REGULAR ARTICLE

Nanotechnology Driven Advanced Imaging and Classification of Brain Tumours

Md A. Mondal, D. Mitra, A. Dhar, A. Saha, A. Dhar, S. Das, P. Ghosh*

Narula Institute of Technology, MAKAUT, Kolkata, 700109 India

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Brain tumours are among the most serious medical disorders, and early and correct discovery is important for successful treatment. Conventional diagnostic methods including computed tomography (CT) and magnetic resonance imaging (MRI) sometimes depend on manual interpretation, which is time-consuming, prone to human error, and limited in spotting minute tumour features. To ad-dress this issue, this study employs nanotechnology to improve tumour detection accuracy. Gold and iron oxide nanoparticles were synthesised, functionalized with tumourspecific ligands, and employed as contrast agents in fluorescence and magnetic resonance imaging (MRI). These nanoparticles improve tumour visualization by enhancing the contrast between healthy and tumour tissues, allowing for accurate localization. To detect and categorize tumour areas with higher sensitivity and specificity, advanced image processing techniques were used to high-resolution imaging data provided by nanoparticle-enhanced modalities. This technology overcomes previous diagnostic tools' short-comings by automating tumour detection and eliminating the requirement for manual segmentation. This work demonstrates the synergistic potential of merging nanotechnology with cutting-edge imaging technologies to provide a non-invasive, precise, and efficient diagnostic tool for brain tumour identification.

Keywords: Brain tumor detection, Nanotechnology, Gold nanoparticles, Iron oxide nanoparticles, VGG16, VGG19, MRI Classification.

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1. INTRODUCTION

Brain tumors are one of the most severe neurological conditions that pose a significant challenge to global healthcare systems due to their high mortality and morbidity rates. As per the statistic of International Association of Cancer Registries (IARC) there are more than 28,000 cases of brain tumors in India every year, with more than 24,000 people succumbing to the disease annually [1].

Early and accurate diagnosis is a critical medical challenge that significantly impacts patient survival and treatment outcomes. However, traditional diagnostic techniques, like Magnetic Resonance Imaging (MRI) and Computed Tomography (CT), often require extensive manual interpretation by medical experts. This process is time-consuming, labor-intensive, and susceptible to human errors, especially when analyzing large datasets or complex tumor types. These limitations can lead to delayed or inaccurate diagnoses, limiting effective medical intervention and decreasing patient survival rates.

To solve these difficulties, combining cutting-edge nanotechnology with powerful image processing algorithms presents a possible approach. Nanoparticles, such as gold and iron oxide nanoparticles, have demonstrated outstanding imaging contrast properties. These nanoparticles, which have been functionalized with tumour-specific ligands, improve imaging modalities such as fluorescence and MRI, allowing for better visualization of tumour areas. Furthermore, their biocompatibility and ability to cross the blood-brain barrier provide them a distinct edge in identifying and targeting brain tumours with great accuracy.

This study proposes a technique that integrates nanotechnology with image processing algorithms to automate brain tumour diagnosis. Imaging data is supplemented with functionalised nanoparticles to improve tumour identification, while image processing techniques like CNN architectures including basic CNNs, VGG-16, and VGG-19 analyse complicated pat-terns in T1-weighted contrast-enhanced MRI (CE-MRI) images. Unlike previous approaches that need preparatory tumour segmentation, the proposed system analyses MRI data immediately, shortening the workflow and improving classification efficiency.

This strategy solves fundamental shortcomings in current diagnostic approaches by combining nanotechnology enhanced imaging precision with deep learning analytical capabilities. The end result is a very accurate, non-invasive approach for categorizing gliomas, meningioma, and pituitary tumours, with the potential to greatly enhance patient care and clinical outcomes.

* Correspondence e-mail: paprighosh06@gmail.com

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2. LITERATURE SURVEY

This section presents related work on the detection of brain tumor.

