ORIGINAL ARTICLE

Using Transfer Learning Approach for Down Syndrome Features Extraction and Data Augmentation for Data Expansion

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Received: 11 September 2023 / Accepted: 19 August 2024

Abstract

Purpose: People with Down Syndrome must be served specially because they have an intellectual disability with abnormality in memory and learning, so creating a model for DS recognition may provide safe services to them, using the transfer learning technique can improve high metrics with a small dataset, depending on previous knowledge, there is no available Down syndrome dataset, one can use to train.

Materials and Methods: A new dataset is created by gathering images, two classes (Down=209 images, non-Down=214 images), and then expanding this dataset using Augmentation to create the final dataset of 892 images (Down=415 images, Non-Down=477 images). Finally, using a suitable training model, in this work, Xception and Resnet models are used, and the pre-trained models are trained on Imagenet dataset, which consists of (1000) classes.

Results: By using the Xception model and the Resnet model, it is concluded that when using the Resnet model the accuracy is 95.93% and the loss function is 0.16, while by using the Xception model, the accuracy is 96.57% and the loss function is 0.12.

Conclusion: Transfer learning is used to overcome the suitability of dataset size and minimize the cost of training, and time processing the accuracy and loss function is good when using the Xception model, in addition, the Xception metrics are the best compared with the previous studies.

Keywords: Transfer Learning; Down Syndrome; Xception.

DOI: https://doi.org/10.18502/fbt.v13i1.20785

1. Introduction

Rapidly increasing development of technology, makes life management easy to control and more safe and reliable, one of these technologies is machine learning, which uses computers to think like humans. Deep learning is the common technique of machine learning. Transfer learning is a new technique of using previous knowledge of past training models [1]. There are many applications of transfer learning like object recognition [2, 3], military recognition [4], fingerprint recognition [5], bioinformatics [6, 7], robotics [8, 9], and automotive car [10] and so on.

Using transfer learning for exploring diseases is the trend these days, like Alzheimer's [11], Covid-19 [12], Tumor detection [13], and Down syndrome. Down syndrome is the most common chromosomal syndrome in humans and the common genetic reason of intellectual disability and delay of development [14-16]. The parents of Down syndrome son are normal. This syndrome increases in pregnant in 45 years old. Some children with Down syndrome can be educated in a typical school, while others need special school [17].

Many researchers focused on using transfer learning in Down syndrome detection. Bo Jin *et al.* [18] studied facial disease classification using deep residual learning. This work was based on using a dataset consisting of multiple classes (hyperthyroidism, beta thalassemia, Down syndrome, and leprosy). This dataset is small so they used transfer learning to enhance the training. they used 8 models as traditional learning (without using transfer learning) and 6 models (using transfer learning), but our work improves better accuracy than the best in the two ways [18] as denotes in the table of comparison.

Bing Feng *et al.* [19] used a Convolutional Neural Network (CNN) to predict the occurrence of Down syndrome. They used nine layers convolved to create a bi-stream CNN, and they merged a couple of models in the fourth layer. They used the genotyping dataset and got good results, but the availability of chromosome map may be a complex way to depend.

In [20] Jesús Moreno and *et al.*, used two models of CNN to recognize the emotion of Down syndrome babies, they also used an Electroencephalogram (EEG) signal in CNN, while Mary and Sridhar [21] studied using CNN for Down syndrome classification. They used Visual Geometry Group (VGG16) model and the used transfer learning the Alexnet model and got 91% accuracy. In [22] authors also used CNN for Down syndrome classification using mini Xception. The gained accuracy was 91.48%. Authors in [23] used CNN to classify the Down syndrome using CNN. The accuracy results the gained wan 95.87%. In [24], authors used CNN and face recognition for Down syndrome, the best accuracy they got was 91%.

2. Materials and Methods

It is an essential technique used to enhance the model performance. It consists of source domain (Ds), which refers to the pre-trained model with a huge dataset that is trained and calculated the weights. Then these weights can be reused in another model, this another model is called a target domain (Dt), where Ds ≠ Dt [13].

The procedure on the left of Figure 1 refers to a traditional machine learning procedure. The procedure on the right corresponds to a transfer learning procedure. Transfer learning allows reuse of the weights knowledge in the Ds as input to the Dt. This transferring leads to a reduction in the cost of processing [25].

