A Novel Unified Scheme for Missing Data Suggestion based on Collaborative Generative Adversarial Network

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A novel unified scheme for missing data suggestion based on Collaborative Generative Adversarial Network

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Abstract: **Image processing is generally a complicated task if it is performed for the medical images, as these image files have different types of attributes that has different properties. There are often times when these attributes are not measured properly and sometimes the medical imaging process produces an image with distorted or diminished pixels in some part of the image, and this will create a problem while image processing is performed. To solve this, we have introduced a model which works on Recurrent Neural Networks (RNN) to predict the possible distorted or the missing parts in the image and then using the Generative Adversarial Network (GAN) that uses Convolutional Neural Network (CNN) in the generator to fix the missing pixel in the image. The discriminator part of the GAN is trained to trace the error made by the generator which is recorded as the penalty in the discriminator and is sent as a feedback to the generator to fix the error and produce an acceptable image. The process is like the Minimax game played between the generator and the discriminator that minimize the error at every time the image is generated. This error fixing part of the GAN proves very useful in order to create a image of the required resolution without compromising with the other sensitive parameters present in the image.**

Keywords: **RNN (Recurrent Neural Network), LSTM (Long Short-Term Memory), GAN (Generative Adversarial Network), Gaussian Mixture Model, SRN (Simple Recurrent Network).**

1.Introduction:

The medical image processing needs to be perfect, to produce an accurate prediction of the diseases and for that there is a need for the image data. These data are generally generated from the medical imaging techniques such as X-Ray Radiography, Thermography, Magnetic Resonance imaging (MRI) and many more types. Each image generated has some specific parameters and properties and this depends on the type of imaging technique used to produce that image. Sometimes the amount of image data required to make the further prediction is not enough, for example taking a case of the brain MRI as it is the complicated one because a single image generated has many parameters to work upon and if a patient miss a check-up for the periodic check-ups then the condition of the person at that specific period is unknown, and as the brain’s MRI data is the complicated one we cannot predict and produce the image through the traditional algorithms like Convolution neural networks, instead of which GANs are usually used which are composed of a generator and a discriminator, in which the role of generator is trained to produce new image based on random data and the role of the discriminator is to check whether the generated data is accepted or not. GAN has the property that it can be used with many learning techniques like, regression techniques, ReLU techniques which is used by the discriminator to test the data, and also the generator part can be used with all types of neural networks like Convolutional network[10]. This collaborative property of GAN can be very useful to generate the missing image data that is best suited for the part.

2.Existing System:

The existing system treat an image patch as a high dimensional manifestation of a low dimensional representation, with the intuition that the covariation within image patches has small intrinsic dimensionality relative to the number of voxels in the patch. To capture the anatomical variability across subjects, we employ a Gaussian Mixture Model (GMM) to represent local structure of 3D patches in the vicinity of a particular location across the entire collection. We then explicitly model the observed and missing information. The existing system do not explicitly model slice thickness, as in many clinical datasets this thickness is unknown or varies by site, scanner or acquisition. Instead, we simply treat the original data as high-resolution thin planes and analyse the effects of varying slice thickness on the results in the experimental evaluation of the method. We also investigated an alternative modelling choice where each missing voxel of patch yi is modelled as a latent variable. This assumption can optionally be combined with the latent low-dimensional patch representation. Intuitively, learning our model with sparse data is possible because each image patch provides a slightly different subset of voxel observations that contribute to the parameter estimation. All subject scans have the same acquisition direction. Despite different affine transformations to the atlas space for each subject, some voxel pairs are still never observed in the same patch, resulting in missing entries of the covariance matrix. Using a low rank approximation for the covariance matrix regularized the estimates

3.Proposed System:

The proposed system uses GAN (Generative Adversarial Network) and RNN (Recurrent Neural Network) to predict the medical examination data with missing parts. It is very common that multiple missing parts in medical examination data exist due to various human factors, for instance, because human subjects occasionally miss their annual examinations.

