

**AUTOMATIC BRAIN MR IMAGE SEGMENTATION USING
QUANTUM-INSPIRED SELF-SUPERVISED NEURAL
NETWORK ARCHITECTURES**

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**DEPARTMENT OF ELECTRICAL ENGINEERING
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NETWORK ARCHITECTURES**

by

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Submitted

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THESIS CERTIFICATE

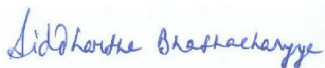
This is to certify that the thesis titled **Automatic Brain MR Image Segmentation using Quantum-Inspired Self-Supervised Neural Network Architectures**, submitted by **Debanjan Konar**, to the Indian Institute of Technology, Delhi, for the fulfilment of the requirements for the award of degree of **Doctorate of Philosophy**, is a bonafide record of the research work done by the student under our supervision. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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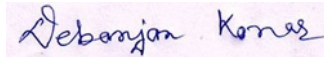
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Debanjan Konar (2015EEZ8421)

A handwritten signature in blue ink that reads "Debanjan Konar". The signature is written in a cursive style and is placed on a light pink rectangular background.

ABSTRACT

The primary aim of the research is to develop novel pattern identification integrated self-supervised frameworks for fully automated segmentation of brain Magnetic Resonance (MR) images for brain tumor detection obviating supervision or training. Initially, we have proposed a Quantum Bi-directional Self-organizing neural Network (QBDSOINN) architecture for binary image segmentation and detection of complete brain tumor using TCIA data set collected from nature repository. The QBDSOINN architecture comprises a trinity of layered architecture viz. input, intermediate/hidden and output layers. Each one of the layers is composed of *qubits* or quantum neurons and these quantum neurons are intra-connected through intra-layer connections. The input, intermediate, and output layers of the network architecture are interconnected using an 8-connected neighborhood-based fashion through forward, and counter-propagation precluding the complex standard quantum back-propagation algorithms. The segmented outcome is obtained once the network stabilizes or converges. The parallel version of the QBDSOINN architecture for pure color image segmentation is also proposed and it is named as Quantum Parallel Bi-directional Self-Organizing Neural Network (QPBDSONN) architecture. The QBDSOINN and QPBDSONN architectures employed standard Sigmoidal activation function in quantum-inspired computing environment and found it suitable for bi-level segmentation while compared with the state of the art techniques and its classical counterpart. However, owing to wide variations of gray levels of brain MR images, a novel Quantum-Inspired Self-supervised Neural Network (QIS-Net) architecture characterized by Quantum-inspired Multi-level Sigmoidal (QMSig) activation function is proposed for fully automatic segmentation of brain MR images from TCIA data set. An adaptive activation procedure is introduced in the QMSig activation function to address the spread of intensity in underlying images. Four distinct adaptive thresholding schemes are incorporated in the underlying architectures encompassing image context-sensitive thresholding in quantum formalism. An optimized version of the QIS-Net architecture referred to as Optimized Activation for Quantum-Inspired Self-supervised Network (Opti-QISNet) is suggested advocating the hyperparameters in optimal settings and yields optimal segmentation of brain MR images. The improvement in segmented outcome in terms of dice score is observed over QIS-Net on the same TCIA data sets collected from nature repository. Despite respectable accuracy and dice score reported by QIS-Net and Opti-QISNet, these *qubits*-based network architectures still suffer from slow convergence problems. A novel Qutrit-inspired shallow Fully Self-supervised neural Network (QFS-Net) model is proposed to enable faster convergence of the network architecture, thereby enabling better segmentation results while compared with QIS-Net and Opti-QISNet and also reported similar accuracy and dice similarity as U-Net and UResNet. The aforementioned network architectures (QBDSOINN, QPBDSONN, QIS-Net, Opti-QISNet, QFS-Net) are validated on 2D brain image slices and hence they fall short in contextual semantic segmentation of Brain MR images. A 3D

version of QIS-Net is developed incorporating 26-connected voxel-wise segmentation for volumetric brain tumor detection using Brats 2019 data sets and reported promising accuracy and dice similarity while compared with 3D CNN-based architectures (3D-UNet, VoxResNet, DRINet, 3D-ESPNet).

KEYWORDS: Quantum Computing ; Brain MR Image; Deep Learning; Medical Image Segmentation.