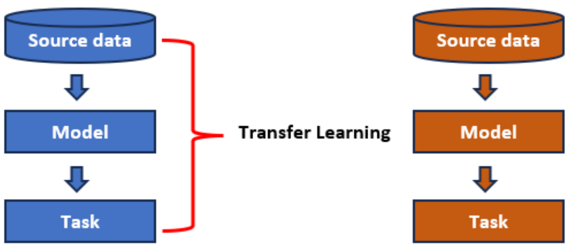

Figure 1. The transfer learning strategy

2.1. Medical Knowledge

It is also known as a trisomy genetic condition. It is a popular chromosomal state related to intellectual disability. There are three types of this syndrome (Trisomy 21, Mosaicism, and Translocation). Trisomy 21 is considered when an extra copy of chromosome 21 is created inside cells, causing 47 chromosomes instead of 46. This is done by failed division of the egg. It constitutes a ratio for 95% of cases. Mosaicism (or mosaic Down syndrome) is caused when there are two types of cells, some containing 46 chromosomes and others containing 47. These chromosomes with 47 contain an extra copy of chromosome 21. This case accounts for 2% of cases. Translocation is the last type of Down syndrome that is caused when the number of chromosomes is 46, but a full or partial part of Chromosome 21 is attached to another chromosome (usually 14). This type accounts for 3% of cases [26]. It is termed by John Langdon Down, the British physician who defined the case first in 1866 [27]. Most persons with DS have remembrance and teaching problems, craniofacial changes, and muscle hypotonia; however, only some have heart problems, leukemia, or abnormalities [28].

2.2. Physical Features of DS

Physical features of DS are typically discovered at birth and are more seeming with growth [29]:

- A flattened nose bridge.
- Almond eyes that point upward.
- A short neck.
- Small ear.
- Short hand and foot.
- Weak muscle.
- Big toe.
- Small pink fingers
- Single crease in the palm [29].

2.3. Methodology

Figure 2 below shows the methodology of this work. The first step is preparing the dataset, despite, there is no dataset that an individual can download and use. A new dataset is created and prepared to be used in this work. This dataset has a binary classification (Down and Non-Down). it is described in details in section “Dataset” below, the total numbers of images in this dataset are 423 images. So expansion of this dataset is required to enlarge the number of images. The big dataset helps to enhance the training metrics. The dataset is still not as big as possible. For this reason, Transfer Learning is used. This technique is used when the dataset is not enough to train. This trick helps this work to produce very satisfied matrices. The transferred learning is transferred from the object recognition model using the ImageNet dataset to make the new model able to recognize the human face, and then using the new dataset in transferred weights and finally calculate the accuracy and loss function.

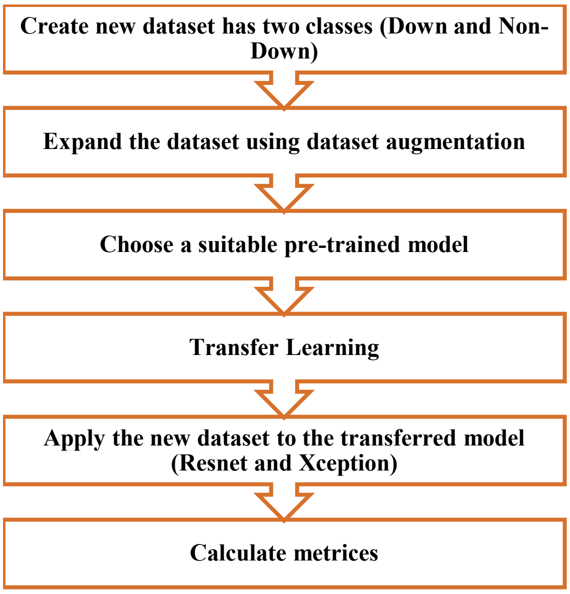

Figure 2. The flow process of the methodology of this work

2.3.1. Dataset

Unfortunately, no dataset of Down syndrome recognition or classification is available; however, the past works that focused on Down syndrome classification depended on gathering datasets and these datasets are not available online. Table 1 shows some of the dependent datasets.