Magnetic Resonance Imaging (MRI) is a crucial imaging technique with excellent spatial resolution and soft tissue contrast, used to detect brain abnormalities such as tumors and neurological disorders [2]. Computed Tomography (CT) scans are also widely used for visualizing human body structures, helping diagnose, monitor, and treat conditions like carcinomas and gliomas [3]. But traditional MRI, CT scan face difficulties in identifying brain tumor without nanoparticles agent. The proposed technique uses ResNet50 [4] and efficient-Net demonstrated higher accuracy, precision, and recall in detecting brain tumors. To further enhance brain tumor detection, self-defined Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) were analyzed [5]. The use of Probabilistic Neural Networks (PNN) for brain tumor classification is also explored, utilizing Principal Component Analysis (PCA) for feature extraction [6]. One study combines fine-tuned ResNet50 with U-Net to classify brain tumors using datasets from TCGA and TCIA, which demonstrated effective results [7]. The Brain Tumor Classification Model (BCM-CNN) employs CNN optimization using the adaptive dynamic sine-cosine fit-ness grey wolf optimizer (ADSCFGWO), achieving 99.98% accuracy with the BRaTS 2021 Task 1 dataset [8]. Automated detection faces challenges due to varying lesion shapes, sizes, and textures, and a fused feature vector approach combining Gabor wavelet features (GWF), histograms of oriented gradient (HOG), local binary patterns (LBP), and segmentation-based fractal texture analysis (SFTA) is used to address these complexities [9]. A technique using sigma filtering, adaptive thresholding, and region detection also classifies tumors as normal, benign, or malignant with C4.5 decision tree and MLP classifiers [10].

MRI scans combined with 2D CNNs are applied to classify brain tumors into glioma, meningioma, or pituitary [11]. Transfer learning with a pre-trained VGG-16 model and Deep CNN is applied to overcome challenges of varying feature spaces and distributions in real-world data [12]. The deep-learning-based system using three CNN models, hyperparameter optimization through grid search, and large clinical datasets outperforms classical models for brain tumor classification [13]. Further improvements are seen with fine-tuned CNN models with ResNet50 and U-Net on the TCGA-LGG and TCIA datasets for MRI applications [7]. The BCM-CNN model employs ADSCFGWO for optimizing CNN hyperparameters [14]. Finally, the VGG-19 Deep Neural Network (DNN) is used for Diabetic Retinopathy (DR) grade classification from fundus images, achieving 96 % accuracy using K-means extracted features from Kaggle datasets [15].

As mentioned earlier, the traditional MRI, CT scan face difficulties in identifying brain tumor without nanoparticles agent. For that, different works [16, 17] have used nanotechnology, nanoparticle based materials in brain tumor imaging.

3. PROPOSED METHODOLOGY

This section describes detailed technique that integrates nanotechnology with image processing algorithms to automate brain tumour diagnosis and accurate detection.

3.1 Overview of the System

This section gives a brief Overview of the proposed method and it is depicted in Fig. 1. The proposed model consist of several steps as follows.

1. **Selection of Nanoparticles**: In order to identify brain tumors with high specificity and sensitivity, the selection of nanoparticles is essential. The biocompatibility, ease of functionalization, and high surface plasmon resonance of gold nanoparticles (AuNPs), which improve imaging modalities including computed tomography (CT) and fluorescence, led to their selection. Furthermore, because iron oxide nanoparticles work so well as contrast agents in magnetic resonance imaging (MRI), they were included.

Tumor-specific ligands, such as antibodies to the epidermal growth factor receptor (EGFR), were functionalized into the nanoparticles to improve targeting by allowing for preferential binding to glioblastoma cells. A polyethylene glycol (PEG) coating was used to reduce non-specific binding and increase blood-brain barrier penetration.

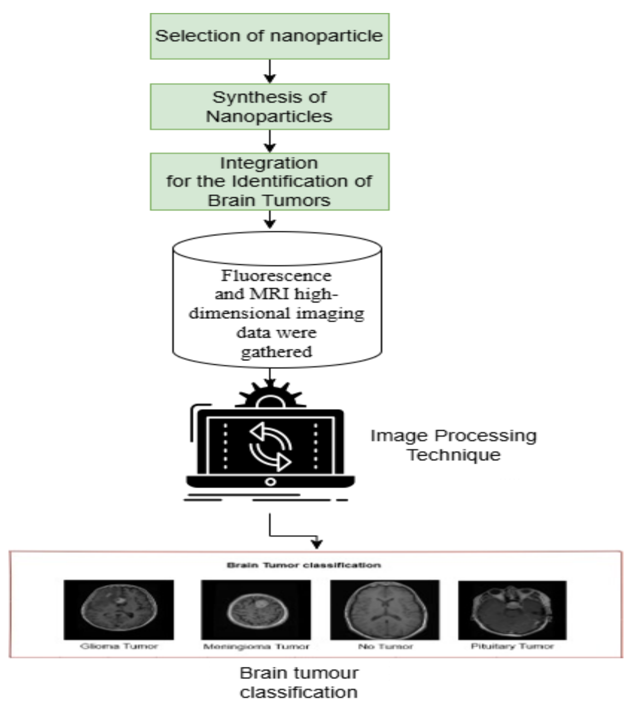

Fig. 1 – Overview of the system

2. **Synthesis of Nanoparticles**: The nanoparticles were synthesized using well-established techniques:

Gold Nanoparticles (AuNPs): Synthesized via the citrate reduction method, where chloroauric acid was reduced by sodium citrate under controlled conditions to produce spherical nanoparticles.

