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REGULAR ARTICLE

Nanotechnology-Integrated Imaging Framework for Brain Tumor Classification

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Brain tumors represent one of the most urgent medical cases, where timely and correct diagnosis is essential for effective treatment. Manual classification of traditional imaging methods, e.g. CT and MRI, are labor-intensive, prone to error and associated with low capability of detecting delicate tumor characteristics. In response to these weaknesses, this study seeks to integrate nanotechnology to enhance the detection accuracy of the tumors. Both fluorescence and MRI imaging using tumor specific ligands involved the functionalized nanoparticles of gold and iron oxide as contrast agents. These nanoparticles have a strongly visible and contrasting effect on tumors and improve the visibility and delineation of tumors in which contrast is increased between malignant and normal tissues, which facilitates the precise localization. Advanced image processing methods were applied to nanoparticle-enhanced high-resolution images to automatically detect and classify tumor regions with improved sensitivity and specificity. This approach eliminates manual segmentation and demonstrates the potential of combining nanotechnology with advanced imaging for non-invasive and accurate brain tumor diagnosis.

Keywords: Tomographic X-ray, Fluorescence imaging, Magnetic Resonance Imaging (MRI), Brain tumor.

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1. INTRODUCTION

The complexity and severity of brain tumours make them one of the most critical neurological disorders affecting healthcare systems across the world. The high mortality rate and their high mortality ensure this morbidity rates. The most recent GLOBOCAN estimates reveal that about 308,000 new cases of brain and central nervous system (CNS) cancers were diagnosed globally in 2020, comprising about 1.6 % of the total cancer cases documented worldwide, and 251,000 deaths were due to the same in 2020 [1, 2].

Early and correct diagnosis is a medical dilemma that has a huge effect on the survival of a patient treatment outcomes. Standard diagnostic modalities like Magnetic Resonance Imaging (MRI) and tomographic X-ray imaging generally involve significant human effort from healthcare practitioners. This approach requires substantial manual effort and time, and errors are likely to occur when dealing with large datasets and intricate tumor characteristics. Such restrictions may result into procrastination or faulty diagnoses, restricting useful medical intervention and reduction in patient survival.

This paper suggests a method that incorporates image processing algorithm with nanotechnology for automatic diagnosis of brain tumour. To enhance tumour identification, imaging data are supplemented with functionalized nanoparticles, and advanced image processing techniques using CNN models such as simple CNNs, VGG-16, and VGG-19 are applied to capture intricate features in T1-weighted CE-MRI images [3]. Contrary to the past methods which require preparation, and tumour segmentation, in the proposed system MRI is analysed in real time, reducing the working time and enhancing the efficiency of classification.

This approach addresses inherent inadequacies in existing method diagnostics by combination of nanotechnology and deep learning acquiring analytical skills that improved precision of images. The obtained outcomes confirm a robust, non-intrusive tumor classification technique capable of accurately identifying gliomas, meningiomas, and pituitary tumors, leading to improved clinical decision-making and patient outcomes.

2. SURVEY OF EXISTING FRAMEWORK

The main modality of brain tumor assessment, Magnetic Resonance Imaging (MRI), nowadays allows clinicians to determine the extent of tumors, characterize the properties of cells and vases using complex sequences, and help to accurately plan the treatment and monitor the course of the treatment in the presence of various neuro-oncological conditions, due to its non-invasive acquisition of high-contrast and multiplanar structural and functional data [4]. There is also the extensive use of Computed tomography (CT) scans assisted with

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visualizing structures of human bodies, diagnose, observe and treat such disorders as carcinomas, and gliomas [5]. Conventional MRI and CT scans have reduced sensitivity for brain tumor identification when nanoparticle contrast agents are not employed. The suggested method uses ResNet50V2 [6] and proficient .Net achieved increased detection accuracy, preciseness and recall in brain detection tumors. Artificial Neural Networks (ANN) along with Convolutional Neural Networks (CNN) were analyzed to enhance the accuracy of brain tumor detection [7]. The study investigates the application of Probabilistic Neural Networks for brain tumor classification, where Principal Component Analysis is employed to derive discriminative features [8]. One of the existing work combined fine-tuned ResNet50V2 to classify brain tumors with U-Net on data repository of TCGA and TCIA that proved to be effective [9]. The designed system with a sequence of CNNs fused together via ensemble learning achieved up to 99.43 % accuracy on Task 1 of the BRaTS 2021 dataset, which highlights the fact that model fusion is beneficial in medical image classification [10]. The automated detection process is complicated by the diverse shapes, sizes, and textures of lesions, which has motivated the use of a hybrid feature extraction framework integrating Gabor wavelet features, HOG descriptors, and segmentation-dependent fractal texture analysis (SFTA) [11]. The classification of brain tumors into glioma, meningioma, and pituitary types is performed through MRI image analysis employing a two-dimensional convolutional neural network framework [12].

