Iranian Journal of Operations Research
Vol. 16, No. 1, 2025, pp. 147-158

IQ Estimation from fMRI Images Using GCNN Model

Sara Motamed[1,*], Mahboubeh Yaqubi bijarboneh[2]

Intelligence has long been a compelling and significant topic in psychology and cognitive science. IQ is considered a fundamental measure of an individual's cognitive abilities, encompassing various aspects such as reasoning, problem-solving, memory, and overall intellectual capacity. Given the importance of IQ in cognitive and psychological evaluations, the main goal of this study is to propose a novel and effective approach to enhance the accuracy of IQ estimation through the processing of complex brain data. In this paper, we develop and analyze a hybrid model combining the Grey Wolf Optimization (GWO) algorithm and a Convolutional Neural Network (CNN), referred to as the GCNN model, to estimate IQ using brain fMRI images from the ABIDE dataset. Experimental results demonstrate that the proposed model significantly outperforms traditional techniques, achieving an estimation accuracy of 93.10%, which is an improvement of approximately 10% over previous methods. Sensitivity analysis was conducted to evaluate the robustness of the model against variations in input features and hyperparameters, confirming its stability and generalizability across different data subsets. These findings highlight the strong capabilities of the GCNN model in interpreting complex medical data and its potential applicability in clinical and research settings.

Keywords: *IQ, Deep learning, Brain fMRI images, Grey Wolf Optimization (GWO) algorithm, Convolutional Neural Network (CNN).*

1. Introduction

IQ is a commonly used metric for measuring human intelligence and reflects an individual's ability to understand, learn, and think. In other words, it is a numerical indicator of cognitive capacity. Over the past few decades, intelligence has been one of the most widely discussed topics in cognitive science and psychology, often generating debate and controversy. Scientists have continuously sought accurate methods to measure IQ—from standardized tests administered in institutions and schools to puzzles designed to assess cognitive performance. Typically, IQ is assessed using a series of standardized tests and subtests, with scores following a normal distribution. Most IQ values cluster around the median, while only a small percentage of individuals score above 140 or below 70 [1]. Recent studies have shown that brain volume has only a limited impact on IQ, with brain structure and integrity playing a more significant role in explaining cognitive performance [25]. These findings suggest that the biological basis of intelligence is more closely linked to structural characteristics of the brain than to its size. The cerebrum comprises the right and left hemispheres of the brain, each divided into four lobes: frontal, temporal, occipital, and parietal. Research has shown that in children and young adults, the frontal and temporal lobes are most associated with IQ, while in middle-aged

[1] Department of Computer Engineering, FSh.C., Islamic Azad University, Fouman, Iran, Email: sara.motamed@iau.ac.ir.
[2] Department of Computer Engineering, SR.C. Islamic Azad University, Tehran, Iran, Email: mahboubeh.yaghoubi@iau.ac.ir.

individuals, the parietal and occipital lobes play a more prominent role [15]. Given this correlation between brain structure and intelligence, it is feasible to estimate IQ using brain fMRI images. Studies have demonstrated that if intelligence levels can be determined through neuroimaging, the results could enhance artificial intelligence systems and aid in the understanding and treatment of conditions such as depression and schizophrenia [11, 15]. In recent years, many efforts have been made to predict IQ from fMRI images. With the advent of deep learning, research in this area has increasingly turned to neural networks to tackle the problem. Deep learning involves the use of neural networks with many hidden layers that learn hierarchical representations of data. For example, in image analysis, deep networks break down the image into multiple layers—mimicking the way human neurons respond to visual stimuli. Convolutional Neural Networks (CNNs) are one of the most widely used architectures in deep learning, successfully applied in tasks such as object recognition and image classification.

Although deep learning has significantly advanced the field of computer vision, IQ prediction from fMRI remains in its early stages, with much room for development. Based on the above, this study proposes leveraging the powerful capacity of deep neural networks to estimate IQ from brain images [2]. This is a complex and evolving research area, with potential implications for understanding the neural basis of intelligence as well as clinical applications. However, several challenges remain. Predicting IQ from fMRI data raises methodological and ethical issues. IQ is a multifaceted trait influenced by genetic, environmental, and neurological factors [13, 20]. Therefore, the relationship between brain structure and intelligence must be carefully studied, and ethical concerns such as data privacy must be addressed. Researchers must ensure anonymization and responsible use of sensitive medical data. In this context, the objective of this study is to develop a hybrid model combining Grey Wolf Optimization (GWO) and CNNs—referred to as the GCNN model—to estimate IQ from brain fMRI images. We hypothesize that this combination will improve the accuracy and efficiency of automated IQ estimation systems.

