SEX INFLUENCES USING MRI IMAGES

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ABSTRACT

Is there a difference in the brains of men and women? Previous neuroimaging research attempted to answer this question using morphological differences between specific brain regions, but the results were mixed. We plan to apply a deep learning technique to address this problem in this work, which will be based on a huge open-access dataset. This article reviews research new insights on the structural differences between men and women, emphasizing the importance of gender as a biological variable in brain research.

1. INTRODUCTION

Recent research suggests that gender has a significant impact on human cognitive skills such as emotion, memory, and perception. Men and women appear to encode memories, perceive emotions, recognize faces, solve problems, and make decisions in different ways. Because the brain is in charge of cognition and behaviors, these gender- related functional variations could be linked to the brain's gender-specific structure.

Diffusion tensor imaging (DTI) is a useful method for determining the architecture of nerve fibers. The anisotropy of nerve fibers can be quantified by computing fractional anisotropy (FA) values in DTI. Differences in FA values are hypothesized to be linked to axon caliber, myelination, and/or fiber structure of nerve fiber routes during development. Researchers have discovered minor alterations related to appropriate brain growth, learning, and healthy ageing by computing FA. Existing research, however, have yet to produce consistent results when it comes to examining the differences in brain anatomy between men and women. Men have stronger intra-hemispheric connectivity via the corpus callosum, while women have greater interhemispheric connectivity, according to Ingalhalikar.

Other studies, on the other hand, found no significant differences in brain structure between men and women. More research is needed to determine if men and women have different brain architecture, according to a recent critical opinion article.

The majority of existing DTI research relied on group-level statistical approaches like Tract-Based Spatial Statistics (TBSS). Recent research suggests that machine learning approaches could give a more powerful tool for evaluating brain images. Deep learning, in particular, can extract nonlinear network structure, achieve complex function approximation, characterize distributed representation of input data, and display the powerful ability to learn the fundamental aspects of datasets from tiny samples. The deep convolutional neural network (CNN) use convolution kernels to extract picture features and can detect the characteristic spatial difference in brain images, potentially outperforming other machine learning and statistical methods.

Here, we have used ResNet model to analyses the difference between men and women by brain images. The Convolutional Neural Network (CNN, or ConvNet) is a class of deep neural networks that is most typically used to analyses visual data. ResNet-50 is a pretrained Deep Learning model for image classification of the Convolutional Neural Network (CNN, or ConvNet). ResNet-50 is a 50-layer neural network that was trained on a million photos from the ImageNet database in 1000 categories. In addition, the model comprises approximately 23 million trainable parameters, indicating a deep architecture that improves image identification. When compared to building a model from scratch, where you must collect large amounts of data and train it yourself, using a pre-trained model is a highly effective option. Of course, there are alternative pretrained deep models to apply, such as AlexNet, GoogleNet, or VGG19, but the ResNet-50 is known for comparative and low error rates on recognition tasks, making it a helpful tool to know.

In this study we are emphasize on three research question RQ1. How accurately different models can detect gender from brain images? RQ2. If you trained a segmentation model only using images from male subjects, would it work well for female subjects and vice-versa? RQ3. In brain MRI which region is responsible to differentiate the subject.

2. RELATED WORK

Beyond diagnosing brain injury or tumors, magnetic resonance imaging has had limited success in identifying three individual differences and brain diseases (MRI). This Study used deep learning/transfer learning on huge data to create industrial-grade brain imaging-based classifiers to infer two types of such 5 inter-individual differences: sex and Alzheimer's disease (AD) [1]. They combined data from 217 sites/scanners to create the 7 largest brain MRI dataset to date (85,721 samples from 50,876 subjects), and used an 8 state-of-the-art deep convolutional neural network, Inception-ResNet-V2, to create a sex 9 classifier with great generalizability [1]. Occlusion testing found that the hypothalamus, superior vermis, 21 thalamus, amygdala, and limbic system areas were crucial for predicting sex, while the hippocampus, 22 Para hippocampal gyrus, putamen, and insula were critical for predicting Alzheimer's disease. To use such a concept in psychiatric 518 diseases and other elements of individual differences, the study suggests that more research is needed [1].