Through GAN, the missing image can be generated from some noise. But in our proposed system, instead of generating a generic sample from an unknown noise, the generator learns to produce a sample with specific conditions or characteristics (such as a label coupled with an image or an amplified tag). The proposed system creates high resolution anatomically plausible images that are consistent with acquired clinical brain MRI scans with large inter-slice spacing using data augmentation. It helps to remove the image imputation problem and creates a multi-domain images-to-image translation task which a single generator and discriminator network can successfully estimate the missing data using the remaining clean data set.

Among all types of RNN, we choose SRN (Simple Recurrent Network) and LSTM

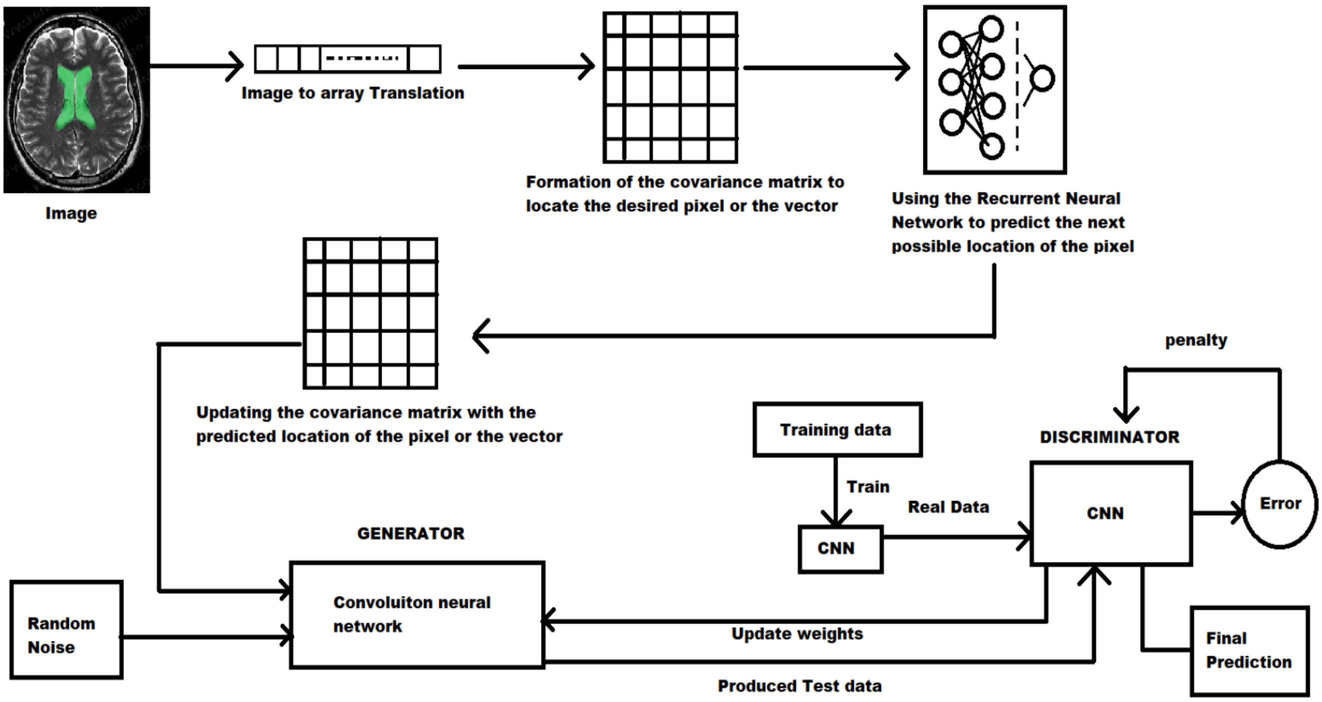

Figure 1: Model Workflow

(Long Short-Term Memory) to predict the missing information as well as the future medical examination of the data, as they show high performance in many related applications. In our proposed method, the temporary paths of the medical examination measurements are modeled using RNN with the missed measurements compensated, which is then used to predict the future measurements which can be used to diagnose the diseases of the subjects.