Iron Oxide Nanoparticles: Synthesized using the co-precipitation method by reacting ferric and ferrous salts in an alkaline medium, followed by stabilization with citric acid to ensure uniform dispersion.

3. **Integration for the Identification of Brain Tumors:** The effectiveness of functionalized nanoparticles' targeting and imaging properties were evaluated. Glioblastoma multiforme (GBM) cell lines were studied in vitro as part of the experimental setup, and mouse models were used for in vivo validation. Iron oxide nanoparticles were used in MRI scans to assess contrast enhancement, and quantum dots coupled to targeting ligands were used to achieve tumor-specific fluorescence imaging.

4. **Data Acquisition and Image Processing**: Fluorescence and magnetic resonance imaging (MRI) high-dimensional imaging data were gathered. The data was preprocessed using methods like denoising and normalization. To detect and classify tumors, features including texture, shape, and intensity were taken out and put into a deep learning model. The image processing technique will analyze the image and detect the brain tumors and it consist of several steps as follows.

A. Image Preprocessing: The data augmentation and image pre-processing pipeline involves the following steps:

• Resizing: The MRI images had been resized to 224 × 224 pixels to meet the input requirement of the VGG models.

• Image Normalization: Pixel values had been normalized to a range of [0, 1] to help improve the convergence during training.

• Augmentation: Data augmentation techniques like random rotations, flips, zooms, and shifts had been applied to enhance the diversity of the training set and reduce overfitting.

• Splitting: The dataset will be break down into training, validation, and test sets (80%, 10%, and 10% respectively) to evaluate the model's generalization performance.

B. Data Processing using VGG19: The data processing unit involves feeding the preprocessed MRI images into the VGG-19 deep learning model, followed by the feature extraction, classification, and evaluation phases. The key steps are as follows:

• Loading Preprocessed Data: The preprocessed images, now resized to 224 × 224 pixels, normalized, and augmented, are loaded into the model using a data generator. This allows the model to efficiently process batches of images during training.

• Feature Extraction using VGG-19: The pre-trained VGG-19 model is used for extracting the feature. Initially, the model's convolutional layers extract high-level features from the MRI images. These features capture complex patterns and structures in the data that are indicative of different types of brain tumors. VGG-19's deep architecture, which includes 19 layers, is leveraged for its ability to detect intricate patterns in the data.

• Fine-tuning the Model: To improve performance for the brain tumor classification task, the model is fine-tuned by training the fully connected layers on the specific tumor types (glioma, meningioma, pituitary, and no tumor). This step involves adjusting the weights of the fully connected layers while keeping the convolutional base frozen initially. Fine-tuning enhances the model's ability to generalize to the specific features of brain tumor images.

• Classification Layer: The final layer of the VGG-19 model is a softmax layer that outputs probability scores for each class (glioma, meningioma, pituitary, and no tumor). The class with the highest probability is chosen as the model's prediction.

3.2 Dataset

The dataset for this study is collected from Kaggle [18] and contains MRI images of different types of brain tumors, including glioma, meningioma, pituitary tumors, and images with no tumor. The dataset consists of approximately 3,704 MRI images, with each image labeled according to the type of tumor or the absence of a tumor.

4. PERFORMANCE ANALYSIS

This section presents the performance evaluation of the implemented models – Simple CNN, VGG-16, and VGG-19 – on the task of detecting brain tumor and classification using Magnetic Resonance Imaging (MRI) data.

The Table 1 summarizes the performance metrics for each model on the test dataset. The experimental results clearly demonstrate the superior performance of VGG-19 for brain tumor detection and classification. The deep architecture of VGG-19, combined with its pre-trained feature extraction layers, enabled it to capture complex patterns in the MRI images more effectively than the simpler CNN or even VGG-16. The Figs. 2, 3 and 4 shows the detection of Glioma tumour, Meningioma tumour and no tumor respectively.

While the simple CNN was faster to train, it showed limitations in handling the intricate features required for accurate tumor classification. VGG-16, although slightly behind VGG-19, proved to be a strong alternative with comparable performance.