The Grey Wolf Optimization algorithm is a bio-inspired meta-heuristic method modeled after the social hierarchy and hunting behavior of grey wolves. The hierarchy includes alpha, beta, delta, and omega wolves, and the algorithm simulates the three main stages of hunting: searching, encircling, and attacking prey. In this study, GWO is employed to optimize the fuzzy parameters of the deep neural network, aiming to enhance detection accuracy. The reason for selecting this class of algorithms lies in their derivative-free nature and stochastic structure, which allow them to solve complex problems without requiring gradient information. Meta-heuristic algorithms are particularly suited for real-world problems with high dimensionality and unknown derivatives. Their ability to perform both local and global searches helps prevent premature convergence to local optima and enables broad exploration of the search space. As the size and complexity of optimization problems increase, finding the global optimum becomes computationally expensive. By incorporating GWO into the training of the deep neural network, this study aims to improve both solution quality and convergence speed.

2. Related Work

Intelligence is a critical factor in psychological evaluations, and brain fMRI -based intelligence prediction offers an objective complement to traditional psychological tests. This approach has the potential to improve the accuracy and reliability of cognitive assessments. Moreover, it holds valuable clinical applications. Understanding the relationship between brain structure and intelligence can aid in diagnosing and treating various neurological and psychiatric disorders, and may inform the development of more targeted therapeutic interventions [17]. The fMRI is a non-invasive, radiation-free imaging technique, making it safe for repeated use in both research and clinical environments. It produces high-resolution images of the brain's anatomy, allowing for detailed analysis of structural features. Predicting intelligence from fMRI scans not only minimizes bias compared to traditional IQ tests but also provides the potential to identify biomarkers related to cognitive function and neurological disorders. This opens up new avenues for interdisciplinary collaboration among neuroscientists, psychologists, educators, and medical professionals [17]. The fMRI-based IQ prediction is particularly useful in cases involving conditions that affect cognitive function, such as traumatic brain injury or neurodegenerative diseases. It can help guide treatment strategies and monitor therapeutic outcomes. As intelligence is a multifaceted trait influenced by genetic, environmental, and neurological factors, advanced imaging techniques like fMRI are essential for understanding its complexity. In the era of precision medicine, matching interventions to individual neurological profiles is crucial, and fMRI -based intelligence estimation contributes significantly to this personalized approach [5].

Increasing our understanding of how brain structure relates to intelligence could lead to breakthroughs across neuroscience, psychiatry, and education. Thus, fMRI -based IQ prediction has strong potential in cognitive research, early diagnosis of cognitive impairments, personalized education, and clinical applications. While challenges and ethical considerations remain, this approach represents a promising frontier in interdisciplinary science. Despite significant progress, many aspects of human intelligence remain poorly understood, and current IQ assessment methods have notable limitations. Over the years, numerous studies have investigated the link between the human brain and intelligence, emphasizing the importance of brain networks and overall brain structure. Given the regulatory role of various brain regions in cognitive performance, brain fMRI has emerged as a useful tool for estimating intelligence. For example, research at the NYU School of Medicine suggests that specific areas of gray matter, particularly in the parietal and frontal lobes, are more strongly associated with IQ than total brain volume [9]. With advances in technology, machine learning and deep learning methods have become central to brain image analysis, aiding in the diagnosis and classification of neurological diseases, tumors, psychiatric disorders, and even traits like gender identity. In this context, Wang et al. proposed a method for IQ prediction using fMRI data. Their approach framed IQ estimation as a regression problem, focusing on gray and white matter features. Using multiple support vector regression (SVR), they identified several critical brain regions, including the left and right thalamus, parahippocampal gyrus, hippocampus, anterior cingulate gyrus, amygdala, lingual gyrus, superior and inferior parietal lobules, angular gyrus, paracentral lobule, and caudate nucleus. Their study also indicated a relationship between age, brain tissue volume, and IQ [6].

