be noted that reachable accuracy using the transfer learning method with two base models and two classifiers is reasonable, while the high-tech deep learning methods using complicated structures are able to reach an accuracy of more than 99.79% [43]–[48]. The developed codes are available on the Kaggle server with execution details. According to the obtained results of this research, transfer learning using the SpinalNet classifier can be improved more in terms of accuracy while the computational load is decreased.

Table III presents the performance of trained NNs for individual classes. Columns in this table represent class, true positive (TP), false positive (FP), false negative (FN), precision, recall, and F1 score values. The model performs well for
classes 0, 1, and 8. The model performs comparatively poorly for class 4 and class 5. When people write 0, they write clearly. When people write 4, they write in different ways often the model gets confused between 4, 5, 9, and 3, while recognizing handwritten digits.

V. Conclusion

The purpose of this research is to present a novel transfer learning code on the MNIST dataset to solve the issues associated with the recognition of handwriting for numbers from 0 to 9. Most transfer learning models in Torch-vision are designed for RGB images. However, they are easily implementable in the MNIST data. The existing hand-writing proposed deep learning models are very expensive in point of computational perspective. It is not possible to develop a highly accurate model (more than 99.60% accuracy) without using complicated networks with huge computational time during the training process. In this research, the PyTorch pre-trained models (VGG19_bn and WideResNet-101) are applied in the MNIST dataset for the first time to maintain the accuracy while reducing the computational load to recognize the handwriting. We split the training set into train and validation subsets to avoid overfitting the models. The proposed method is developed and validated in the Kaggle notebook, and the results prove the accuracy of 99.77% without causing any high computational time during the training process of the network. We applied that optimized training process for COVID-19 detection. Moreover, researchers can use the proposed approach and apply it to different datasets aiming to obtain good performance while not causing high computational load and training process.

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