A Review On Gender Recognition Using Human Brain Images

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Abstract – *Gender identity reflects how our brain perceives us. A person's gender identity and sexual orientation are permanently encoded in the prenatal brain, so they do not change over time and are unaffected by age, ethnicity, or other factors. Due to its complicated spatial structure and lack of significant differences visible to the naked eye, identifying gender using the human brain is a difficult task. This article describes various methods for detecting human gender using MRI images of the brain. Using various machine learning and deep learning approaches, reliable and efficient gender-related features can be extracted from a person's MRI images to identify a person's gender.*

***Key Words*: Gender identification, Magnetic Resonance Image, Descriptors, Convolutional Neural Network**

1. INTRODUCTION

"Gender identity" refers to one's perception of themselves and their identity as men, woman, a blend of both or neither [1]. Gender roles are determined by observable characteristics such as behaviour and appearance in society, while a specific set of intrinsic and external factors determines this self-identified phenomenon. A person's gender identity may be the same as or different from the sex assigned at birth. The way men and women encode memories, perceive emotions, recognize faces, solve problems, and make decisions differs. The brain controls cognitive functions and behaviours. Therefore, gender-specific brain structures may be involved in these functional differences between males and females [2]. A woman's hippocampus, which is critical for learning and memory, is bigger and functions differently than a man. In contrast, a man's amygdala, which is responsible for feeling emotions and remembering them, is bigger than that of a woman [3].

Recent studies have found that machine learning algorithms are far more effective in analyzing brain images. A deep convolutional neural network (CNN) extracts image features using convolutional kernels and can reveal the characteristic spatial differences of brain images. Thus, it has a better chance of finding these features than other, more traditional machine learning and statistical methods [4]. The different methods of gender recognition based on human brain scans 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

For gender recognition from three-dimensional brain scans, [5] uses a three-dimensional descriptor called WHGO (Weighted Histogram Gradient Orientation) and an SVM (Support Vector Machine) classifier. The proposed method achieves higher accuracy and can support clinical treatment and research in neurological and psychiatric disorders.

Multi-layered 3D convolutional extreme learning machines (MCN-ELMs) were used to analyze structural gray matter (GM) scans from 876 healthy adults participating in the Human Connectome Project (HCP) to categorize their brains[6]. Using 10-fold cross-validation, this system distinguishes male and female brains with 98.06 percent accuracy, surpassing previous state-of-the-art algorithms. It could also be used to understand other brain diseases. In addition, the results show that the human brain can be divided into two unique classes: male and female brains. Therefore, to better understand psychiatric problems, it may be best to treat males and females separately.

In many studies, three-dimensional CNNs (3-dimensional convolutional neural networks) are used to recognize structural MRI images of the brain, such as T1- and T2-weighted images. It is not possible to use these images directly because diffusion tensor images provide information about the movement of water molecules in the brain. Using T1, T2, and DTI, a multichannel 3D CNN was constructed and the effect of the brain structure image on gender discrimination was evaluated in [7].

Gray matter concentration and structural connectivity have been the focus of previous studies. A multivariate pattern analysis method called Hierarchical Sparse Representation Classifier (HSRC) was used in [8] for the gender identification task and obtained 96.7% accuracy. It has been found out that the cortical 3-D morphological features within the frontal lobe of the brain played the most significant role in explaining gender differences in brain morphology. The suggested HSRC algorithm improves classification accuracy while consuming less compute and storage space for high-dimensional MRI data. It also directly selected features, making discriminative voxels more understandable in MRI data.

In [9], structural brain differences were exploited to determine the gender, age, and mental health status of children and adolescents using a 3D convolutional neural network based on a multitask learning technique. Two publicly available dataset ABIDE-II and ADHD-200 were used in this model.

3. METHEDOLOGY

Gender identification is a complex phenomenon, and the diversity of gender expressions contradicts a simple or uniform explanation. Hence, the extent to which it is determined by social vs. biological factors continues to be an ongoing debate [10]. Here, gender identity of a person is determined by examining a person's MRI image. The various methods of gender identification methods using brain images are discussed below.

3.1 WHGO descriptor and SVM Classifier

WHGO is a new 3D descriptor for describing spatial disparities in the brain [5]. It involves i) gradient calculation ii) Quantify orientations iii) Weight calculation iii) Weighted histogram calculation. This study utilized datasets from the '1000 Functional Connectomes Project'. A leave-one-out cross-validation approach has been used in this framework. Feature selection, codebook creation, 3D spatial partition, picture representation, kernel calculation, and SVM-based decision making are all part of this approach. During feature extraction, a dense sampling method was employed to get local areas, and the proposed feature descriptor was used to describe the local regions to obtain a feature matrix. This method can find out the regions of interest related to gender.

3.2 Multi-Layer 3D Convolution Extreme Learning Machine

Multilayered 3D convolution and 3D pooling have been used to preprocess structural MRI data [6]. Extreme learning is a type of feedforward neural network with only one layer. Kernel parameters are initialized at random and thereafter fixed without adjusting. The net output feature maps are then combined into a vector and used as the ELM input. Then, three ELM classifier output labels have been voted on to determine the sample's final label.

