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Brain Tumour Detection using Deep Learning: A Review

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***Abstract*— Brain tumour to be effectively treated, it is essential to identify and diagnose it.Medical image processing has advanced tremendously in recent years due to machine techniques for learning. Convolutional neural networks (CNNs) are deep learning models that have shown remarkable performance in several health care applications, such as the identification of brain tumours that are malignant. CNNs are a useful tool for clinical image analysis because they are capable of extracting pertinent features from enormous datasets without the necessity of feature engineering But problems including the absence of standardised datasets, the requirement for substantial volumes of annotations, and the comprehensibility of the models continue to be issues. Despite these difficulties, machine learning algorithms have tremendous possibilities for healthcare picture interpretation, and recent developments like explainable artificial intelligence, federated training, and transferred learning show promise for overcoming these restrictions. Additionally, new potential for machine learning algorithms to enhance brain tumour detection and diagnosis have been created by developments in imaging technologies including computed tomography (CT), positron emission tomography (PET), and magnetic resonance imaging (MRI). A patient's health can be shown in greater detail by the combination of digital health records and other sources of healthcare data, which can help healthcare providers make better treatment decisions. In conclusion, the identification and evaluation of brain tumours have demonstrated encouraging results when using machine learning algorithms, notably CNNs. However, further research is necessary to address the current challenges and limitations and to fully realise the potential of this technology in improving patient outcomes.**

***Index Terms*— Convolutional Neural Networks, Deep learning, Medical Imaging, Magnetic Resonance Imaging, and Medical Image Analysis.**

I. INTRODUCTION

Magnetic resonance imaging is the most effective method for identifying brain tumours (MRI). The scans result in the generation of a significant amount of image data. However, because brain tumours are complex and have characteristics based on MRI, a manual examination may be prone to errors.
The application of system getting to know algorithms has ushered in a new technology of possibilities inside the field of medicine. From scientific selection-making to drug studies, the combination of system learning has the capability to revolutionise each factor of healthcare. Especially, the improvement of device getting to know strategies for responsibilities associated with pc vision has emerged as an increasing number of applications, given the developing computerization of clinical statistics. Substantially, the adoption of electronic fitness information

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(EHR) by means of US workplace-based total doctors quadrupled between 2007 and 2012, reaching an outstanding 39.6% utilisation price. Within those electronic health facts, clinical pictures occupy a pivotal position, yet their evaluation remains predominantly dependent on human radiologists, who're inherently restricted by using factors inclusive of pace, fatigue, and enjoyment.

Because the demand for radiological information continues to surge, healthcare institutions have sought cost-powerful answers, such as outsourcing radiographic reports to nations like India. This shift highlights the urgent need for superior technology which can increase and, in a few instances, update the tasks traditionally carried out by way of human radiologists.

The world of scientific imaging incorporates a plethora of techniques, and their usage is on the upward thrust. A look at through Smith-Bindman et al. Spanning from 1996 to 2002 said a mind-blowing 30.9 million imaging assessments within six massive included healthcare systems inside the U.S. Drastically, the usage of CT, MRI, and puppy scans saw massive increases of 7.8%, 10%, and a great fifty seven%, respectively, for the duration of this period. The inception of Artificial Intelligence (AI) in medicine can be traced back to pioneering systems like MYCIN by Shortliffe, which proposed antibiotic treatment regimens for individuals. Over the years, AI algorithms have evolved from heuristic-based approaches to manual, handcrafted feature extraction techniques, and subsequently, to the application of supervised learning techniques. Between 2015 and 2017, supervised learning methods gained prominence in the methodologies outlined in public literature. Concurrently, the exploration of unsupervised machine learning techniques began to create the way for more robust, adaptable AI AI remedies in the field of medical imaging. One of the critical challenges in this context is the limitation of current AI algorithms and unsupervised machine learning techniques in providing full-resolution MRI images, making the identification of brain tumours more challenging. The proposed system aims to address this issue by leveraging Convolutional Neural Networks, which have surfaced as a frontrunner in medical image processing. CNNs excel in preserving spatial information relationships, a pivotal feature in radiography where the precise understanding of how different anatomical structures interconnect is vital. Furthermore, the suggested method greatly speeds up the diagnostic procedure while also improving the accuracy of brain tumour detection. Physicians with varying levels of expertise can benefit from this technology, providing a valuable tool for decision support and improving patient care. Ethical considerations also loom large on the horizon. As AI systems become increasingly integrated into healthcare, concerns regarding patient privacy, data security, and algorithm transparency come to the forefront. Ethical guidelines and regulations must be developed and rigorously adhered to, ensuring that AI is deployed responsibly and with the utmost consideration for patient welfare. Generalization and robustness of machine learning models are vital for their successful implementation in clinical practice. These models must be capable of performing consistently across diverse patient populations and under various conditions. Ensuring that algorithms are not overly biased toward specific demographic groups is essential to avoid healthcare disparities