Brain tumors are classified into glioma, meningioma, and pituitary categories by processing MRI images using 2D convolutional neural networks (CNNs) [13]. A pretrained VGG-16 model integrated within a deep CNN and leveraged via transfer learning is employed to handle variations in feature spaces and data distributions in real-world applications [14]. The proposed deep learning system utilized grid search-based hyperparameter tuning across three CNN models and large-scale clinical data, outperforming traditional approaches in brain tumor analysis [15]. Enhancements in areas include ResNet50 and U-Net CNN models on fine-tuning the MRI work of TCGA-LGG and TCIA databases [9]. BCM- CNN model uses ADSCFGWO hyperparameter optimization in CNN [16]. Experimental results indicate that the VGG-19 deep neural network, coupled with K-means clustering, can classify diabetic retinopathy grades from fundus images with an accuracy of 96 % on Kaggle data repository [17].

Traditional MRI and CT imaging methods face challenges in identifying brain tumors when nanoparticle agents are not used. Accordingly, numerous researchers [18, 19] have examined nanotechnology-driven and nanoparticle-dependent approaches for improving tumor imaging quality.

3. METHODOLOGY

An innovative diagnostic framework is created that uses nanotechnology improvements and sophisticated image dealing algorithms to enhance the automation and accuracy of brain tumor.

3.1 System Architecture Overview

Figure 1 outlines the overall framework of the proposed method. It comprises a number of steps, which are discussed in the following sections.

1. Nanoparticles Selection: To select nanoparticles for detection of brain tumors, the nanoparticles should offer high specificity and sensitivity. Due to their ease of functionalization, high biocompatibility, and unique surface plasmon resonance properties, gold nanoparticles (AuNPs) were selected to enhance imaging modalities, including tomographic X-ray imaging and fluorescence. Moreover, the iron oxide nanoparticles have to be smaller in size because of their nature are such good contrast-enhancing agents in magnetic resonance they included imaging (MRI). The nanoparticles are coated with EGFR antibodies and other tumor-specific ligands, allowing precise binding to glioblastoma cells. A polyethylene coating of non-specific binding was reduced by applying glycol (PEG) bond and enhance blood-brain barrier penetration.

2. Nanoparticles Synthesis: Synthesis of nano particles is carried out by established conventional approaches.

Gold Nanoparticles (AuNPs): The synthesis of spherical gold nanoparticles was carried out using a citrate reduction process, wherein sodium citrate acts as the reducing agent for chloroauric acid under controlled experimental conditions.

Iron Oxide Nanoparticles: They have been produced through the coprecipitation technique whereby ferric and ferrous salts are mixed in alkali medium, after which it is stabilized by citric acid in order to maintain homogenous dispersion.

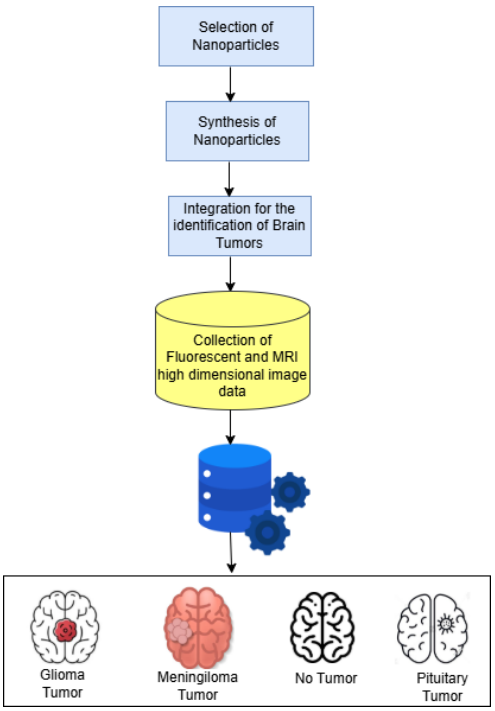


Fig. 1 – Flowchart of hybrid scheduling algorithm [10]

3. Brain Tumor Identification: The functionalization of the tumors effective targeting and imaging characteristics of nanoparticles were assessed. Cell lines of

glioblastoma multiforme (GBM) were examined in vitro as an experimental set up. In vivo validation was done on mouse models.

4. Data procurement and image analysis: High-dimensional imaging data were collected using fluorescence imaging and magnetic resonance imaging (MRI). The acquired data were preprocessed using techniques such as denoising and normalization to enhance image quality and ensure consistency. Relevant features, including texture, shape, and intensity characteristics, were extracted to facilitate accurate tumor identification and classification. These features were later provided to a deep learning model for processing. The image processing pipeline is designed to systematically scan medical images and detect brain tumors through a series of well-defined steps.

a. Image preprocessing: The data augmentation process has been incorporated in the image preprocessing pipeline alongside various steps necessary to prepare the MRI images to the model training. For compatibility with VGG-based architectures, the MRI images were initially resized to 256 × 256 pixels. Subsequently, the images were normalized by scaling the pixel intensities are rescaled to ensure they remain within the [0, 1] range, which contributes to training stability and convergence.

