A Review on Intelligence Quotient prediction Based on Human Brain

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Abstract –*The intelligence of a person is his/her ability to learn, understand and solve problems. The intelligence quotient (IQ) is a metric for measuring a person's intelligence. IQ measurements help diagnose various mental disorders, like autism and other conditions. Human intelligence is closely linked to brain function, and so different levels of intelligence are caused by differences in certain brain areas and neural factors. There is little research on detecting someone's IQ using human physiological characteristics rather than skill tests. A review of intelligence quotient prediction based on human brain images and signals is presented in this paper.*

Key Words*: *Intelligence Quotient (IQ), Magnetic Resonance Image (MRI), Electroencephalogram (EEG), Convolutional Neural Network, Support Vector Regression (SVR), Small Visual Geometry Group (SVGG), Visual Geometry Group (VGG), Residual Network (ResNet)

1. INTRODUCTION

Although intelligence has been defined in different ways, it encompasses how well we properly plan, reason, wisely resolve issues, learn and draw conclusions, and, in the end, survive in today's world. An IQ test generates a score known as the "Intelligence Quotient" which is used to determine a person's cognitive strength and capabilities [1]. An IQ test determines how well you can perform on one. It tests pattern recognition and data manipulation skills. Practice and persistence can help you improve your score. In an online study on the intelligence quotient (IQ), researchers found the test's scores may not accurately reflect someone's intelligence. They discovered no single test could effectively assess a person's ability to do mental and cognitive activities.

Furthermore, researchers examined the MRI scans of participants' brains and found distinct cognitive abilities were linked to different brain circuits, which confirms that different parts of the brain govern distinct abilities [2]. Because the size, structure, and activity level of different areas of the brain have all been linked to intelligence in humans, detecting the intelligence of an individual from brain images or brain signals will be more accurate. This paper reviews various methods of human intelligence classification and recognition based on the brain. The different methods of Intelligence quotient recognition based on the human brain are explained in Chapter 3. Chapter 4 shows the comparison of the different methods. The conclusion of the study is presented in Chapter 5.

2. LITERATURE REVIEW

A machine learning-based prediction modeling approach was employed to see if intelligent scores could be predicted from spatially highly defined (voxel-wise) patterns of regional gray matter volume [3]. Across functional brain networks, gray matter volume has been found to be an excellent predictor of individual differences in intelligence.

A person's IQ score is classified using the transfer learning-based CNN approach of [4] into four classes based on his or her IQ. The MRI (Magnetic Resonance Image) of the brain is used to determine a person's IQ. For the classification task, four pre-trained CNN models were utilized. Out of the four models tested, ResNet-50 had the best accuracy rate with 85.95%.

An extended dirty model-based feature selection method has been proposed in [5] to predict IQ scores from brain-MR images. The correlation coefficient of 0.718 and average root mean square error of 8.695, between the estimated and actual IQ values, are obtained when using multi-kernel Support Vector Regression (SVR). SVR with single kernels produced an average correlation coefficient of 0.684 and an average root mean square error of 9.166.

Based on the Brainnetome-Atlas, an evaluation framework including advanced feature selection and regression approaches has been used to predict IQ scores. A Brainnetome-Atlas-based functional connectivity assessment was used to estimate IQ scores in [6]. Fine-grained parcellations of brain networks are provided by Brainnetome Atlas. A predictive framework integrating advanced feature selection and regression approaches have been used to determine continuous IQ scores in a sample of 360 college students. Five regression models were compared to determine which performs best at predicting continuous IQ scores. Moreover, the method for predicting male and female patients is different due to gender differences in the neurobiology of intelligence.

An effective approach for calculating an individual's IQ using their EEG in resting eye conditions has been presented in [7]. The prediction model is based on sub-band power ratio features from the left hemisphere of the brain and an artificial neural network (ANN). It has been discovered that various groups of intelligence quotient can be categorized based on brainwave sub-band power ratios with 100% training and 88.89% testing accuracy.

3. METHODOLOGY

The intelligence quotient is used as a measure of the ability to plan, reason, comprehend, abstract, and learn [6]. Traditionally, intelligence tests such as the Wechsler Intelligence Scale and Raven Progressive Matrices have been used to assess intelligence (RPM). But the IQ scores from these tests are not accurate. As a person's intelligence is correlated to the brain, this study reviews the various intelligence quotient prediction methods from the human brain. The different approaches for intelligence quotient prediction from the human brain are discussed below.

3.1 CNN-based IQ Classification

An individual's intelligence quotient is classified into one of the four Weschler adult intelligence scale (WAIS) classes: superior, superior, high average, and average using pre-trained CNN models [4]. 2-dimensional brain slices from three brain views (Coronal, Sagittal, and Transversal) are extracted from 3-dimensional brain scans and fed into three CNNs (Smaller Visual Geometry Group (SVGG), Visual Geometry Group (VGG16)[8], and Residual Network 50 (ResNet-50))[9][10].

