Intelligence Quotient Classification from Human MRI Brain Images Using Convolutional Neural Network

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***Abstract*—In cognitive neuroscience, exposing human intelligence has been of major interest to the researchers. Intelligence quotient (IQ) is a quantification of the intelligence of a person. It is a number which indicates an individual's intellectual capacities and potentials. Determining one's intelligence quotient helps us recognize a person's different mental deformities, disorders, autism, etc. IQ of a person is related to the human brain. The level of intelligence can be attributed to variations in certain regions of the brain and neural parameters. However, there is not much research pertaining to a person's IQ detection based on human physiological factors other than conducting skill tests. Inspired by the correlation between brain structure and intelligence, it is proposed to classify a person's IQ into one of the four classes using Convolutional Neural Network (CNN) by extracting the IQ-related features from human brain MRI images. The IQ classification in this work is based on Wechsler's Intelligence Scale.**

***Index Terms*—IQ (Intelligence quotient), Deep learning, CNN (Convolutional Neural network), VGG (Visual Geometry Group), ResNet-50 (Residual Network 50), SVGG (Smaller Visual Geom- etry Group), ABIDE (Autism Brain Imaging Data Exchange)**

I. Introduction

A person's intelligence is the ability to understand, learn, and to think. The Intelligence quotient (IQ) is a numerical indicator of the cognitive ability of a person. Typically, a series of multiple standardized tests and subtests has been used to assess IQ. Intelligence quotient recognition tests widely used are the Wechsler Adult Intelligence Scale (WAIS) test [1], Wechsler Intelligence scale for children test, Standard Binet Intelligence scale tests, and Universal nonverbal intelligence tests. IQ score fits the normal distribution, in which most of the IQ values will be near or around the average value. Very few people can get an IQ score higher than 140 or less than 70.

Intelligence is correlated with variations in different brain structures and neural parameters. The cerebrum denotes the right and left brainhemispheres. There are four lobes in every hemisphere (frontal, temporal, occipital, and parietal). More of the temporal lobes and fewer frontal lobes are related to IQ in children and younger adults. In the middle age, more of parietal and less frontal lobes are involved. Over the years, understanding, and quantifying human intelligence has been a significant area of interest. Considering the correlation between brain structure and intelligence, it is proposed to classify a person's IQ from the brain MRI images. Here, the IQ of a person is classified into one among the four classes using Convolutional neural network. Within each class, the IQ level is assigned based on the Wechsler Intelligence Scale. The four classes considered in this work are Very Superior class (130+), Superior class (120-129), High average class (110- 119), Average class (100-109).

II. Literature Survey

The intelligence quotient reflects a person's memory, mathematical and thinking abilities, language competencies, visual and spatial processing capacity. Detecting the IQ score of a person helps us diagnose various intellectual deformities, disorders. IQ is also a popular biomarker for autism spectrum (ASD) disorder. Many of the standardized IQ assessments include the Wechsler Adult Intelligence Scale (WAIS) test, Standard Binet Intelligence scale tests, children's Wechsler Intelligence scale, and Universal nonverbal intelligence tests. WAIS test is a commonly used, worldwide intelligence test. For this test, the average intelligence score is set as 100 where most scores fall between 85 and 115. WAIS test not only offers IQ scores but also scores of spatial thinking, memory, processing speed, and verbal comprehension. The new version of this test contains ten tests and five additional sub-tests. As per researchers, IQ determination cannot reliably assess the mental and cognitive ability of an individual through a single or series of tests. Intelligence tests show varying IQ values when conducting the same tests on different occasions or at the same time [2]. IQ scores ob tained through these tests can vary due to emotional stress, distress, anxiety, lack of experience with the testing procedure, mental illness, premature birth, misuse of medications, malnutrition, social environment, etc. [3]. If the IQ tests are accurate or true is an on-going debate. According to psychologist W. Joel Schneider, socio-cultural language barriers cause misjudgment of intelligence, when determining intelligence scores from IQ tests.