Deep learning, inspired by the architecture of the human brain, is now a key area of research worldwide. These models are especially useful because they can automatically extract relevant features during training, eliminating the need for manual feature engineering. Consequently, deep learning has been widely applied in IQ classification tasks [6, 9]. Building on these developments, the present study proposes an improved deep learning-based model for predicting IQ from fMRI data.

3. Proposed Model

Neuroimaging studies have proposed several theories about the mapping between brain structure and function underlying human intelligence. In fact, intelligence is related to changes in different brain structures and neural parameters. The cerebrum consists of the right and left hemispheres, each containing four lobes: frontal, temporal, occipital, and parietal. The temporal and frontal lobes are generally associated with IQ in children and youth, while the parietal and occipital lobes are more associated with IQ in middle age. Gray matter in specific brain regions, particularly in the parietal and frontal lobes, plays a significant role in human intelligence relative to the size of the whole brain. Therefore, it is possible to estimate individuals’ IQ based on physiological factors by extracting and classifying IQ-related features from fMRI images. For example, the Parieto-Frontal Integration Theory (P-FIT) is a popular model which suggests that sensory information is first collected and processed mainly in the occipital and temporal regions. The next stage involves structural symbolization, abstraction, and elaboration of sensory information in the angular gyrus, supramarginal gyrus, and superior parietal lobule. Finally, interaction between parietal regions and frontal lobes supports higher-order cognitive functions such as problem solving, evaluation, and hypothesis testing. In this study, we expect the Long Short-Term Memory (LSTM) network to focus on salient brain regions extracted from fMRI images.

Given the correlation between brain structure and intelligence, it is feasible to estimate intelligence from brain fMRI scans. Studies have shown that such imaging-based intelligence estimation can enhance the capabilities of artificial intelligence systems. However, since fMRI images may suffer from quality issues and various types of noise, preprocessing steps are necessary to achieve optimal results. These steps include image corrections such as contrast adjustment and resizing to improve segmentation accuracy. Subsequently, a hybrid deep learning model is applied for IQ detection from brain images [16, 22]. Intelligence is one of the most complex traits in humans, and despite extensive research by scientists and philosophers, it remains incompletely understood [7]. Currently, IQ tests are commonly used to measure individuals' reasoning speed and problem-solving ability, but they do not capture the full spectrum of intellectual capacities. Consequently, with the advancement of artificial intelligence and machine learning, recent studies have focused on estimating IQ directly from brain fMRI images. In this article, we propose a hybrid model combining the Grey Wolf Optimization (GWO) algorithm and a Convolutional Neural Network (CNN) to detect IQ from brain images. The GWO is a population-based metaheuristic algorithm inspired by the social hunting behavior of gray wolves. It has a simple yet effective process and can be easily generalized to large-scale optimization problems. In each pack, the hunting hierarchy is modeled as a pyramidal structure consisting of four levels, as shown in Figure 1.

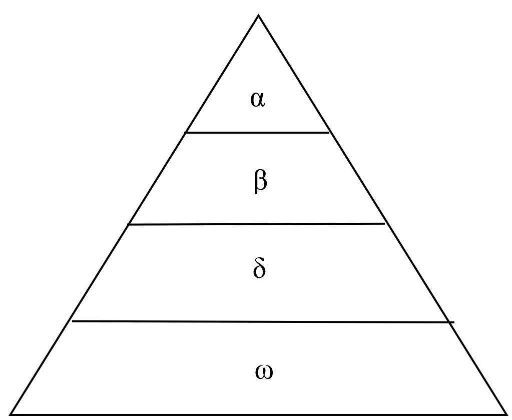

Figure 1. Pyramid structure of GWO model

The wolves in the pack leadership hierarchy are called alpha wolves, which can be either male or female. These wolves dominate the pack. Beta wolves assist alpha wolves in the decision-making process and can potentially replace them. Delta wolves rank below beta wolves and include older wolves, hunters, and those caring for pups. Omega wolves occupy the lowest rank in the hierarchy pyramid, having the fewest rights compared to the rest of the pack; they eat last and do not participate in decision-making.

