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BIG DATA CLUB

Project Proposal

FEDERATED LEARNING FOR SKIN CANCER DETECTION

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1 Abstract

In today's modern world, Skin cancer is the most common cause of death amongst humans. Skin cancer is abnormal growth of skin cells most often develops on the body exposed to the sunlight, but can occur anywhere on the body. Most skin cancers are curable at early stages. So an early and fast detection of skin cancer can save the patient's life. With the new technology, early detection of skin cancer is possible at the initial stage. These cancer cells are detected manually and it takes time to cure in most of the cases.

We have proposed a skin cancer detection system using federated learning for early detection of skin cancer disease. It is more advantageous to patients. The diagnosing methodology uses Image classification methods and Federated Learning algorithms. The dermoscopy image of skin cancer is taken and it goes under various pre-processing techniques for noise removal and image enhancement. It classifies the given image into Benign or Malignant.

2 Introduction

According to the WHO's statistics, the number of people will affected by the skin cancer will rise up to almost 13.1 millions by 2030. Skin cancer is a condition in which there is an abnormal growth of melanocytic cells in the skin. Skin cancer may appear as a malignant or benign form. Benign Melanoma is simply appearance of moles on skin. Malignant melanoma is the appearance of sores that cause bleeding. Malignant Melanoma is the deadliest form of all skin cancers. In fact, a person falls victim to Melanoma every 57 seconds [5].

As it is with every variety of cancer, early screening and detection of skin cancer is the most hopeful sign of making a full recovery. Early detection of skin cancer yields a ten year survival rate of 94%. However, this survival rate drops drastically as the cancer progresses and reaches the next stages. Ten year survival rates come to a meagre 15% in the case of Melanoma, when it is detected in the final stage [5]. However, early detection of skin cancer is an expensive affair. As skin lesions look quite similar to each other, it is difficult to determine whether a lesion is benign or malignant. Extensive analysis needs to be performed to identify the category of the lesion. Traditionally, an image using a special device, known as a dermatoscope, is taken to study the lesion closely. Unfortunately, dermatoscopes are expensive and not widely available with dermatologists.

One of the challenges of visual screening is the visual similarity between skin diseases. In the last few years, significant advancements have taken place in the domain of computer vision. With the advent of new algorithms, it has become possible to differentiate between clinically similar skin conditions. These algorithms do not require the images to be taken from special purpose devices, such as dermatoscopes, and can be applied on images obtained from general purpose cameras.

Honestly, a significant amount of research has been performed on this topic; multiple techniques, noninvasive in nature, are proposed. such as artificial neural networks (ANN), convolutional neural networks (CNN), Kohonen self-organizing neural networks (KNN), and generative adversarial neural networks (GAN) for skin cancer detection. However, deep learning models are data-intensive, i.e., they often require millions of training examples to learn effectively. Medical images may contain confidential and sensitive information about patients that often cannot be shared outside the institutions of their origin, especially when complete de-identification cannot be guaranteed. As a result, large archives of medical data from various consortia remain widely untapped sources of information. Without sufficient and diverse datasets, deep models trained on histopathology images from one hospital may fail to generalize well on data from a different hospital (out-of-distribution) [2][4] In this study, we explore federated learning (FL) as a collaborative learning paradigm, in which models can be trained across several institutions without explicitly sharing patient data and utilized to classify the cancer images into either malignant or benign melanoma.

3 Motivation

Skin cancer is an alarming issue and it must be detected as early as possible. The diagnostic is a manual process that is time consuming as well as expensive. But, today world science has become advanced by using deep learning and it can be helpful in many ways. Besides, the existence of bias or the lack of diversity in images from a single institution brings about the need for a collaborative approach which does not require data centralization. And. that is why deep learning specially Federated Learning is used to detect skin cancerous cells in our project proposal.

4 Goal and Main result

4.1 Goal

In this project, we want to solve the skin cancer diagnosis problem using a new approach that is capable of handling several criteria:

- First, it should a good model so that the cost and time required for the diagnosis will be less than the traditionally manual diagnosis;
- Second, while the model is built, we want that no patient's sensitive information will be recorded or collected, so that the patients' privacy won't be harmed;
- Finally, to achieve a model that is good enough to serve a variety range of patients, we want the ability to collaborate between institutions so that we can access as many clean data as possible.

4.2 Main result

After the completion of this project, we will obtain a model for skin cancer diagnosis - an application of our knowledge about Federated Learning and Deep Learning.