Over the years, scientists have been investigating the link

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between the human brain and intelligence with several studies. The results of these studies demonstrate the significance of both the entire brain and individual brain networks. They suggest brain MRI scans to detect intelligence since different areas of the brain regulate a person's intelligence. Human brain scans will offer a modern way of identifying and understanding human intelligence, based on the findings from the NYU School of Medicine. The gray matter in specific brain regions is highly responsible for human IQ as opposed to the total brain size. Relevant brain regions include parietal lobes and frontal lobes [4]. Hence it is possible to determine a person's IQ based on human physiological factors by extracting and classifying IQ related features from brain MRI images.

While technology advances, machine learning, and deep learning-based brain image processing is used for image based diagnosis and classification of neurodegenerative diseases, tumors, psychological disorders, gender identity, etc. A novel method for IQ detection using an MRI image is presented in [5]. Here IQ detection is considered as a regression task. Gray matter and white matter features are extracted for detection. Feature extraction is based on an extended dirty model. IQ score is estimated using multiple kernel Support Vector Regression (SVR). The most frequently selected brain regions in this method are the left thalamus, right thalamus, left parahippocampal gyrus, left hippocampus, left anterior cingulate gyrus, right amygdala, left lingual gyrus, left superior parietal lobule, right inferior parietal lobule, left angular gyrus, left paracentral lobule, left angular gyrus and left caudate nucleus. It is also found out that age is correlated to brain tissue volume and intelligence quotient.

Deep learning is a sub-field of artificial intelligence in machine learning, which consists of networks that can learn from unstructured data without supervision. Since the brain is a complex structure, deep neural networks can be used to extract the complex IQ-related characteristics from brain images. CNN's are widely deployed in every significant areas of scientific contribution. Different CNN models can be used for deep learning-based diagnostics and classification problems [6]. In deep learning based on CNN, feature extraction does not require manual intervention. The network itself extracts the features while training. Hence in this work, it is proposed to make use of the capability of CNN for IQ classification tasks.

III. Proposed System

The proposed system classifies the intelligence quotient of a person into one of the four classes using brain MRI scan images. The four classes are very superior, superior, high average, average. It is a challenging task because of the complex structure of the human brain. Here, the extraction and classification of features related to IQ are carried out using the Convolutional Neural Network. The block diagram for the proposed CNN-based IQ classification system is shown in Fig. 1. The range of IQ for each class is based on the Wechsler Intelligence Scale. At first, the input brain images are divided into four groups, and image sets are labeled.

This CNN based IQ classification system is divided into two phases such as training and testing phase. In the training phase, pre- processing, feature extraction, and classification is done to make a prediction model. The generated model is used to classify IQ from the test data in the testing phase.

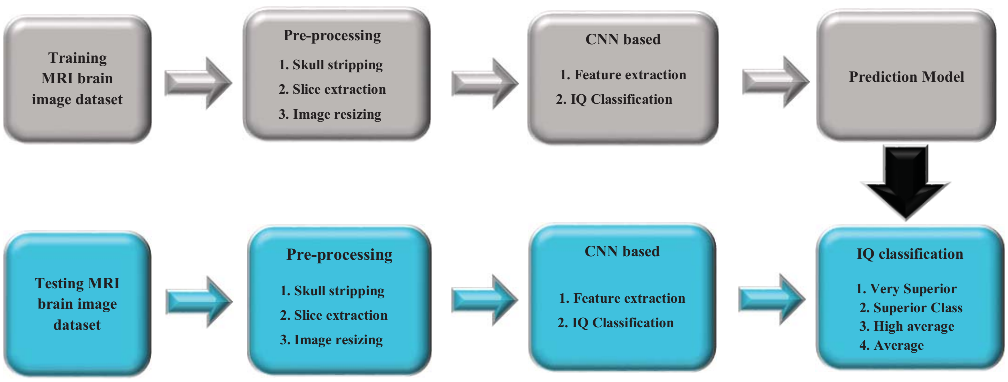


Figure 1: Proposed IQ classification system

A. Input images

Three dimensional MRI brain scan images are used as the input images. MRI images provide much more soft tissue specifics than Computed Tomography (CT) scan images and x-ray images. Compared to other imaging techniques, it has a high spatial resolution. The brain image dataset used in this system is ABIDE. It is collected from 1000 functional connectomes projects.