The Grey Wolf Optimization (GWO) algorithm models the hunting behavior of gray wolves and consists of three main steps:

- Tracking and chasing the prey.
- Approaching, encircling (surrounding) the prey, and leading it astray until it stops moving.
- Attacking the prey.

In this algorithm, the hierarchical structure and social behavior of wolves during hunting are mathematically modeled to design an optimization method. Optimization is primarily guided by the alpha, beta, and delta wolves. One wolf is considered the main leader (alpha), with beta and delta wolves also influencing the search, while the rest are followers. Gray wolves have the ability to estimate the prey's location.

When the prey is surrounded and stops moving, the attack begins, led by the alpha wolf. This process is modeled by reducing the vector a. Since **A** is a random vector within the interval [-2**a**, 2**a**], decreasing **a** reduces the range of A. If |**A**| < 1, the wolf moves toward the prey (and other wolves); if |**A**| > 1, the wolf moves away from the prey. In the GWO algorithm, all wolves update their positions based on the positions of the alpha, beta, and delta wolves [3].

In this article, we improve the GWO algorithm by combining it with a deep neural network and fuzzy control of key parameters to enhance IQ detection accuracy. Deep neural networks are widely used models in deep learning applied across various fields. The sequence of steps in the proposed model is as follows:

Preprocessing: Two-dimensional slices are first extracted from three-dimensional fMRI images. This stage includes three parts:

- **Cranial removal:** The process of separating brain tissue from surrounding non-brain areas [19].
- **Creating 2D slices from 3D images:** Brain slices are extracted from three anatomical planes: sagittal, coronal, and transverse.
    - The sagittal plane divides the brain into left and right halves.
    - The coronal (frontal) plane divides the brain into anterior and posterior parts.
    - The transverse (horizontal) plane divides the brain perpendicular to the longitudinal axis.

These slices are then passed to the feature extraction stage for more precise analysis.

Optimization and Training: After initializing the population, all parameters are input to a deep neural network to optimize the positions of alpha, beta, and delta wolves. The deep neural network consists of two convolutional layers and one fully connected layer that learns the data patterns.

The GWO algorithm requires initializing only two parameters: **a** and **C**, and it can be extended to n-dimensional search spaces. In this approach, **a** and **C** are controlled using fuzzy logic. According to the equations provided, parameter a directly influences coefficient **A** and controls the wolves' behaviors dynamically. The coefficient **A** models the attack and hunting process, known as exploitation. Because **A** varies within [-1, 1], the wolves' next positions oscillate between their current locations and the prey location. Therefore, parameter **a** affects both exploitation (local search) and exploration (global search). The mathematical modeling of the encircling process is represented by equations (1) and (2) [4].

$$D = \left| C.X_p(t) - X(t) \right| \quad (1)$$
$$X(t+1) = X_p(t) - AD \quad (2)$$

Where **C** and **A** are the vectors of coefficients, $\mathbf{X_p}$ is the location vector of hunting and **X** is the location vector of each of the wolves, and **t** is the repetition number. Two vectors **A** and **C** are calculated by equations (3) and (4) [4].

$$A = 2a.r_1 - a \quad (3)$$
$$C = 2r_2 \quad (4)$$

The parameter **a** decrease linearly from 2 to 0 during the iteration process, and $\boldsymbol{r_1}$ and $\boldsymbol{r_2}$ represent random vectors within the interval [0, 1]. Vector **C** models obstacles in nature that slow down the wolves' approach to the prey; in fact, **C** adds weight to the hunting process, making it more challenging for the wolves to reach the prey. In this article, different ranges are considered for the variations of coefficient **A**. In "(4)", the value of **C** represents these natural obstacles. It is a random and variable value within the range [0, 2], which directly affects the position of the prey. Unlike the parameter **a**, this value does not decrease linearly but is selected entirely at random, thus assigning random weights to the hunting process. The purpose of presenting the proposed model is that it automatically extracts features from the input data and provides more accurate classification results [10].

4. Results and Discussion

Based on the literature review, it was observed that existing models for artificial and natural image classification are either too complex or cannot be scaled effectively for multi-domain image sets. Moreover, the accuracy of these models directly depends on the type of dataset and features used for training and validation, which further limits their scalability. To overcome these limitations, this section proposes the design of a hybrid GWO-CNN model for artificial image recognition in big data applications [18, 28]. All implementations in this article were done using Python. The dataset is divided into training and testing subsets. Next, the dataset and the main phases of the proposed model's implementation are described.