5 Background and Related works

5.1 Background

5.1.1 Federated Leaning (FL)

Healthcare data is highly sensitive and access or exploitation is strongly prohibited by legislation. Data therefore can't be shared across healthcare institutions. With conventional Machine Learning algorithms, models can only be trained on local data from one healthcare institution. As a result, the model's predictions tend to be biased towards a certain demographic and potentially overlook cases of rare disease. This is where Federated Learning comes into the picture, with the promise of training a centralised model based on decentralised data.

In general, **Federated Learning** (FL) is a ML algorithmic framework that allows multiple parties to perform ML under the requirements of privacy protection, data security, and regulations [10]. In FL architecture, model construction includes two processes: model training and model inference [7].

The way FL is defined implies a certain level of security as the parties don't have to share their local data. This sounds really promising as with FL, data islands once kept locked up can finally be exploited to build high quality machine learning models without raising privacy concerns.

The parties here can be corporations, healthcare institutions, or mobile users. The participants don't necessarily have to be collaborators, they can be opponents who wish to have a well-performing model that can helps with business decisions and enhance competitiveness. There's usually (but not always) a central server housing the central model to manage the training process.

In general, a FL training process consists of the following steps [6]:

1) The server determines a model to be trained, initialises the model.

2) The server selects a subset of the parties and sends them the global model.

3) The selected parties receive the global model and train it on local data. Then they send the model updates back to the server.

4) The server aggregates all the model updates.

5) Steps 2), 3) and 4) are repeated until the global model meets the desired accuracy.

5.1.2 TensorFlow

In this project, we will use the highest level API of Tensorflow - Keras and the Federated Learning (FL) API layer of TFF - ***tff.learning***

TensorFlow is a free and open-source software library for machine learning and artificial intelligence. It can be used across a range of tasks but has a particular focus on training and inference of deep neural networks.

tff.learning is a set of higher-level interfaces that can be used to perform common types of federated learning tasks, such as federated training, against user-supplied models implemented in TensorFlow.

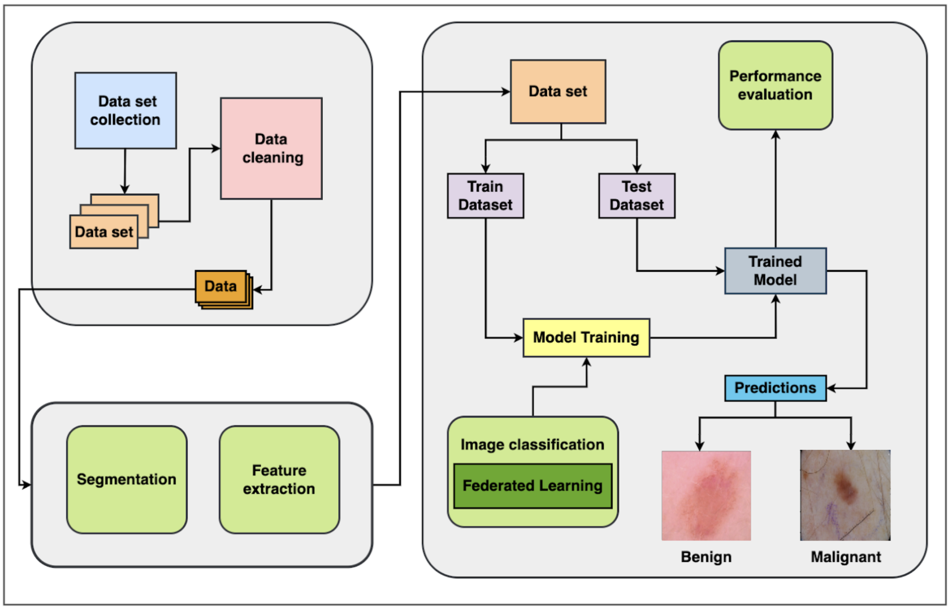
5.2 Related works

The diagnosis of skin cancer is done by dermatologists where they can access the images of cancer patients and analyze the result whether the patient has cancerous cells or not. Because of having cancerous cells, dermatologists suggest it as malignant melanoma and benign on vice versa. The issue with this framework is, it sets aside a lot of time to process a ton of patients and furthermore it takes a great deal of labor to expand the rate of recognition which makes the cost go up. The developing computerized system can automate this skin cancer detection process that will assist the dermatologists, and makes their work easier and faster. Different methods or techniques have been developed for years to make the skin cancer diagnosis.