In this study, deep learning architectures are utilized to classify brain MRI images as normal or pathological [2]. Gender and age have been introduced as higher attributes for more exact and meaningful categorization. A deep learning Convolutional Neural Network (CNN)-based technique and a Deep Neural Network (DNN) are also presented for effective classification. In this paper, LIM performs better in the first instance when considering Accuracy, Specificity, Sensitivity, Precision [2]. In the second scenario, it was revealed that utilising LIM, CNN-DNN, and the other four techniques, brain classification works better for brains of different ages and genders than for brains of the same genderism, AlexNet, ResNet, LeNet, LIM, and CNN-DNN have overall accuracy of 82 percent, 64 percent, 44 percent, 87 percent, 88 percent, and 80 percent, respectively, and best accuracy of 92 percent, 81 percent, 52 percent, 97 percent, 100 percent, and 92 percent, respectively, using age and gender as attributes.

This study proposed utilising a deep learning architecture called the EfficientNet-B3 model to automatically classify brain tumours in MRI data. This model can decipher MRI images with three different types of cancers: meningioma, glioma, and pituitary tumours. The results showed a brain tumour classification accuracy of 99.35%, with precision, recall, and f1-score of 100%, 100%, and 100%, respectively.

3. MATERIALS AND METHODS

In this section, we describe the materials and methods utilized in this project. A summary of our methodology is showed in Figure 7.

3.1 Dataset

In this experiment we have used Calgary-Campinas Public brain MR dataset [9] to answer our research questions. The dataset comprises of reconstructed images that can be use in deep learning model. We have used the original images dataset and had converted the images into the appropriate format to feed into the model. The images need to be extracted from the bunch of raw neuroimages files. The extraction can be done using open-source file converter or it can be done using python script. In this implementation we have used both approaches. Due to limitation of computation resources, we have considered the limited numbers of images in this dataset. There is total 4000 images of two different subjects including male and female.

The dataset consists of brain images of adults old between 29 to 80 years. The CC-359 is comprised of 359 datasets, approximately 60 subjects per vendor and magnetic field strength. The dataset is approximately age and gender balanced, subject to the constraints of the available images. It provides consensus brain extraction masks for all volumes generated using supervised classification.

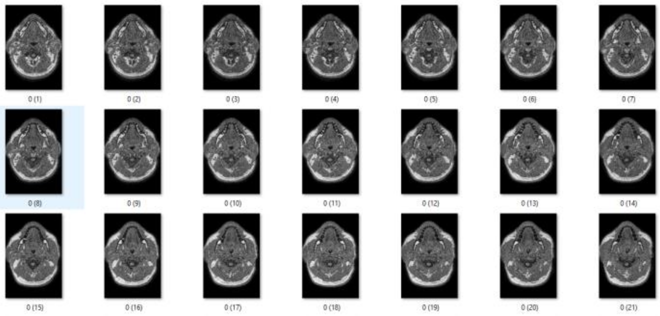

Fig. 1. Sample Dataset Images

We used different data augmentation technique to our dataset, where images of various sizes. For data augmentation we used batch size of 8 and converted image dimension to 224*224.

3.2 Processing Models

1. ResNet

Residual Network (ResNet) or residual neural network could be a deep learning model which is a a part of CNN used to classify images. it's mainly suitable for big datasets, It can train up to hundreds or maybe thousands of layers with countless training parameters. a number of the similar training models are AlexNet, GoogleNet, and VGG19. the most effective part about ResNet makes it possible to train up to hundreds or perhaps thousands of layers and still achieves convincing performance.

The problem of training very deep networks was solved with the introduction of those Residual blocks and also the ResNet model is created from these blocks. The core idea of ResNet is “identity shortcut connection” that skips one or more layers, as shown within the following figure:

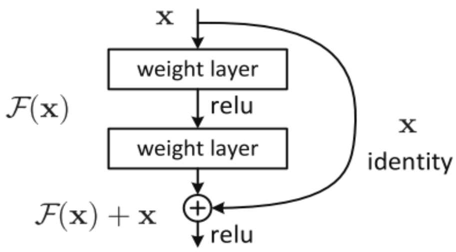

Fig 2. Residential Block

In the above figure, we are able to notice is that there's a right way connection that skips some layers of the model. This connection is understood as "skip connection" and is that the heart of residual blocks. Without the skip connection, input ‘X gets multiplied by the weights of the layer followed by adding a bias term.

Now the activation function, f () and we get the output as H(x).

$$H(x)=f(wx + b) \text{ or } H(x)=f(x)$$

With the introduction of a new skip connection technique, the output is H(x) has changed to

$$H(x)=f(x)+x$$

But the dimension of the input may be varying from that of the output with a convolutional layer or pooling layers. Hence, this problem can be tackled with these two approaches:

- Zero is padded with the skip connection to increase its dimensions.
- 1×1 convolutional layers are added to the input to match the dimensions. In such a case, the output is:

$$H(x)=f(x)+w1.x$$

Here is an additional parameter w1, which is added.