Data augmentation procedures such as random rotations, horizontal and vertical flips, zooming and shifting were employed to augment training data and minimize overfitting. Finally, to measure the generalization performance, the data repository was divided into training (70 %), validation (15 %), and testing (15 %) sets.

b. VGG-19 data processing: The VGG-19 deep learning model is designed to work with preprocessed MRI images and identify the features needed, classify them, and evaluate their charcteristics. It is done by resizing the images to 256 × 256 pixels, normalizing the images and loading them in batches to ensure that the process of training is not a waste of time. The convolutional layers of a pre-trained VGG-19 network are used to extract high-level features and identify a complex structure pattern of the various tumors of the brain. In order to enhance the performance of the classifier, the fully connected layers are optimized to target individual classes: glioma, meningioma, pituitary tumor and no tumor and initially leave the convolutional base fixed. With the softmax layer, the model computes the probability of each class, and the one with the highest output is used as the ultimate prediction of the model.

3.2 Data Repository

The MRI data repository used in this investigation was obtained from Kaggle [20] and consists of approximately 4,806 labeled images. These MRI scans represent various brain tumor types, including glioma, meningioma, and pituitary tumors, along with normal brain images, all of which are annotated according to tumor classification.

4. PERFORMANCE ASSESMENT

The detection and identification of brain tumors based on MRI data were conducted on the basis of applying and evaluating the CNN, VGG-16, and VGG-19 models. Table 1 has summarized the performance measures of each of the models on the validation data repository. The findings of the experiment demonstrate the high level of performance of the optimized VGG-19 model in terms of the accurate detection and classification of brain tumors. VGG-19's deeper hierarchical design and pre-trained feature extraction layers allow it to capture intricate patterns in MRI data more effectively than both simpler CNN architectures and VGG-16. Although the basic CNN model trains faster, it lacks the capacity to handle the complexity required for accurate tumor classification. VGG-16, while a viable alternative, exhibits slightly lower performance compared to VGG-19 and does not achieve comparable results.

Table 1 – Runtime performance analysis

Applied Model Approach	Model Effectiveness (%)	Precision Analysis (%)	Recall Value (%)	F1 Score Measure (%)
CNN	89.7	89.3	87.6	88
VCG-16	94.3	93.4	92.9	93
VGG-19	95	94.5	94.0	94.6

5. CONCLUSION

This study proposes an innovative technology to brain tumor diagnosis by integrating computerised Nano based image processing techniques and advanced imaging techniques. Synthesized and functionalized gold and iron oxide nanoparticles are utilized as contrast mediums in fluorescence and magnetic resonance imaging (MRI), significantly enhancing image quality and visualization of tumor regions. This enhancement improves detection sensitivity and diagnostic specificity. The high-quality imaging data are then processed using sophisticated automated image processing techniques, eliminating the need for manual segmentation and simplifying the diagnostic workflow. By combining nanoparticle-enhanced imaging with automated analysis, the proposed approach addresses key limitations of traditional diagnostic methods, like high dependency on humanl interpretation and vulnerability to human error. This multidisciplinary model explains the transformative potential of development of nanotechnology combined with the current calculational techniques to create non-invasive, accurate and expandable diagnosis of brain tumor. This approach has enabled early stage diagnosis with great precision which minimizes chances of delayed or ineffective medical intervention which eventually translates to better patient outcomes. Future studies can be aimed at optimizing the nanoparticle formulations such that their targeting efficiency, productivity, and environmental sustainability is improved.

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Система візуалізації з інтегрованими нанотехнологіями для класифікації пухлин головного мозку

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Пухлини головного мозку є одним з найтерміновіших медичних випадків, де своєчасна та правильна діагностика є важливою для ефективного лікування. Ручна класифікація традиційних методів візуалізації, наприклад, КТ та МРТ, є трудомісткою, схильною до помилок та пов'язаною з низькою здатністю виявляти делікатні характеристики пухлини. У відповідь на ці недоліки, це дослідження спрямоване на інтеграцію нанотехнологій для підвищення точності виявлення пухлин. Як флуоресцентна, так і МРТ-візуалізація з використанням пухлиноспецифічних лігандів включають функціоналізовані наночастинки золота та оксиду заліза як контрастні речовини. Ці наночастинки мають сильний видимий та контрастний ефект на пухлини та покращують видимість та розмежування пухлин, при цьому збільшується контраст між злоякісними та нормальними тканинами, що сприяє точній локалізації. До зображень високої роздільної здатності, посилених наночастинками, були застосовані передові методи обробки зображень для автоматичного виявлення та класифікації ділянок пухлини з покращеною чутливістю та специфічністю. Цей підхід виключає ручну сегментацію та демонструє потенціал поєднання нанотехнологій з передовою візуалізацією для неінвазивної та точної діагностики пухлин головного мозку.

Ключові слова: Рентгенівська томографія, Флуоресцентна візуалізація, Магнітно-резонансна томографія (МРТ), Пухлина головного мозку.