4.1. ABIDIE Dataset

The ABIDE (Autism Brain Imaging Data Exchange) fMRI brain image dataset provided by NITRC (Neuroimaging Informatics Tools and Resources Clearinghouse) was used in the experiments of this thesis. The dataset contains 3D brain images in the NIFTI (Neuroinformatics Informatics Technology Initiative) file format. Phenotypic information also includes age, gender, and IQ scores of different individuals. The phenotypic file lists three types of IQ scores: Full IQ (FIQ), Performance Intelligence Quotient (PIQ), and Verbal Intelligence Quotient (VIQ). In this thesis, FIQ is considered as the measure of intelligence. FIQ scores for many subjects were not listed in the dataset; therefore, FIQ for those subjects was calculated from PIQ and VIQ values using equation (5) [21]:

$$\text{FIQ} = -11.611 + 0.551\text{VIQ} + 0.566\text{PIQ} \quad (5)$$

4.2. Evaluation Results

A review of previous work in this field shows that recent studies on individual IQ prediction have mostly focused on predicting fluid intelligence (the ability to solve new problems). However, there are no studies that predict crystallized intelligence (the ability to accumulate knowledge) or general intelligence (a combination of fluid and crystallized intelligence). In this paper, we test whether deep learning can predict total IQ, which depends on both functional IQ and verbal IQ, thus reflecting both fluid and crystallized intelligence, using fMRI images. Recent studies have started using machine learning—especially deep learning—to predict intelligence, but many questions remain unanswered. In more than 20 relevant studies, the predicted fluid intelligence had a mean squared error ranging from 86 to 103. This relatively low accuracy suggests the need for more sophisticated deep learning algorithms or indicates that some fMRI images may not contain enough information to predict problem-solving abilities, which peak at younger ages. Therefore, we used the ABIDE dataset, which includes a wide range of data from multiple centers, to achieve the best possible results.

Most research on general intelligence has been based on stylistic reviews as well as experimental and practical studies. One notable related study focused on machine learning methods, specifically support vector machines. In contrast, deep learning research in this area has typically used smaller datasets for training and testing, often relying solely on convolutional neural networks (CNNs) for classification, which has resulted in weaker predictive performance. Table 1 presents IQ estimation accuracy using different brain region slices and various models.

Table 1. Comparison of the accuracy criteria by the models implemented on the ABIDE dataset

Models	Transversal image accuracy	Sagittal image accuracy	Coronal image accuracy
ResNet-50	66.80%	61.00%	58.75%
VGG16	54.50%	73.00%	68.80%
CNN	70%	85.90%	76.40%
Proposed Model	78%	91.00%	81.20%

As shown in Table 1, the proposed model achieved the highest accuracy compared to previous models. Table 2 presents a comparison of various evaluation metrics for the proposed model on the ABIDE dataset.

Table 2. Comparison of different criteria using the proposed model on the ABIDE dataset

Evaluations	Accuracy	F۱—score	Precission	Recall
Proposed Model	93.10%	88.00%	90.00%	86.77%

Figure 2 shows the error rate for the training and testing data over 30 executions. According to Figure 2 and Table 2, the detection rate reached an accuracy of 93.10% after thirty iterations.

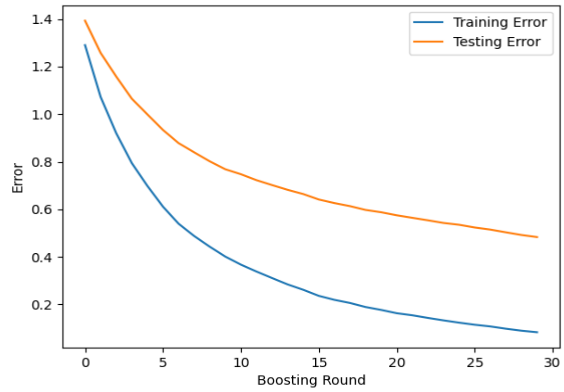

Figure 2. Error rate by the proposed model

Table 3 provides a comparative overview of recent works on IQ prediction, highlighting the key strengths and limitations of the approaches presented in these studies.