A closed elastic curve technique along with intensity threshold method is proposed in [9] detect the skin lesion boundary accurately. Authors in [8] have proposed an artificial neural network approach with Back-propagation neural network (BNN) and Auto-associative neural network. Adnan, Mohammed, et al. [1] explored federated learning (FL) as a collaborative learning paradigm, in which models can be trained across several institutions without explicitly sharing patient data. they shown that using federated learning with additional privacy preservation techniques can improve the performance of histopathology image analysis compared to training without collaboration. The simulation results in [3] demonstrated that federated learning achieves higher convergence within limited communication rounds while maintaining participants' anonymity. We hope that our project will show the benefits and help federated learning to be implemented widely.

6 Our methodology

In order to achieve our earlier mentioned goals, we propose building a model through 3 big steps, with the core lies in how to train our non-IID data from different sources while privacy must be preserved. In these following subsections, we will dive in how to turn the ideas into reality.



The process of skin cancer detection

6.1 Data collection and Data cleaning

Like most other methods, we first need to collect and clean our data. In FL, this process happens at every medical center. Cleaning the data is always considered a necessary step to achieve a robust model, i.e. a model capable of handling noise with high accuracy.

6.2 Image segmentation and Feature extraction

After collecting and cleaning data, we can feed the data to our model now, but we shouldn't, yet. There are still something to work on to improve the computation complexity, which matters in most of the cases since each edge still has a limited computation resources. This is where image segmentation and feature extraction come in!

6.2.1 Image segmentation

Segmentation or image segmentation in particular, is the process of partitioning a digital image into multiple image segments, also known as image regions or image objects.

More specifically, segmentation has two main objectives:

- First, it is used to decompose the image into parts for further analysis;
- Second, segmentation is used to perform a change of representation. The pixels of the image should be organized into higher-level units that are either more meaningful or more efficient for analysis (or both).

Once image segmentation is performed efficiently, the computation complexity of the model will be dramatically improved, results in less time and cost for computation.

Nowadays, there are several popular techniques to perform image segmentation, which are histogram-based threshold, edge-based, region-based, morphological and active-contour.

6.2.2 Feature extraction

Sometimes, our input data to an algorithm is too large to be processed and it is suspected to be redundant (much data, but not much information), then the input data should be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called feature extraction.

If the features extracted are carefully chosen, it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.

For efficiently further analyzed, the selected features should meet these criteria, which are:

- Containing information required to distinguish between classes;
- While being insensitive to irrelevant variability in the input;
- And also being limited in number, to permit efficient computation of discriminant functions and to limit the amount of training data required.

Some of the techniques for feature extraction include asymmetry-based, diameter-limited gradient direction histograms, cluster compactness evaluation, borders monitoring and blue white veil.

6.3 Model training and Performance evaluation

After having several ready datasets, we can now train our model. Each node will have a copy of the initial training model and will train the model using its dataset. Then, the weights from several nodes (maybe all in cross-silo setting) will be selected and sent to the center as the input for the aggregating function to compute the new weights for the model. The new weights will then be sent back to each node, normally with accuracy improved.

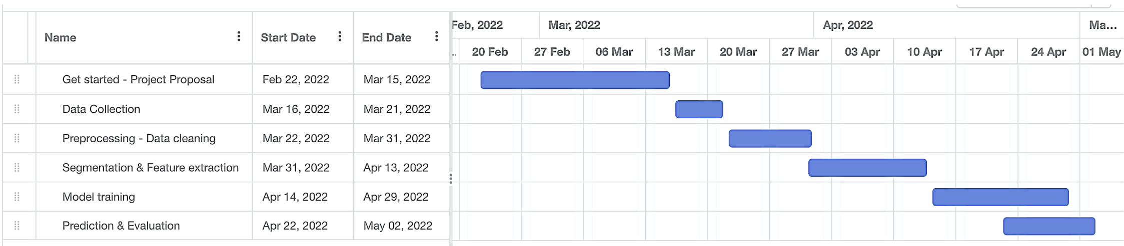
This process can be repeated again and again as new data will be fed to each node over time, to keep improving the model.

Since all the data remains intact at every node (we actually only send the weights), patients' privacy will preserved, while we still can make use of the advantages of larger datasets from different sources.

Also in this step, We have to predict the images using the trained model. After the prediction of the testing images, we evaluate our model with the accuracy, precision, recall and other score measures.

7 Project Schedule

We expect to complete this project in 2 months from 22 February to May. As mentioned, we will build this model through 3 big steps and will be divided into 6 implementation phases.



Gantt chart for Project Schedule

8 Project website

The link to our Project Website: GitHub Page

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