In order to handle data with missing parts without extra training data composed of missing examples, we propose missing data imputation using RNN. In our proposed method, the trained RNN is used both for missing data imputation and target data prediction.

In the model, if there are no missing data, the RNN is processed normally, and if there are missing data, the output of the RNN in the previous step is used as the input of the current step. With such a missing data imputation method, the target data with missing parts may be predicted by our proposed RNN.

4.Implementation:

The image is a collection of the pixels and every pixel holds a certain value and can be converted into arrays. The value associated with each pixel when combined together shows the property of the particular area in the image, and can be used to locate the missing part in the image. So, converting the image to the array helps to form the covariance matrix of the array. Covariance matrix is generally used to find dependencies between variables (or in this case the vectors involved in the matrix)

Considering, N and M be the desired columns of the image matrix with x_i and y_i as the values and n as the size.

$$\text{Cov(N,M)} = 1/n \sum_{i=1}^{n}(xi - xmean)(yi - ymean)$$

Once covariance matrix is generated, we can use this to detect the faulty pixel in the image using the defective pixel detection based on distance (DPD_D) method. Once the pixel is located then there is a possibility that other defected pixel can be found in that area, for this Recurrent neural network (LSTM) is trained to find the next possible location based on the current location of the defected pixel.

For that, the retained covariance matrix of each images is then converted into vectors of size NxN, now its easy to map the image. This generated vector matrix is given as the

the generator eventually gets better as the knowledge Base of the algorithm Increases, it improves itself from the output generated by the Discriminator. CNN, RNN are some algorithms that can be used as Generator Algorithm. So, we train the generator with the following procedure:

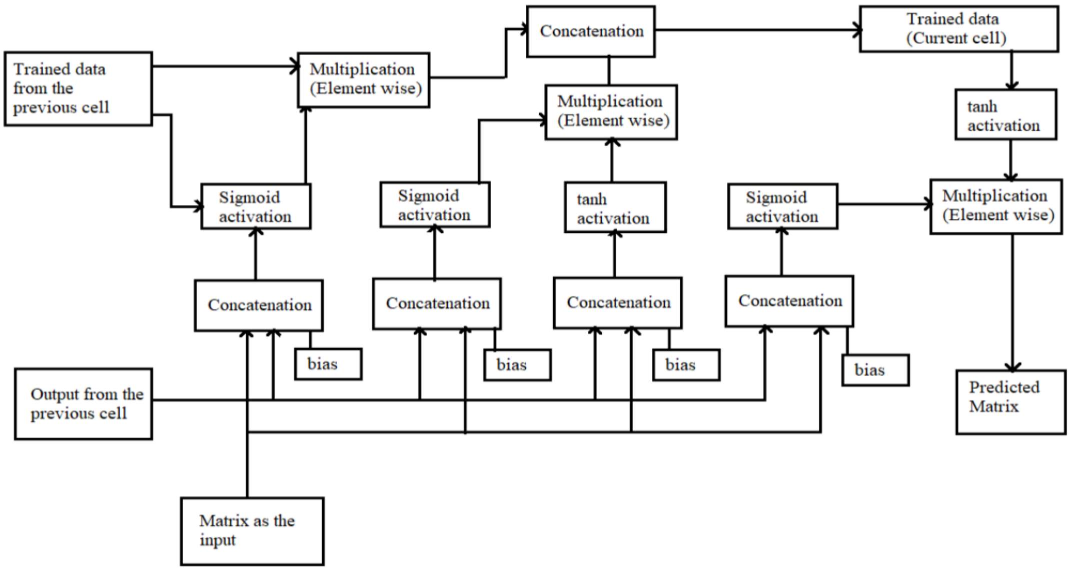

Figure 2; Workflow of a cell of the LSTM

input to the LSTM with activation function tanh as its range goes from [-1,1] and here we need to concentrate on the negative values on the covariance matrix as this points to diminished part of the image that has to be generated. Now the model is ready to train, we can use the values that are derived from the DPD_D as the weight to the model which will help the model to predict the required value for the same position in the other image, so as to dynamically update the covariance matrix. This updated covariance matrix is then augmented with the covariance matrix generated in the generator.