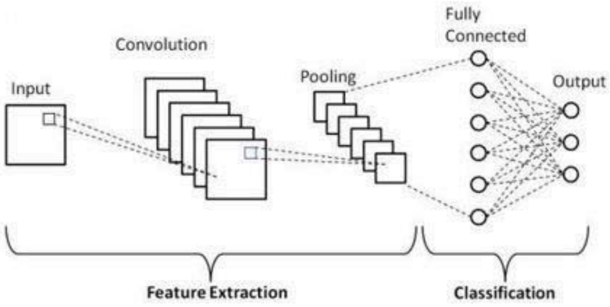


Figure 2: A simplified CNN architecture

B. Preprocessing

Pre-processing refers to raw data transformations to convert it into a clean dataset. This makes data ideal for creating and training deep learning models. The collected three-dimensional brain images themselves can be used with 3D CNN for IQ classification, but they have high complexity and high requirements. Thus we need to extract two-dimensional slices from 3D images in the pre-processing stage. In this work, the pre-processing stage essentially involves three steps. They are

- Skull stripping: The skull stripping is the process of brain tissue segmentation from the surrounding region. This is performed in MRIcro using the brain extraction technique (BET) [7]. By default, BET returns a picture with the removed non-brain matter. The next step is to remove the 3D images from the two-dimensional slices.
- Slice Extraction: Using different brain imaging software the required slices can be extracted from the 3D image. The slices of the brain are taken from three brain views. The three views are sagittal view, coronal view, and transversal view. The sagittal plane separates the left and right sides of the brain into sections. Coronal planes or frontal planes are oriented vertically which divides the brain into anterior and posterior regions. Slicing of the brain perpendicular to the long axis of the body produces a transverse or horizontal plane.
- Image resizing: To train a Convolutional Neural Network, and to make predictions on new data, the brain images should meet the size requirement of the neural network. The images are resized to dimensions $150\times150\times3$, $224\times 224\times3$ and $96 \times 96 \times 3$ for ResNet-50, VGG16, and SVGG architectures respectively.

C. Feature extraction and Classification

Here, a novel framework for the classification of IQ based on neuroimaging features has been proposed. Automatic IQ related feature extraction and classification are performed using CNN.

- Simplified CNN architecture: CNN or ConvNets are complex neural networks consisting of a sequence of convolution layers, pooling layers, and fully connected layers [8], [9]. The way these layers are organized influences the speed and accuracy of CNN based systems.

  A simplified CNN model is shown in Fig. 2. CNN's fundamental block is the convolution layer. This layer performs convolution operation by sliding a kernel over input images. The output of the convolutional layer is a feature map. The pooling layer reduces the dimension of the feature map. The commonest type of pooling is Max pooling. Pooling is done by sliding a window over its input and takes the maximum value in the window. A fully connected layer flattens the output from the final pooling layer into a dimensional vector. A CNN model consists of two components, feature extraction component, and classification component [10]-[12]. Convolutional and pooling layers perform feature extraction. The fully connected layer acts as the classifier. The convolutional layer learns complex features from the input data. FC layer discovers how to use these features to categorize the image accurately. SVGG, VGG16, and ResNet-50 are the three CNN architectures used in this work.
- Smaller Visual Geometry Group (SVGG): It is the smaller version of Visual geometric group 16 network architec- ture. This consists of 5 convolution layers, 3 Max pooling layers, 1 fully connected layer, and two dense layers. The dimension of the input image should $96\times96\times3$ in this architecture.
- Visual Geometry Group 16(VGG16): This is a neural network architecture suggested by K.Simonyan and A.Zisseman [13]–[15]. It consists of 16 layers, 13 convo- lutional layers, and 3 fully connected layers. It is a type of CNN that has been pretrained. The convolution layers are accompanied by three fully connected layers. The first two layers of FC contain 4096 channels. The third layer of FC has 1000 channels. The softmax layer is the final layer. This generates output by applying the softmax function to the total input coming from the previous layers as an activation. The required dimension of input images is size $224\times224\times3$. It is a widely used CNN architecture for large scale image recognition.
- ResNet-50: The ResNet-50 is a CNN architecture which is 50 layers deep. ResNet is the short form for residual network [15]-[17]. It is commonly used for the classification of images. This neural network makes use of skipping connections to leap over certain layers. It is composed of 5 stages. Each stage is composed of a convolution and identity block. The convolution block consists of three convolution layers and the identity block also consists of three convolution layers. This has

48 convolution layers in all, along with 1 Maxpool and 1 Average layer. This prevents the 'vanishing gradient' issue of deep neural networks.