Therefore, the dataset is gathered manually from Google image search. It consists of two classes (Non-Down and Down). The Non-Down class consists of

Table 1. A summary of existing research on Down syndrome datasets

Reference	Down	Non-Down	Total
[30]	24	24	48
[31]	50	50	100
[32]	50	80	130

Table 2. New dataset statistics with and without Augmentation

New Dataset	Down	Non-Down	Total
Without Augmentation	209	214	423
With Augmentation	415	477	892

209 images while the Down class consists of 214 images. The data set is available call for it by email. This dataset is expanded using data augmentation. The final Non-Down images are =415 and the Down images are= 477. Table 2 below shows the statistics of new dataset.

2.3.2. Augmentation

Data augmentation is a popular technique that is used when the dataset is not as big as possible [33]; therefore, by using the augmentation strategy it can be expanded. Some operations are applied to images to create a new one, like (rotation by different angles, flipping, cropping, etc.). This expansion on images increases the performance of training [34].

Algorithm 1 below denotes the process of data augmentation

Algorithm 1: Data Augmentation

Step1: Read Image I.
Step2: For each I

(Rotate,
Resize,
Shift width,
Shift right,
Shear,
Flip)

Step3: Save each modified I as Ii where i is an index (i=0,1,2,3,...)

2.3.3. Transfer Learning

Transfer learning is used to improve the output matrices in deep learning models, especially if the dataset is not as huge as needed. Figure 3 below denotes how an individual can use the weights that get from training a model on a huge dataset like "Imagenet" dataset. This dataset is used for training large scale object recognition models. It can classify 1000 labels. This dataset is used with many models and saved to be ready when one wants to use it. If this dataset is used to be trained from scratch, it may take a long time to complete training; therefore, using the pre-trained model by pulling the weights and reusing them in a new model in addition to a new dataset.

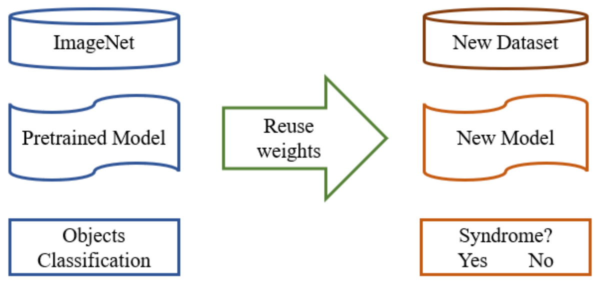

Figure 3. Transfer learning between Imagenet dataset and the new dataset (Down and Non-Down)

2.3.4. Resnet Model

It is a multilayer Convolutional Neural network CNN model. Each layer depends on the previous layer. It is used for computer vision application model. This network is trained by a backpropagation progression that depends on gradient descent, pull down the loss value and outcome the weights that minimize it [18].

2.3.5. Xception Model

It is a CNN model that consists of 71 layers deep. It is usually used as a pre-trained model on million images on the Imagenet dataset. The term "Xception" combines the terms "Extreme Inception," which describes the model's depth-wise separable convolutions and inception-like architecture, with "ception," signifying a development in the Inception architecture's design. This model makes use of an extended version of depth-wise separable convolutions in an attempt to improve efficiency and performance [32, 35].

3. Results

The model has been implemented using Python 3, and it has been applied to the collected Syndrome dataset using two different pre-trained models (Resnet Model and Xception Model). The accuracy and loss results are denoted by Figure 4 a, b, c, and d below, respectively:

Figure 4 (a and b) denotes the accuracy function for the Resnet and Xception models, respectively, and as denoted, the Xception mode archives better accuracy along the learning curve. Figure 4 (c and d) shows the