Table 3. Methods used to diagnose IQ

References	Title	Method	Accuracy	Advantages	Disadvantages
[14]	Accounting for Temporal Variability in fMRI Improves IQ Prediction	Bi-directional LSTM	~ 75%	Utilizing time series structure and dynamic connectivity	The need for high-quality data and large data volumes
[29]	Alternating Diffusion Map Based Fusion	Diffusion Map Fusion	~ 70%	Integration of multiple brain data sources to improve performance	High computational complexity
[30]	Multi-Task Learning Model for IQ Prediction (Chen et al., 2019)	Multi-task Learning	~ 72%	Simultaneous multi-task learning while preserving the geometric structure of data	Requires precise hyperparameter tuning
[12]	Deep Learning on Structural MRI (Cao et al., 2022)	CNN, Deep Learning	~ 78%	Ability to extract complex features without	Ability to extract complex features from structural MRI data without

				manual engineering	manual engineering
[26]	Connectome Signatures from Resting-state fMRI (Sui et al., 2022)	Connectome-based Predictive Modeling (CPM)	~ 73%	Model based on brain connectomes	Limited to resting-state data, making interpretation more challenging
[23]	Voxel-Level Brain States Prediction Using Swin Transformer (2025)	Swin Transformer + CNN	Learned high-resolution fMRI with reduced scan time	Accurate prediction of brain states	High accuracy
[27]	Prediction of IQ from Resting-state fMRI (2024)	Machine Learning	R=0.71	Accurate prediction of performance IQ	Suitable for children using resting-state data
[24]	Choosing Explanation Over Performance (2024)	Explainable ML + Connectome	"The Pearson correlation coefficients for crystallized intelligence (gC) and fluid intelligence (gF) IQ scores were 0.71 and 0.63, respectively."	Moderate accuracy with high interpretability	Clarity in brain analysis

As can be seen from Table 3, the proposed model demonstrates superior performance compared to the other methods presented.
The key contributions and novel aspects of this research are summarized as follows:

- **Proposed a hybrid GCNN model** that integrates the Grey Wolf Optimization (GWO) algorithm with a Convolutional Neural Network (CNN) to enhance feature extraction and parameter optimization for improved IQ prediction accuracy.
- **Focused on predicting full-scale IQ (FIQ)**, incorporating both fluid and crystallized intelligence components, using brain fMRI images—an area underexplored in prior studies.
- **Utilized the ABIDE dataset**, which includes a diverse range of individuals from multiple sites, enhancing the robustness and generalizability of the proposed model.
- **Achieved 93.10% accuracy**, outperforming existing methods and demonstrating the effectiveness of the GCNN architecture in capturing complex neuroimaging features.

- **Conducted sensitivity analysis** to evaluate the model's stability under variations in input and parameters, ensuring the reliability of the results.

5. Conclusions

Neuroimaging (brain imaging) refers to the techniques used to visualize the structure and function of the human central nervous system. Various methods are employed directly or indirectly to map brain anatomy and its activities. Neuroimaging studies help us understand both normal and abnormal brain functions, such as disease prediction, brain region failures, intelligence estimation, and other vital processes. These studies are crucial for identifying structural abnormalities in the brain and safeguarding future generations from neurological diseases. Since all human behavior is guided by the brain’s anatomical structure, and neuroimaging has shown that individual differences in brain anatomy correspond to variations in behavior, it becomes possible to categorize people’s abilities. Intelligence is one of the key parameters underlying these abilities, varying from person to person, and its measurement allows classification into higher or lower intelligence groups. Research has also demonstrated that many central regions in the nervous system significantly contribute to intelligence. One of the established metrics for measuring intelligence is the Intelligence Quotient (IQ). The model proposed in this article combines the Grey Wolf Optimization (GWO) algorithm with a Convolutional Neural Network (CNN). CNNs are capable of extracting intermediate-level features through filters applied to the input data. The goal of this model is to classify brain fMRI images and estimate IQ improvements accurately.

References

[1] Adebayo, G. O., & Yampolskiy, R. V. (2022). Estimating intelligence quotient using stylometry and machine learning techniques: A review. *Big Data Mining and Analytics, 5*(3), 163–191. https://doi.org/10.26599/BDMA.2022.9020002.