Table 1 – Evaluation Metrices

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**
CNN	88.5	87.2	86.8	87.0
VGG-16	93.2	92.5	91.8	92.1
VGG-19	94.0	93.6	93.0	93.3

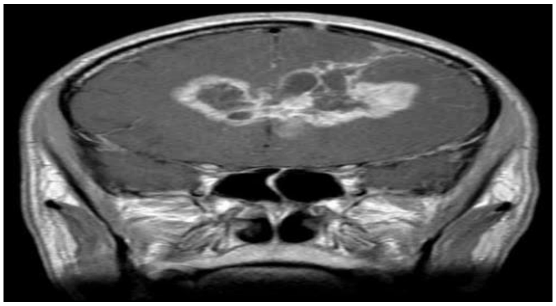

Fig. 2 – Detected as Glioma tumour

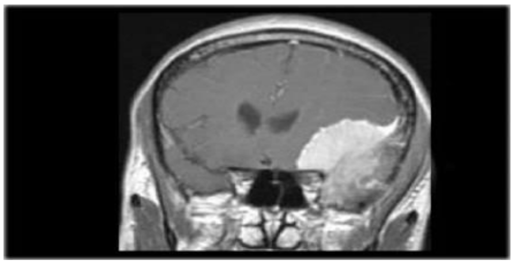

Fig. 3 – Detected as Meningioma tumour

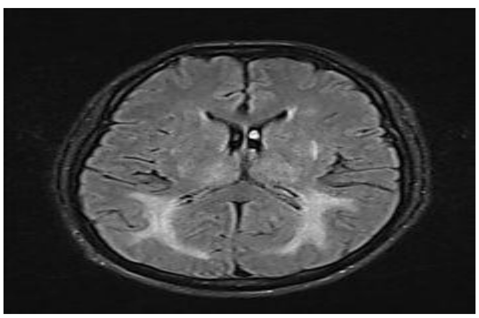

Fig. 4 – Detected as no tumour

5. CONCLUSIONS

This work suggested a novel method for brain tumour diagnosis by means of automated image processing combined with nanotechnology and cutting-edge imaging technologies. Synthesised and used as contrast agents in fluorescence and magnetic resonance imaging (MRI), functionalised nanoparticles containing gold and iron oxide These nanoparticles greatly improved image quality, allowing exact visualisation of tumour areas and hence raised detection sensitivity and specificity. Advanced image processing techniques were used to handle the enhanced imaging data, therefore removing the requirement for hand segmentation and simplifying the diagnosis procedure. By means of automated analysis combined with nanoparticle-enhanced imaging, important constraints in conventional diagnostic techniques – such as excessive dependence on manual interpretation and susceptibility to errors – are addressed, therefore opening the path for a more reliable and efficient diagnosis system. This multi-disciplinary method highlights the transformational potential of merging nanotechnology with contemporary computational tools for non-invasive, accurate, and scalable brain tumor diagnosis. By aiding early diagnosis and exact categorisation, it considerably increases the odds for prompt and successful medical intervention, eventually boosting patient out-comes. Future studies might address the optimization of nanoparticle formulations to enhance targeting efficiency and biocompatibility.

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Розширена візуалізація та класифікація пухлин головного мозку на основі нанотехнологій

Мд А. Мондал, Д. Мітра, А. Дхар, А. Саха, А. Дхар, С. Дас, П. Гхош

Інститут технологій Нарула, MAKAUT, Колката, 700109 Індія

Пухлини головного мозку є одними з найнебезпечніших медичних патологій, і раннє та точне виявлення має вирішальне значення для ефективного лікування. Традиційні методи діагностики, такі як комп'ютерна томографія (КТ) і магнітно-резонансна томографія (МРТ), часто залежать від ручної інтерпретації, що є трудомістким, суб'єктивним і може не виявляти дрібні структурні особливості пухлин. У цій роботі застосовано нанотехнології для підвищення точності виявлення пухлин. Було синтезовано та функціоналізовано золоті та оксид-залізні наночастинки з використанням лігандів, специфічних до пухлин, після чого вони були використані як контрастні агенти у флуоресцентній візуалізації та МРТ. Ці наночастинки значно покращують контрастність між здоровими та ураженими тканинами, що забезпечує більш точну локалізацію пухлини. Для обробки високоякісних зображень, отриманих за допомогою методів візуалізації з нанопідсиленням, застосовано сучасні методи комп'ютерного зору та глибокого навчання, зокрема VGG16 і VGG19. Це дозволяє автоматизувати процес виявлення пухлин, усуваючи необхідність у ручному розмічуванні. Результати дослідження демонструють синергетичний ефект поєднання нанотехнологій з передовими методами візуалізації, що забезпечує неінвазивний, високоточний та ефективний інструмент діагностики пухлин головного мозку.

Ключові слова: Виявлення пухлин головного мозку, Нанотехнології, Золоті наночастинки, Оксид заліза, VGG16, VGG19, Класифікація МРТ.