GAN or Generative Adversarial Network works with the help of two Major modules named as the Generator and Discriminator. Let's have a detailed look into their functions and process. The Outputs from

1. Some Sample Random Noise which in this case is our Image Data.

2. Generate result-set from the random noise.

3. Compute a checking parameter by comparing the Loss from the result-set and the loss generated from the Discriminator. Selection of the appropriate Loss Function (in this case MINIMAX) according to your required USE-CASE is necessary.

4. Use a suitable Gradient Descent method to update the weight after receiving a output from the Discriminator.

Discriminator's training Data comes from the two sources Real world Data and Fake Data (generated from the Generator). The end goal is to reduce the disparity between Real-world Data and Fake Data.

Training Steps we see in the Discriminator are:

1. Discriminator uses a penalty system to correct itself after a wrong classification of a given instance, this helps to increase the accuracy of the generated image

2. Uses Back-propagation method as we see in the below diagram to optimize the loss.

Conclusion:

The proposed medical examination data prediction methods using SRN and LSTM for medical examination data prediction. For comparison, we also implement data prediction method based on linear regression as the baseline method. In order to successfully apply SRN and LSTM to real data which occasionally contains missing information, we propose missing data imputation using RNNs. The prediction made by our methods may help find potential patients before they have their medical examination. Those potential patients will be strongly recommended not to miss their medical examination, or will be suggested to take specific type of medical examination which may fit their health state.

References:

1.Adrian V Dalca, Andreea Bobu, Natalia S Rost, and Polina Golland. Patch-based discrete registration of clinical brain images. In International Workshop on Patch-based Techniques in Medical Imaging, pages 60–67. Springer, 2016. 4

2.Adriana Di Martino, Chao-Gan Yan, Qingyang Li, Erin Denio, Francisco X Castellanos, Kaat Alaerts, et al. The autism brain imaging data exchange: towards a large-scale evaluation of the intrinsic brain architecture in autism. Molecular psychiatry, 19(6):659– 667, 2014. 4

3.Chao Dong, Chen Change Loy, Kaiming He, and Xiaoou Tang. Learning a deep convolutional network for image super-resolution. In European Conference on Computer Vision, pages 184–199. Springer, 2014. 4

4.Amod Jog, Aaron Carass, and Jerry L Prince. Improving magnetic resonance resolution with supervised learning. In ISBI, pages 987–990. IEEE, 2014.

5.Roderick JA Little and Donald B Rubin. Statistical analysis with missing data. Wiley, 2014.

6.Ozan Oktay, Wenjia Bai, Matthew Lee, Ricardo Guerrero, Konstantinos Kamnitsas, Jose Caballero, Antonio de Marvao, Stuart Cook, Declan ORegan, and Daniel Rueckert. Multi-input cardiac image superresolution using convolutional neural networks. In International Conference on Medical Image Computing and ComputerAssisted Intervention, pages 246–254. Springer, 2016.

7.W. Wang, R. Wang, Z. Huang, S. Shan, and X. Chen, “Discriminant analysis on Riemannian manifold of Gaussian distributions for face recognition with image sets,” IEEE Conference on Computer Vision and Pattern Recognition, Boston, MA, pp. 2048- 2057, 2015

8.Selvarajah S, Kaur G, Haniff J, Cheong KC, Hiong TG, van-der-Graaf Y, Bots ML. Comparison of the Framingham Risk Score, SCORE and WHO/ISH cardiovascular risk prediction models in an Asian population. International Journal of Cardiology 2014; 176:211–218.

9. Q. Ding, et al., “Missing-data classification with the extended full dimensional Gaussian mixture model: applications to EMG-based motion recognition,” IEEE Trans. Industrial

Electronics, vol. 62, no. 8, pp. 4993-5005, 2015.

10. Dongwook Lee , Junyoung Kim , Won-Jin Moon, Jong Chul Ye. Collaborative GAN for missing data imputation.