D. ***Prediction Model***

The deep learning algorithm takes MRI brain data with a known input-output relationship and creates a model based on these relationships. This prediction model is used to make predictions on unlabeled MRI data. In this work, the IQ classification model predicts, to which IQ range/class the test data belongs.

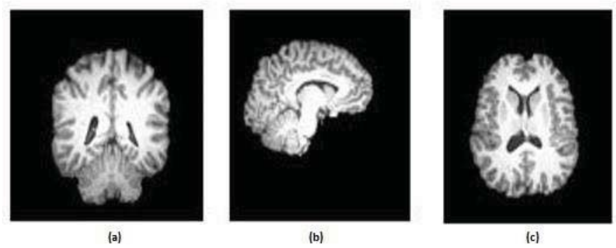


Figure 3: Skull stripped brain slices (a) Transversal image (b) Sagittal image (c) Coronal image

IV. EXPERIMENTAL RESULTS

Here the classification of the intelligence quotient from human MRI brain images is carried out using three CNN architectures. They are SVGG, VGG16, ResNet-50.

A. *Dataset*

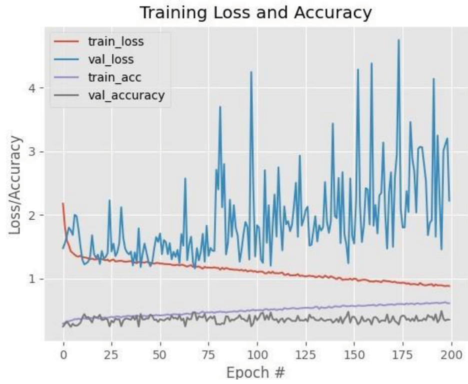
The MRI brain image dataset ABIDE (Autism Brain Imaging Data Exchange) provided by NITRC (Neuroimaging Informatics Tools and Resources Clearinghouse) is used. The brain images are three dimensional and the image file format is NIFTI (Neuroimaging Informatics Technology Initiative). The dataset's phenotypic information includes age, gender, and IQ scores of different individuals. The phenotypic file has listed three forms of IQ scores namely Full IQ (FIQ), Performance IQ (PIQ), Verbal IQ (VIQ). For this analysis, FIQ is taken as the measure of intelligence. FIQ scores are not listed for many subjects in the dataset. Therefore FIQ for those subjects is calculated from PIQ and VIQ values [18] using Eq. (1).

$$FIQ = -11.611 + 0.551VIQ + 0.566PIQ \quad ..... (1)$$

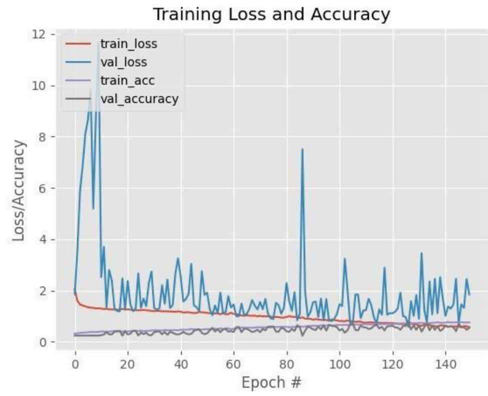
B. *Pre-processing*

The brain MRI images are preprocessed using MRIcro. It is a free software which is used to display medical images. It can also be used for the segmentation of the medical images, normalization, skull stripping, rescaling, extraction of the area of interest, removal of noise. In this work the pre-processing methods used are