A. Problem Statement

The challenge is to develop a solution for identifying and categorising brain tumours Magnetic Resonance Imaging (MRI). This system must effectively recognize the existence of a brain tumour, categorise it into various types, conduct segmentation to distinguish between the tumour's core and enhancing areas.

B. Objectives

- Improve the accuracy of the classification model to distinguish between non-tumor, meningioma, glioma, and pituitary.
- Perform segmentation to accurately delineate all tumour structures.
- Integrate the above objectives i.e classification and segmentation.

II. LITERATURE SURVEY

The review of the literature examines important studies on different approaches and results related to Brain Tumor Detection with CT, MRI, and PET that advance our knowledge of this crucial area of medical imaging analysis. The following summarizes key insights, methods, contributions, and limitations from the selected papers, drawing connections to the proposed project.

The authors introduce an innovative approach for classifying brain tumors using MRI images.They combine pre-trained deep learning models with multi-level feature extraction and concatenation to achieve high testing accuracies of 99.34% and 99.51% with Inception-v3 and DenseNet201 features, respectively. This method surpasses existing state-of-the-art methods, addressing the need for improved brain tumor classification accuracy. The paper acknowledges the challenges in brain tumor classification but does not explicitly highlight specific gaps or limitations in prior research[1].

The abstract emphasizes the critical need for early diagnosis of brain tumors to improve patient survival rates and reduce mortality. It acknowledges the challenges of manual tumor segmentation from MR images and proposes computer-assisted techniques for automation. The paper explores various traditional and 16 transfer learning models and hybrid machine learning models are used to classify brain tumor pictures. It presents VGG-SCNet, a novel stacked classifier network that achieves remarkable 99.2%, 99.1%, and 99.2% f1 scores in terms of precision, recall, and f1 scores., respectively. While the abstract doesn't delve into specific literature review, it contributes by offering an efficient automated tool for brain tumor classification, addressing the limitations of manual diagnosis[2].

This abstract discusses the importance of data augmentation in training deep learning networks for medical tasks, especially when limited data is available, such as in brain tumor detection from MRI scans. It compares various data augmentation techniques, including one based on principal component analysis, for ResNet50. The study achieves a notable F1 detection score of 92.34% using transfer learning from ImageNet. The contribution lies in demonstrating the effectiveness of data augmentation strategies and proposing a novel approach that outperforms conventional methods in brain tumor detection. It does not explicitly review prior literature or mention specific gaps or limitations in existing work[3].

The abstract briefly touches on the significance of high-quality medical images and the potential of AI-based automatic diagnosis. While it lacks an extensive literature review, the paper's notable contribution lies in the introduction of efficient and highly accurate tools for brain tumor classification, using pre-trained deep learning models ResNext101_32×8d and VGG19, potentially streamlining the diagnostic process for medical professionals and addressing cost and time constraints[4].

The abstract briefly recognizes the underutilization of computer-aided detection in brain tumor diagnosis and the challenges posed by interference factors. While it doesn't extensively delve into prior literature, the paper's key contribution lies in presenting a practical convolutional neural network (CNN) model for brain tumor feature detection, emphasizing segmentation and recognition of MRI brain tumors. This model incorporates convolution layers for enhanced efficiency and combines artificial and machine learning features, demonstrating feature fusion to improve diagnostic accuracy. The paper offers valuable theoretical guidance for future research in the domain of computer-aided brain tumor detection, potentially advancing this field[5].