[2] Arya, A., & Manuel, M. (2020, September). Intelligence quotient classification from human MRI brain images using convolutional neural network. In *2020 12th International Conference on Computational Intelligence and Communication Networks (CICN)* (pp. 75–80). IEEE. https://doi.org/10.1109/CICN49253.2020.9242552.

[3] Balafar, M. A., Ramli, A. R., Saripan, M. I., & Mashohor, S. (2010). Review of brain MRI image segmentation methods. *Artificial Intelligence Review, 33*(3), 261–274. https://doi.org/10.1007/s10462-010-9155-0.

[4] Boustani, A. E., Aatila, M., Bachari, E., & Oirrak, A. E. (2020). MRI brain images classification using convolutional neural networks. In *Advanced Intelligent Systems for Sustainable Development (AI2SD’2019) Volume 4—Advanced Intelligent Systems for Applied Computing Sciences* (pp. 308–320). Springer.

[5] Dubois, J., Galdi, P., Paul, L. K., & Adolphs, R. (2018). A distributed brain network predicts general intelligence from resting-state human neuroimaging data. *Philosophical Transactions of the Royal Society B, 373*(1756), 20170284. https://doi.org/10.1098/rstb.2017.0284

[6] Finn, E. S., Shen, X., Scheinost, D., et al. (2015). Functional connectome fingerprinting: Identifying individuals using patterns of brain connectivity. *Nature Neuroscience, 18*(11), 1664–1671. https://doi.org/10.1038/nn.4135.

[7] Frangou, S., Chitins, X., & Williams, S. C. R. (2004). Mapping IQ and gray matter density in healthy young people. *NeuroImage, 23*(3), 800–805. https://doi.org/10.1016/j.neuroimage.2004.05.027.
[8] Glasser, M. F., Sotiropoulos, S. N., Wilson, J. A., et al. (2013). The minimal preprocessing pipelines for the Human Connectome Project. *NeuroImage, 80*, 105–124. https://doi.org/10.1016/j.neuroimage.2013.04.127.
[9] He, N., & Kou, C. (2024). Prediction of IQ from resting-state fMRI in children and adolescents. *International Journal of Developmental Neuroscience, 84*(7), 779–790. https://doi.org/10.1002/jdn.10375.
[10] Jung, R. E., & Haier, R. J. (2007). The Parieto-Frontal Integration Theory (P-FIT) of intelligence: Converging neuroimaging evidence. *Behavioral and Brain Sciences, 30*(2), 135–154. https://doi.org/10.1017/S0140525X07001185.
[11] Ke, F., Liu, H., Zhou, M., Yang, R., & Cao, H.-M. (2021). Diagnostic biomarker exploration of autistic patients with different ages and different verbal intelligence quotients based on random forest model. *IEEE Access, 9*, 123861–123872. https://doi.org/10.1109/ACCESS.2021.3071118.
[12] Kong, R., Li, J., Orban, C., et al. (2019). Spatial topography of individual-specific cortical networks predicts human cognition, personality, and emotion. *Cerebral Cortex, 29*(6), 2533–2551. https://doi.org/10.1093/cercor/bhy123.
[13] Li, Y., Liu, Y.-Y., Li, Y., Qin, Y., Li, Y., Yu, C., … He, Y. (2009). Brain anatomical network and intelligence. *PLoS Computational Biology, 5*(5), e1000395. https://doi.org/10.1371/journal.pcbi.1000395.
[14] Li, Y., Ma, X., Sunderraman, R., Ji, S., & Kundu, S. (2023). Accounting for temporal variability in fMRI improves IQ prediction. *Human Brain Mapping, 44*(13), 4772–4791. https://doi.org/10.1002/hbm.26415.
[15] Liu, F., Shi, Y., & Chen, Z. (2021). Intelligence quotient test for smart cities in the United States. *Journal of Urban Planning and Development, 147*(1), 04020053. https://doi.org/10.1061/(ASCE)UP.1943-5444.0000637.
[16] McDaniel, M. A. (2005). Big-brained people are smarter: A meta-analysis of the relationship between in vivo brain volume and intelligence. *Intelligence, 33*(4), 337–346. https://doi.org/10.1016/j.intell.2004.11.005.
[17] Oommen, A. (2014). Factors influencing intelligence quotient. *Journal of Neurology & Stroke, 1*(4), 00031. https://doi.org/10.15406/jnsk.2014.01.00031.
[18] Rosenberg, M. D., Finn, E. S., Scheinost, D., et al. (2016). A neuromarker of sustained attention from whole-brain functional connectivity. *Nature Neuroscience, 19*(1), 165–171. https://doi.org/10.1038/nn.4179.
[19] Roy, Y., Banville, H., Albuquerque, I., Gramfort, A., Falk, T. H., & Faubert, J. (2019). Deep learning-based electroencephalography analysis: A systematic review. *Journal of Neural Engineering, 16*(5), 051001. https://doi.org/10.1088/1741-2552/ab260c.
[20] Shen, X., Finn, E. S., Scheinost, D., et al. (2017). Using connectome-based predictive modeling to predict individual behavior from brain connectivity. *Nature Protocols, 12*, 506–518. https://doi.org/10.1038/nprot.2016.178.
[21] Sripada, C., Angstadt, M., Rutherford, S., Taxali, A., & Shedden, K. (2020). Toward a “treadmill test” for cognition: Improved prediction of general cognitive ability from task activation. *Human Brain Mapping, 41*(12), 3186–3197. https://doi.org/10.1002/hbm.25007.
[22] Supekar, K., Swigart, A. G., Tenison, C., Jolles, D. D., Rosenberg-Lee, M., Fuchs, L., & Menon, V. (2013). Neural predictors of individual differences in response to math tutoring in primary-grade school children. *Proceedings of the National Academy of Sciences, 110*(20), 8230–8235. https://doi.org/10.1073/pnas.1222154110.