The data preprocessing steps include skull stripping (removal of the skull from brain scans), slice extraction (extracting bi-dimensional slices of three brain views from skull-stripped 3D brain images), and image resizing (Resizing bi-dimensional slices into the standard input dimension of the CNN). Then, CNN performs automatic intelligence-related feature extraction and IQ categorization. Five convolution layers, three Max pooling layers, one fully linked layer, and two dense layers make up the SVGG neural network architecture. VGG comprises sixteen layers, thirteen convolutional layers, and three fully linked layers. ResNet-50 is a 50-layer architecture of 48 convolution layers, 1 Maxpool layer, and 1 average layer.

3.2 Sparse Learning-based IQ estimation

In [5,] a novel feature selection strategy based on expanding the dirty model was employed to predict IQ from structural MRI brain scans. From brain scans, two types of imaging features are extracted: Gray Matter Volume and White Matter volume. The pipeline of brain image preprocessing includes processes such as removing the skull, removing the cerebellum, segmenting the gray matter and white matter, and separating the cerebrospinal fluid. The enhanced dirty model is then used to choose relevant features in order to construct an IQ estimator using a Support Vector Regression (SVR) model. For distinct datasets, feature selection and SVR model learning are carried out separately. This method of IQ estimation entails two steps: first, identifying the scanning site of a test image, and second, using the appropriate estimator, to estimate the test subject's IQ.

3.3 Brainnetome-Atlas-based Functional Connectivity and Regression model

Here, FCs based on the Brainnetome Atlas is used to determine the IQ score [6]. The brainnetome atlas [11] contains precise morphological and physiological information about each brain area, which could aid researchers to discover areas of functional connectivity or activation. The FC features selected in the training dataset were then applied to multiple regression methods to predict the IQ scores, and the test data was then fed into the regression model to estimate the predicted IQ and verify its accuracy. This method involves the following steps.

ReliefF-based feature extraction, building the prediction model, and testing the model. ReliefF[12] is capable of accurately estimating datasets with dependent and independent characteristics while requiring minimal computation power. This approach uses a nested Leave one out cross-validation (LOOCV), with the outer loop measuring prediction accuracy and the inner loop determining the attribute selection number. To obtain the IQ score, data from the testing data set was fed into a regression model developed with a learning dataset.

3.4 EEG and ANN-based IQ classification

Artificial Neural networks and sub-band power ratio information from the left hemisphere of the brain with closed eyes were used to build the IQ brain-behavior model[7]. The left hemisphere is well-known for its involvement in sequential and logical functions. As a result, this approach concentrates on the information extracted from the left hemisphere brainwave, which is fed to the brain-behavior model. With cutoff frequencies of 0.5 Hz and 30 Hz, the EEG signals were filtered using a bandpass Hamming filter.

The artificial neural network is made up of three layers: an input layer, a hidden layer, and an output layer. Sub-band power ratios were used as input to the neural network framework. The energy spectral density of the theta, alpha, and beta frequency bands of EEG signals are used to compute sub-band power ratios by employing Fast Fourier transform before feature extraction. For each sub-band, box plots were used to evaluate the relevant characteristics of different IQ classes. An iterative back-propagation algorithm using the Levenberg–Marquardt algorithm [13] was used in the training phase.

4. COMPARISON

The comparison of various gender recognition approaches using brain images is shown in Table 1.

No	Title	Method	Dataset	Accuracy
1	Intelligence Quotient Classification from Human MRI Brain Images Using Convolutional Neural Network [4]	1. SVGG 2. VGG 3. ResNet-50	MRI brain images from 1000 functional Connectome Project (FCP)	61% 73% 85.9%
2	MRI-Based Intelligence Quotient (IQ) Estimation with Sparse Learning [5]	Extended dirty model and SVR	Autism Brain Imaging Data Exchange (ABIDE) (MRI Brain Images)	Average Correlation Coefficient -0.718 for multi-kernel SVR & 0.684 for Single Kernel SVR Average Root mean square error -8.695 for multi-kernel and 9.166 for single kernel SVR
3	Predicting individualized intelligence quotient scores using brainnetome-atlas-based functional connectivity, [6]	ReliefF + Lasso	MRI Brain Images	Correlation of r = 0.72 and 0.46 between prediction and true value
4	Classification of intelligence quotient via brainwave sub-band power ratio features and artificial neural network [7]	Artificial Neural Network	EEG signals	88.89%

5. CONCLUSION

The information processing capacities of the brain are characterized by cognitive functioning, which is measured in terms of intelligence. Intelligence can vary considerably from person to person and with age.IQ score is a number that indicates the intelligence of a person. Traditionally, this score is determined by conducting various standard psychometric tests. IQ scores calculated from these tests are not accurate, as the test score can vary due to different factors. As the IQ scores determined from brain images and signals do not vary considerably, this study reviewed different IQ prediction methods based on the human brain. Currently, only a few researchers are focused on estimating an individual's IQ with the help of brain-based data and machine learning algorithms. Out of the four methods, EEG based IQ prediction system provides higher accuracy.

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