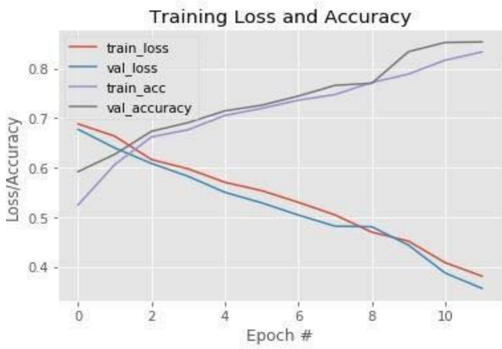
Skull stripping, extraction of brain slices, image resizing. MRIcro brain extraction tool is used to strip the skull. By default, BET generates an image with the removed non-brain matter. The other option outlines the surface of the brain in the original picture without eliminating any brain region. MRIcro also performs slice-extraction. The two- dimensional slices are extracted from three brain planes. The three planes are the sagittal plane, the coronal plane, the transverse plane Fig.3. shows a sample of skull stripped brain slices. The two-dimensional skull stripped brain slices are resized because all images should have the same dimension in order to feed it into the neural network as an input. The images are resized to a dimension of 150x150x3, 224x224x3, and 96x96x3 for ResNet-50, VGG16 and SVGG architecture respectively



(a) SVGG based system



(b) VGG based system



(a) ResNet-50 based system

Figure 4: Accuracy and loss curves of the three IQ classifica- tion systems

C. *Feature extraction and Classification*

Classification of IQ has been carried out here using SVGG, VGG16, ResNet-50. The three convolutional neural networks are fed in 5000 bi-dimensional slices from each of the three brain views. 80 percent of the images in the dataset are randomly chosen as training samples, after the labeling process. Each class selects the same proportion of the images. The remaining 20 percent of the dataset is used for testing.

SVGG based Classification: While training and testing the input samples, the accuracy obtained from the SVGG- based IQ classification system for sagittal images is 61% for coronal images 58.70%, for transversal images almost 51%. Here sagittal images provide greater accuracy in the IQ classification. It can be seen from graph Fig.4 (a) that, the maximum accuracy of SVGG based system is obtained only on the 200th epoch.

Table I: Accuracy Comparison

No. of 3D brain images for each class	No. of MRI Slices from individual image	Total no. of slices for training	Total no. of slices for testing	CNN Architecture used	Transversal image accuracy	Sagittal image accuracy	Coronal image accuracy
50	25	4000	1000	SVGG	51.625%	61%	58.75%
50	25	4000	1000	VGG16	54.5%	73%	68.8%
50	25	4000	1000	ResNet-50	66.80%	85.9%	76.4%

1) VGG16 based Classification: In VGG16, an accuracy of 72% is obtained from sagittal images, 68.8% from coronal images, and 54.5% from transversal images. Transversal im- ages give the least accuracy. On graphical analysis Fig.4 (b), it is found out that accuracy of 72% is achieved on the 140th epoch.

2) ResNet-50 based Classification: ResNet-5O architecture classifies IQ with 85.9% accuracy for sagittal images, 76.4% accuracy for coronal images, and 66.8% for transversal im- ages. Of the three brain views, sagittal and coronal images achieve a better result. As seen from the graph Fig.4(c), on the 11th epoch, the ResNet-50 was achieved with the maximum validation accuracy (which is 85.9 percent). Table 1.presents the accuracy of three CNN-based IQ classification systems on three different brain input dataset (Transversal, Sagittal, Coronal).

D. ***Results***

The experimental results obtained after performing IQ clas- sification using three CNN architectures are given below.

- ResNet-50 proves to be more accurate in IQ Classification task than SVGG and VGG16, with a maximum of 85.9 percent accuracy.
- Among the three brain view dataset used, the sagittal dataset is found to be the best choice and transversal or axial brain dataset is found to be the worst choice for IQ classification from brain MRI images.

V. Conclusion

The Intelligence quotient of a person can be attributed to the structure and capability of the human brain. Various neural parameters influence the level of human intelligence. Significant research has not been undertaken for IQ detection of a person based on physiological factors. Most of the related work focuses on IQ detection based on standardized tests. In this context, this project proposed the deep learning-based IQ classification, inspired by the correlation between brain structure and intelligence. The classification of IQ is performed by using state of art CNN's. Here, it is found out that, sagittal and coronal view brain images are the best candidate for IQ classification. Among these, sagittal images provide higher accuracy. By deploying 3D CNN, the intelligence quotient can be measured from the three-dimensional brain images themselves, thereby reducing the process of slice extraction.

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