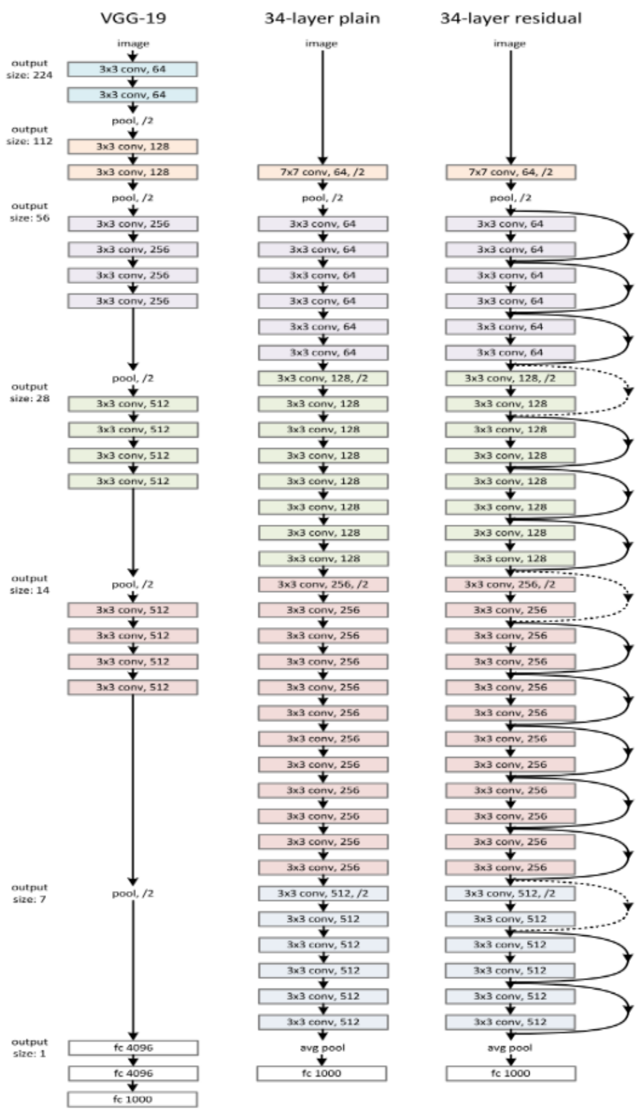

Fig. 3. ResNet Architecture

These skip technique in ResNet solves the problem of gradient disappearing in deep CNNs by allowing an alternative shortcut for the gradient segment. Also, the skip connection helps that if a layer hurts the architecture's performance, it will be ignored by regularization.

Number of layers	Number of parameters
ResNet18	11.174M
ResNet34	21.282M
ResNet50	23.521M
ResNet101	42.513M
ResNet152	58.157M

Table. 1. ResNet output for Imagenet

Above is summary of the output size at every layer and the dimension of the convolutional kernels at every point in the structure.

2. EfficientNetB1

EfficientNet scales up models using a simple, yet effective technique called compound coefficient. Compound scaling equally scales each dimension with a given set of scaling coefficients, instead of scaling up width, depth, or resolution randomly. The authors of efficient created seven models in various dimensions using the scaling approach and AutoML, which outperformed the state-of-the-art accuracy of most convolutional neural networks while being much more efficient.

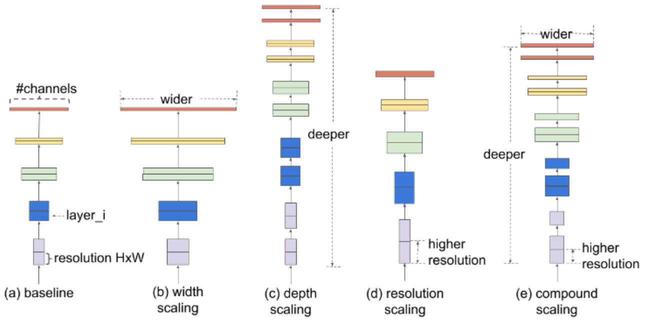

Fig. 4. Different scaling methods vs compound scaling

EfficientNet is predicated on the baseline network created by the AutoML MNAS framework's neural architecture search. The network is fine-tuned to attain maximum accuracy, but it's penalized if it's computationally intensive. The architecture employs a mobile inverted bottleneck convolution, cherish Mobile Net V2, but is far larger due the rise in FLOPS. to form the EfficientNets family, the baseline model is scaled up.