सार

अनुसंधान का प्राथमिक उद्देश्य मस्तिष्क के चुंबकीय अनुनाद (MR) छवियों के ब्रेन ट्यूमर का पता लगाने या पर्यवेक्षण या प्रशिक्षण के लिए पूरी तरह से स्वचालित विभाजन के लिए उपन्यास पैटर्न पहचान एकीकृत स्व-पर्यवेक्षण ढांचे को विकसित करना है। प्रारंभ में, हमने बाइनरी इमेज सेगमेंटेशन के लिए क्वांटम बी-दिशात्मक स्व-आयोजन तंत्रिका नेटवर्क (QBDSOINN) आर्किटेक्चर का प्रस्ताव किया है और प्रकृति भंडार से एकत्रित टीसीआईए डेटा सेट का उपयोग करके पूर्ण मस्तिष्क ट्यूमर का पता लगाया है। QBDSOINN वास्तुकला में स्तरित वास्तुकला की एक त्रिमूर्ति शामिल है। इनपुट, इंटरमीडिएट / हिडन और आउटपुट लेयर्स। परतों में से प्रत्येक *qubits* या क्वांटम न्यूरोन्स से बना है और ये क्वांटम न्यूरोन्स इंटर-लेयर कनेक्शनों के माध्यम से जुड़े हुए हैं। नेटवर्क आर्किटेक्चर के इनपुट, इंटरमीडिएट और आउटपुट लेयर को आपस में फॉरवर्ड के माध्यम से 8-कनेक्टेड पड़ोस-आधारित फैशन का उपयोग करके इंटरकनेक्ट किया जाता है, और जटिल मानक क्वांटम बैक-प्रोपोगेशन एल्गोरिदम को छोड़कर काउंटर-प्रॉपगैगेशन। नेटवर्क स्थिर या परिवर्तित होने के बाद खंडित परिणाम प्राप्त होता है। शुद्ध रंग छवि विभाजन के लिए QBDSOINN वास्तुकला का समानांतर संस्करण भी प्रस्तावित है और इसे क्वांटम समानांतर द्वि-दिशात्मक स्व-आयोजन तंत्रिका नेटवर्क (QPBDSOINN) वास्तुकला के रूप में नामित किया गया है। QBDSOINN और QPBDSOINN आर्किटेक्चर ने क्वांटम से प्रेरित कंप्यूटिंग वातावरण में मानक सिगमॉइडल सक्रियण फंक्शन को नियोजित किया और इसे अत्याधुनिक तकनीकों और इसके शास्त्रीय समकक्ष की तुलना में द्वि-स्तरीय विभाजन के लिए उपयुक्त पाया।

हालांकि, मस्तिष्क एमआर छवियों के ग्रे स्तरों की व्यापक विविधता के कारण, क्वांटम से प्रेरित बहु-स्तरीय सिगमॉइडल (क्यूएमएसआईजी) सक्रियण फंक्शन द्वारा विशेषता एक उपन्यास क्वांटम-प्रेरित स्व-पर्यवेक्षित तंत्रिका नेटवर्क (क्यूआईएस-नेट) वास्तुकला समारोह पूरी तरह से स्वचालित विभाजन के लिए प्रस्तावित है। टीसीआई डेटा सेट से मस्तिष्क एमआर छवियों का। अंतर्निहित छवियों में तीव्रता के प्रसार को संबोधित करने के लिए QMSig सक्रियण फंक्शन में एक अनुकूली सक्रियण प्रक्रिया शुरू की जाती है। क्वांटम औपचारिकता में छवि संदर्भ-संवेदनशील थ्रेशोल्ड को शामिल करते हुए अंतर्निहित आर्किटेक्चर में चार अलग-अलग अनुकूली थ्रॉलिंग योजनाएं शामिल हैं। क्यूआईएस-नेट आर्किटेक्चर के एक अनुकूलित संस्करण को क्वांटम-प्रेरित स्व-पर्यवेक्षित नेटवर्क (ऑप्टी-क्यूआईएसनेट) के लिए अनुकूलित सक्रियकरण के रूप में संदर्भित किया गया है, जिसका सुझाव है कि इष्टतम सेटिंग्स में हाइपर-मापदंडों की वकालत करना और मस्तिष्क एमआर छवियों के इष्टतम विभाजन की पैदावार। पासा स्कोर के संदर्भ में खंडित परिणाम में सुधार, प्रकृति भंडार से एकत्र किए गए टीसीआई डेटा सेटों पर क्यूआईएस-नेट पर देखा गया है। क्यूआईएस-नेट और ऑप्टी-क्यूआईएसनेट द्वारा रिपोर्ट की गई सम्मानजनक सटीकता और पासा स्कोर के बावजूद, ये \ "एम्फ {क्वेट}}-आधारित नेटवर्क आर्किटेक्चर अभी भी धीमी गति से अभिसरण समस्याओं से ग्रस्त हैं। एक उपन्यास Qutrit- प्रेरित उथले पूरी तरह से स्व-पर्यवेक्षित तंत्रिका नेटवर्क (QFS-Net) मॉडल नेटवर्क आर्किटेक्चर के तेजी से अभिसरण को सक्षम करने के लिए प्रस्तावित है, जिससे QIS-Net और Opti-QISNet के साथ तुलना में बेहतर विभाजन परिणाम सक्षम होते हैं और इसी तरह की सटीकता की भी सूचना दी है और यू-नेट और UResNet के रूप में पासा समानता। उपर्युक्त नेटवर्क आर्किटेक्चर (QBDSOINN, QPBDSOINN, QIS-Net, Opti-QISNet, QFS-Net) 2 डी मस्तिष्क छवि स्लाइस पर मान्य हैं और इसलिए वे ब्रेन एमआर छवियों के संदर्भ में अर्थ संबंधी विभाजन में कम आते हैं। QIS-Net का एक 3D संस्करण विकसित किया गया है जिसमें वाष्प 2019 डेटा सेटों का उपयोग करते हुए वॉल्यूमेट्रिक ब्रेन ट्यूमर का पता लगाने के लिए 26-जुड़े स्वर-वार विभाजन को शामिल किया गया है और 3 डी CNN- आधारित आर्किटेक्चर (3D-UNet, VoxResNet, DRINet) के साथ तुलना करते हुए सटीकता और पासा समानता की रिपोर्ट की गई है।, 3 डी-ईएसपीएननेट)।

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