This strategy can give an alternative way for structural MRI research and a potential alternative diagnosis of brain disorders with structural abnormalities by swiftly and successfully differentiating males from females. In the classification task, the number of ELM hidden nodes is crucial. The classification accuracy of three networks and voting accuracy improves gradually as the hidden layer nodes are increased. Most state-of-the-art classification algorithms, including as KNN (K Nearest Neighbors), LDA (Linear discriminant Analysis), and SVM, are outperformed by ELM. The MCN is a good feature extraction method when compared to PCA and paired t-test.

3.3 3D CNN Classifier

In [7], a 3D-CNN using diffusion tensor images was employed for gender identification. The feature extraction unit consists of a three dimensional Convolution layer, Batch Normalization, Activation(relu), Max Pooling layer which are repeated 5 times as a single layer. By feeding the derived feature map to the recognition unit, men and women are classified.

3.4 Hierarchical Sparse Representation Classifier (HSRC)

The HCP structural pipelines were used to pre-process the data [8]. It registers T2-weighted structural images, yielding more precise registration and segmentation outputs. A Hierarchical Sparse Representation Classifier (HSRC) algorithm is used for effective feature selection and classification because sparse representation is not capable of coping with data with too big dimensionality. General statistical tests like the t-test are inadequate for filtering 0-1 distributed features, while feature extraction algorithms like Principal Component Analysis (PCA) integrate all characteristics to create new dimensionality reduced attributes.

Sparse representations, on the other hand, select basic features from the original feature space explicitly, preserving the actual implications of cortical morphological features and providing a better interpretation. It is found that the frontal lobe and limbic lobe have the most morphological variations for gender, with others dispersed throughout the parietal lobe, temporal lobe, corpus callosum.

3.5 3D Convolutional Neural Network Multitask Learning Model

Voxel-based morphometry (VBM) was used to pre-process brain gray and white matter in order to train a 3D convolutional neural network with a multitask learning method to assess gender, age, and mental health status from structural brain disparities [9]. Attention maps were created using gradient-based approaches, which provided clinically relevant selection of the most representative brain regions for decision-making models.

Three-dimensional convolution, batch normalization, and 3D max pooling layers are followed by dense and dropout layers in the prediction model. Each of the three output blocks has its own output layer, dense, batch normalization, and output layer. Gender and age prediction are handled by the output block.

3.6 CNN+ LSTM Network

Long short-term memory (LSTM) and convolutional neural network (CNN) networks can be coupled end-to-end to capture temporal and spatial properties of functional connection sequences at the same time [9]. Three 1D convolutional layers with three distinct size filters (4-, 8-, and 16-time windows), one concatenation layer incorporating features from three convolutional layers, one max-pooling layer meant to down-sample, two LSTM network layers, and a fully connected layer make up the CNN. + LSTM network.

4. COMPARISON

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

5. CONCLUSION

The phrase 'gender identity' refers to one's personal sense of belonging to a specific gender, which can be male, female, none of these, or a combination of both. People whose gender identity does not match their biological sex have been referred to by a variety of labels. Gender expression and sexual preference are permanently encoded in the prenatal brain; thus, they do not alter over time and are unaffected by age, ethnicity, or other factors. As a result, precise and fast extraction of gender-related information from MRI scanned images of a person aids in the identification of a person's gender from the human brain. In this paper, different gender identification methods based on brain MRI images has been reviewed. It is found that the gender determination approach based on multi-layer 3D convolution extreme learning machine gives highest accuracy of 98% than other methods.

Table-1 Comparison

No	Title	Method	Dataset	Accuracy
1	Gender Identification of Human Brain Image with A Novel 3D Descriptor [5]	3D WHGO & SVM	MRI data from 1000 functional Connectome Project (FCP)	95%
2	Gender identification based on human brain structural MRI with a multi-layer 3D convolution extreme learning machine [6]	ELM -MCN	MRI data from Human Connectome Project (HCP)	98%
3	A 3D-CNN Classifier for Gender Discrimination from Diffusion Tensor Imaging of Human Brain [7]	3D CNN Classifier	IXI dataset	97%
4	Gender Identification of Human Cortical 3-D Morphology Using Hierarchical Sparsity [8]	Hierarchical Sparse Representation Classifier (HSRC)	MRI data from Human Connectome Project (HCP)	96.77%
5	Estimating Gender and Age from Brain Structural MRI of Children and Adolescents: A 3D Convolutional Neural Network Multitask Learning Model [9]	3D Convolutional Neural Network Multitask Learning Model	ABIDE-II and ADHD-200	AUC of 0.85
6	A Deep Network Model on Dynamic Functional Connectivity with Applications to Gender Classification and Intelligence Prediction [10]	CNN+LSTM	MRI data from Human Connectome Project (HCP)	93%

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