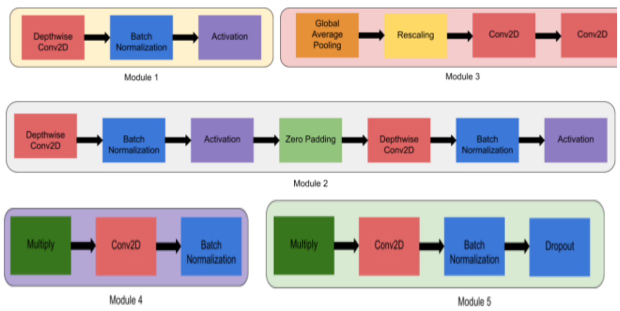

Fig. 5. Different scaling methods vs compound scaling

The total number of layers used in a EfficientNet models is All the layers can be made from the 5 modules in the fig.5
These modules are further combined to form sub-blocks which will be used in a certain way in the blocks.

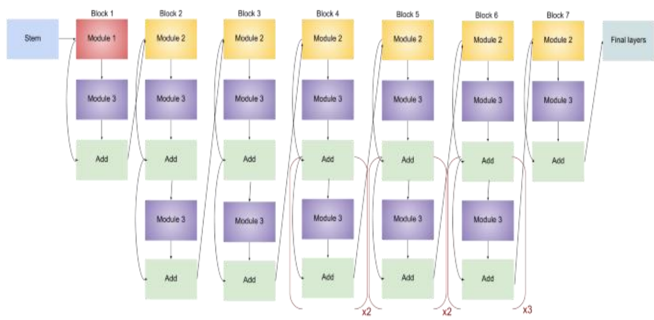

Fig. 6. EfficientNetB1 architecture

3.3 Methodology

This paper comprises of a ResNet and EfficientB1 model that distinguishes gender from the CC359 dataset. The dataset contains a considerable number of brain MRI images. The ResNet and EfficientB1 are pretrained classification models. The models use the TensorFlow platform in the background to generate the gender of the particular image. The implementation of this study is available on https://github.com/Nisha453/ENEL645-Final-Project.

Several gender differences are thought to rise during the critical time of postnatal development when hormones act on brain structural organization and may also further influence brain anatomy on adult life. Medical have also observed the separate effects of hormones and sex chromosomes on brain development. Regarding grey matter, the main sexually dimorphic areas linked with the development of gender identity are represented by the central subdivision of the bed nucleus of the stria terminalis and the third interstitial nucleus of the anterior hypothalamus.

The dataset CC359 is used to detect the gender and trained on deep learning models like VGG1, xception, inception, ResNet, EfficientB1. In this project we are using the 3D, T1-weighted reconstructed brain MR images which was generated from the multi-channel raw data.

The main challenge faced while preparing the dataset is to format the Neuroimaging Informatics Technology Initiative dataset into image dataset. A single nii file approximately contains 288 images. For that we have developed a script that converts bulk of the nii data into the image format.
Below is a representation on how we have carried out the project.

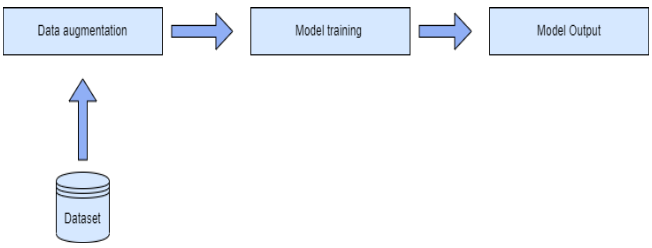

Fig. 7. Overview of our methodology.

For the model training it will first load the pre trained model. The fully connected layers of the pretrained models are excluded and the top layer for the prediction is added to the model. The combination of the convolutional layer and the new fully connected layers are used to predict the output, while training these two models, It has been observed that the ResNet performs fast computation of layer than the EfficientNetB1 while training the model.

Our experiment has main three objectives to determine

1. **Prediction of the sex using the brain MRI images**
   - To predict the sex from the MRI images we have used transfer learning with the various pretrained models like resnet, efficientnetB1, VGG16 and Inception and the results are discussed on the later section.

2. **Model trained on the female subject can work to predict results on the male subject and vice versa.**
   - The resnet has been trained only with the female subjects and we have tested the model by feeding the male object.
   - Also, we have trained the resnet model only on the male objects and tested the model on the female object.