[23] Sun, Y., Chahine, D., Wen, Q., Liu, T., Li, X., Yuan, Y., Calamante, F., & Lv, J. (2025). Voxel-level brain states prediction using Swin Transformer. *arXiv preprint*. https://arxiv.org/abs/2506.11455.
[24] Thiele, J. A., Faskowitz, J., Sporns, O., & Hilger, K. (2024). Choosing explanation over performance: Insights from machine learning-based prediction of human intelligence from brain connectivity. *PNAS Nexus, 3*(12), pgae519. https://doi.org/10.1093/pnasnexus/pgae519.
[25] Thilakavathy, P., & Diwan, B. (2023). Intelligent quotient estimation from MRI images using combination of deep learning. *The Journal of Supercomputing, 79*(26), 35788–35812. https://doi.org/10.1007/s11227-022-04711-0.
[26] Tong, X., Xie, H., Carlisle, N. B., Fonzo, G. A., Oathes, D. J., Jiang, J., & Zhang, Y. (2022). Transdiagnostic connectome signatures from resting-state fMRI predict individual-level intellectual capacity. *Translational Psychiatry, 12*, 367. https://doi.org/10.1038/s41398-022-02134-2.
[27] Van Essen, D. C., Smith, S. M., Barch, D. M., Behrens, T. E. J., Yacoub, E., & Ugurbil, K. (2013). The WU-Minn Human Connectome Project: An overview. *NeuroImage, 80*, 62–79. https://doi.org/10.1016/j.neuroimage.2013.05.041.
[28] Wang, L., Wee, C.-Y., Suk, H.-I., Tang, X., & Shen, D. (2015). MRI-based intelligence quotient (IQ) estimation with sparse learning. *PLOS ONE, 10*(3), e0117295. https://doi.org/10.1371/journal.pone.0117295.
[29] Xiao, L., Stephen, J. M., Wilson, T. W., Calhoun, V. D., & Wang, Y.-P. (2019). Alternating diffusion map-based fusion of multimodal brain connectivity networks for IQ prediction. *IEEE Transactions on Biomedical Engineering, 66*(8), 2140–2151. https://doi.org/10.1109/TBME.2018.2884129.
[30] Zhang, Y., Ji, H., & Li, X. (2023). Self-supervised deep learning for image reconstruction: A Langevin Monte Carlo approach. *SIAM Journal on Imaging Sciences, 16*(4), 2247–2284. https://doi.org/10.1137/23M1548025.