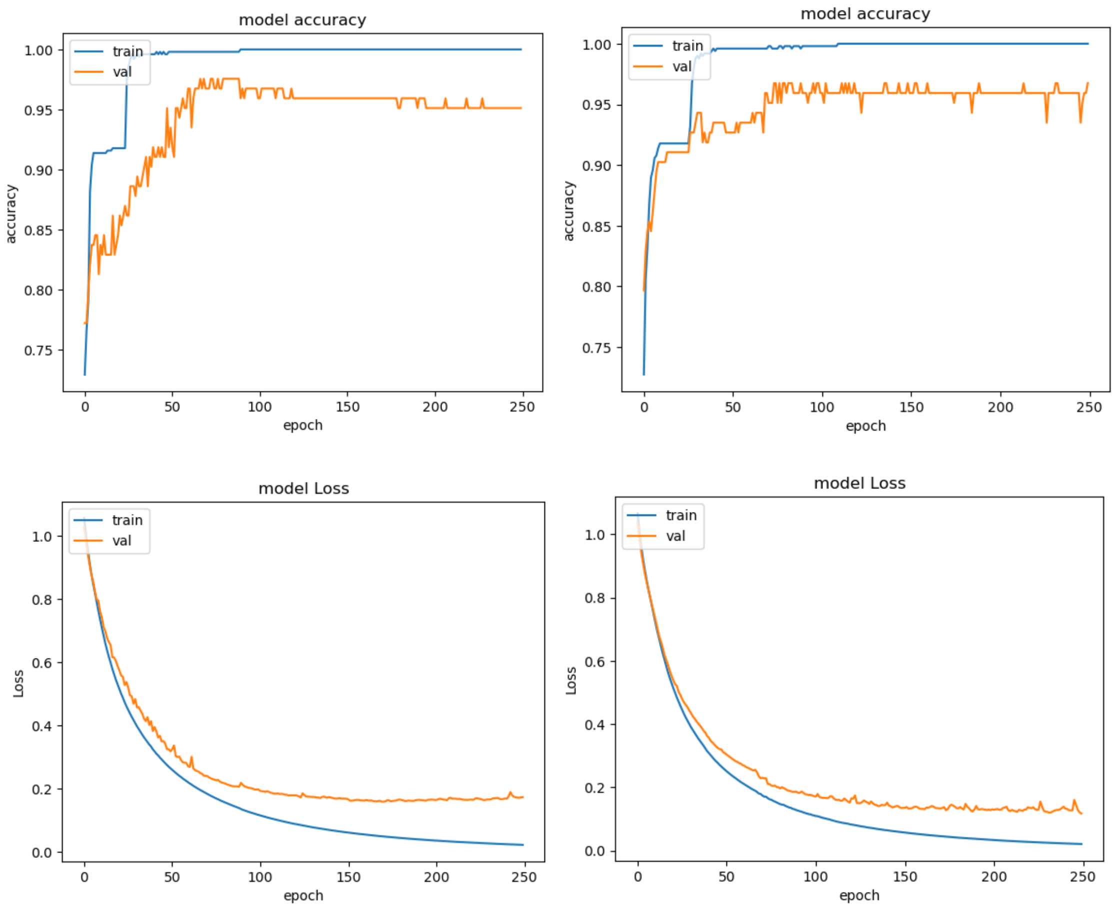

Figure 4. Suggested model results; a) Resnet accuracy function; b) Xception accuracy function; c) Resnet loss function; d) Xception loss function

loss function for the two models, and as observed, the loss function is lower in Xception than Resnet.

The results of validation accuracy for the Resnet Model and Xception Model, respectively, are as denoted in Table 3 below, by comparing with the previous studies, our model achieved the best results:

Table 3. A comparison of accuracy for exciting research and this work

Reference	Validation Accuracy	Transfer Learning
[18] Best result in first method	93.3%	**Yes**
[18] Best result in second method	95.%	**Yes**
[21]	91%	Non
[22]	91.48%	Non
[23]	95.87%	Non
[24]	91%	Non
[32]	96.5%	Non
Suggested Method (1)	95.93%	**Yes**
Suggested Method (2)	**96.57%**	**Yes**

4. Conclusion

People with DS must be served specially because they have an intellectual disability with abnormality in memory and learning, so, creating a model for DS recognition may provide safe services to them; therefore, many researchers are interested to be helpful in this problem. In this work, some difficulties are faced. First, there are no available datasets for DS, so, in this work, a new DS dataset is created, 432 images, and then expanded using data augmentation to 892 images. The created and expanded dataset is still not enough for good training; therefore, secondly, a transfer learning is used to overcome the suitability of dataset size and minimize the cost of training, and time processing. Thirdly, using a suitable training model and examining the effect of each one, in this work, the Resnet and Xceptions model are used. The accuracy is 95.93% and 96.57%, respectively, and the loss function is 0.16 and 0.12, as denotes, the accuracy and loss function are good when using the Xception model. In addition, the Xception metrics are the best comparing with the previous studies.

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