3. **Which region of the brain images are essential for the decision?**
   - To determine the part of the brain region that contributed most towards the label prediction, we calculated the confidence of the tested data sample which is generated from the one MRI scan. It has various images of same human brain with the different perspective.

The graph has been plotted for the predicted male dataset confidence as well as the female dataset confidence.

4. RESULTS AND DISCUSSION

We have derived the result by considering the top accuracy as per karas API [7]. We have implemented this study by including different models such as EfficientNet, Xception, Inception, ResNet, and VGG. Our comparison shows that ReseNet50 is well suitable for the dataset we have used in this study. We have achieved overall 73% training accuracy and 77% validation accuracy. The performance of the different models is shown in Table 2. We have agreed to work on ResNet50 to investigate our all-research questions.

Our study shows that ResNet is efficient in terms of computation time and accurate result than the listed model. However, the top accurate model from the Keres API would not be able to make significant impact on this dataset as per their performance.

Model Name	Training	Validation
ResNet50	73%	77%
EfficientNetB1	66%	68%
VGG16	58%	70%
Inception	54%	58%
Xception	53%	50%

Table 2. Performance of the Deep learning models

EfficientNetB1 performs the second-highest result than the ResNet50 in our study. In figure 8 the results of the training and validation set of EfficientNetB1 is described on the male and female subject. The figure shows a gradual increment of training set accuracy during the training while the validation test has decreased at one point.

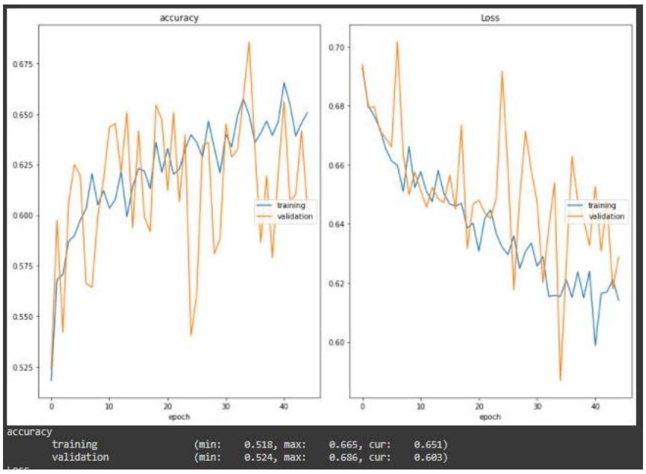

Fig. 8. Result of EfficientNetB1

To investigate our RQ1 in which the aim is to determine how accurately we can detect the gender using this model. we have worked on sample test set that consist of images of Male and female subject. We have saved the model consist of best weights and tested that model on the separate test case. As shown in figure 9 model can 73% accurately differentiate the sex. It also shows the consist increment in the training and validation set during the training of image.

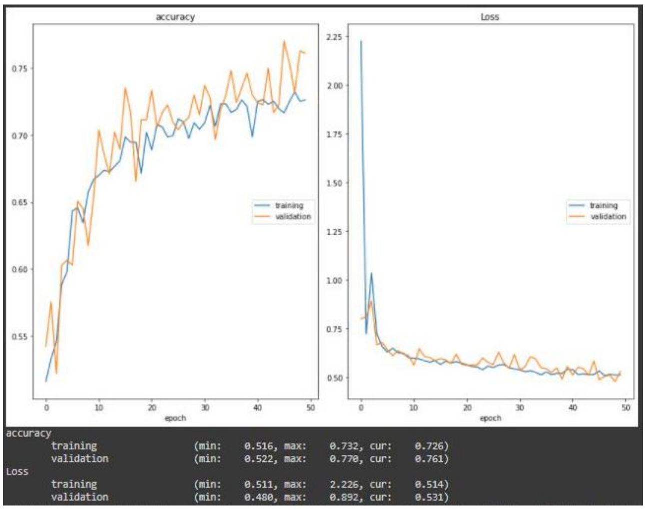

Fig. 9. Result of RQ1 using ResNet50

For RQ2 we have achieved the result described in figure 9. In this figure the training curve is steady after reaching to one point and the validation curve is steady throughout the learning. As per the result we have found that if we train the data only using male subject then it will not differentiate the female subjects MRI. The reason for this behavior is during the training of male subject it doesn't have female MRI's parameter to differentiate the sex. Therefore, it has predicted the female data as male when we have tested the result. This behavior works similar for the female subject data. When we trained the model only using female data it predicts the male data as female data.

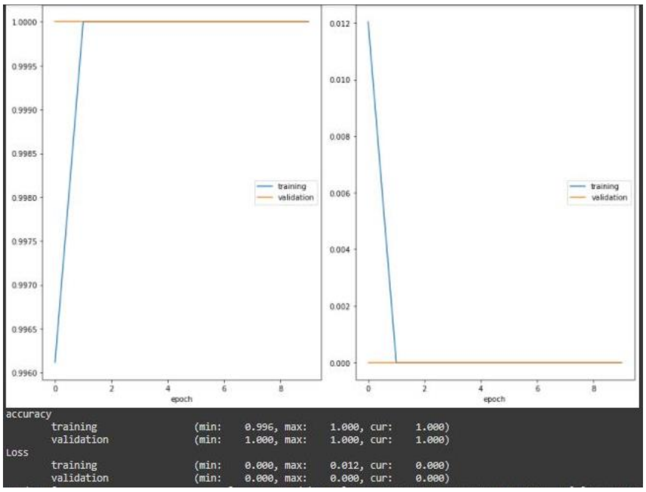

Fig. 10. Result of RQ2 using ResNet50

The RQ3 emphasize on the investigation of brain MRI region that is responsible to differentiate the gender. We have found that the brain of male is 10% larger than the female therefore the size of the brain in the MRI images makes significant impact on this decision. Second factor to differentiate the sex from the brain MRI is the presence of greyer factor in the female brains. Also, the structures including caudate nucleus, hippocampus, amygdala and cerebellum is different for both the sex that helps to classify the images [8].

Furthermore, when we train the model using the only female subjects and try to predict the male subject, the accuracy of training and validation was 100%. While testing the male brain MRI image, the model was identifying it as a male one and the vice versa.

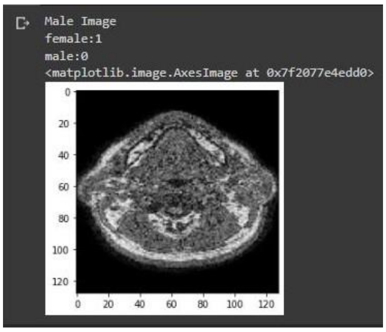

Fig. 11. Result of the model only trained by female subjects

The main reason behind behavior is that the model doesn't have the any non-female images to develop the feature that can discriminate between the female and non-female brain images.

The last experiment was performed to observe the main area of the brain which has the most influence on the prediction of the sex.

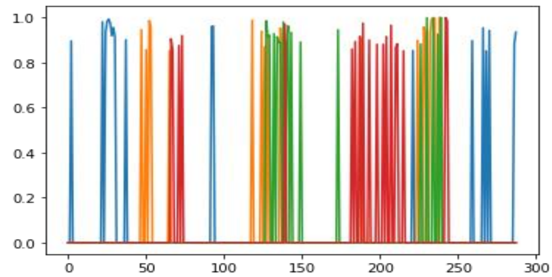

Fig. 12. Region for female dataset

Here, the different color represents the different data samples. From the graph, it can be seen that from the 288 samples the images fall between the 125-150 and 225-250 has the high confidence intensity

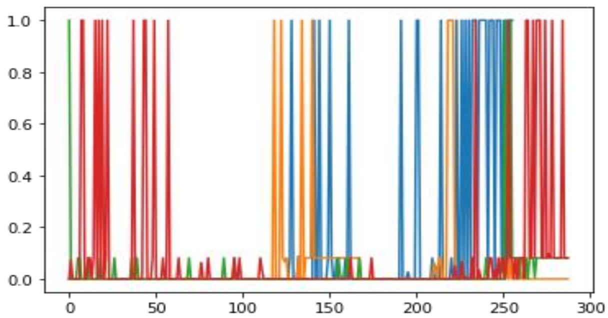

Fig. 13. Region for male dataset

Same results can be seen for the male brain MRI experiment. But the results are little less evident than the female objects.

5. CONCLUSION

Our study shows that the current deep learning models are powerful for gender detection. Specially, performances of transfer learning models are promising to consider their time effectiveness. It can also be deduced that the pattern and characteristic features of people of the same gender are likely to be similar. Gender can also be considered a role in the future examination of the brain, based on statistical tests and performance indicators. Because of the noise and heterogeneity in the data, the approaches were unable to distinguish between normal and abnormal photos. Also, we used only half the data from the dataset considering the capacity of various models and GPU.

6. REFERENCES

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