The abstract recognizes the critical importance of early brain disease detection and the transformative role of artificial intelligence (AI) in neurology. While not delving deeply into the literature, it conducts a comprehensive review of 147 recent articles, primarily focusing on machine learning and deep learning approaches for detecting Alzheimer's disease, brain tumors, epilepsy, and Parkinson's disease. This paper's significant contribution lies in its effort to identify the most accurate techniques for brain disease detection and offering valuable insights that can enhance future diagnostic approaches in the field of neurology[6].

The abstract underscores the global concern surrounding brain tumors and the pressing need for improved and timely diagnosis. It acknowledges the prevalent use of CNN models in prior research but the challenges related to large datasets. The paper's primary contribution is the introduction of the Caps-VGGNet hybrid model, effectively addressing dataset limitations by automatically extracting and classifying features. This model outperforms conventional and hybrid models, achieving exceptional accuracy, specificity, and sensitivity, offering a significant advancement in the field of brain tumor diagnosis[7].

The paper addresses the issue of low accuracy in traditional brain tumor detection. While it doesn't extensively discuss prior literature, the significant contribution lies in introducing a Multi-CNNs approach that fuses multimodal information, extending from 2D-CNNs to 3D-CNNs for better handling three-dimensional modal characteristics. This approach improves fault tolerance, modal information extraction, and network convergence through the use of real normalization layers. Moreover, it introduces improved feature learning in the lesion area using a weighted loss function. The efficacy of the method is demonstrated by the experimental results, which show better performance than single-mode brain tumor detection methods and 2D detection networks.. This paper offers an innovative approach to enhance brain tumor detection accuracy through multimodal fusion and enhanced network architecture [8].

The article recognizes the critical importance of early brain tumor detection and the growing popularity of deep learning-based methods for this purpose. While it doesn't extensively review the literature, the significant contribution lies in the comprehensive analysis of seven transfer learning-based deep learning methods combined with five traditional classifiers for brain tumor detection from 2D MRI images. The best model achieved an impressive 99.39% accuracy with a 10-fold cross-validation, providing valuable insights into the selection of suitable approaches for accurate and early diagnosis, thereby advancing the field of brain tumor detection[9].

The paper briefly mentions its focus on Alzheimer's disease classification using a CNN-based framework. While it doesn't delve into a literature survey, its significant contribution lies in emphasizing techniques for faster convergence and higher accuracy within its proposed framework. The paper also hints at future directions, including the exploration of transfer learning models, multi-classification, and further investigations into Alzheimer's disease prediction, which holds promise for advancing research in this area[10].

III. METHODOLOGY

Our extensive survey report offers a thorough summary of all the methods applied in the field of Brain Tumor detection.

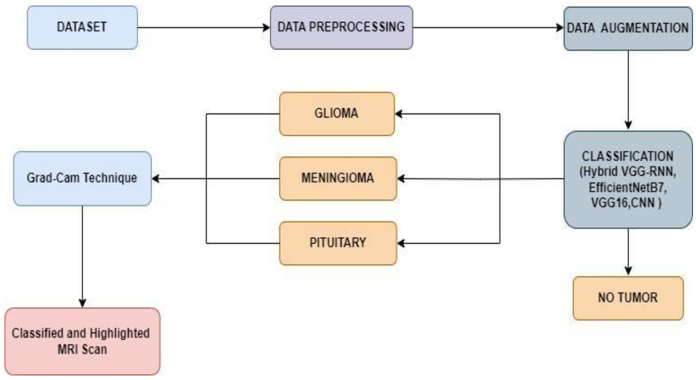

Figure 2. System Design

A. Data Collection: The first step is collecting a substantial dataset of MRI brain images, comprising scans from brain tumor disease patients

B. Data Preprocessing : The MRI images undergo rigorous preprocessing, which involves transforming raw images into a format that is suitable for training a deep learning model. This includes rescaling the pixel values to a standardized range, adjusting brightness, zooming, and flipping images to augment the dataset. These preprocessing steps are essential for improving the model's ability to generalize to new data and achieve better performance on tasks such as image classification. n consistent and informative image data.

C. Data Augmentation: Data augmentation is a technique used to increase the diversity of a dataset by applying various transformations to the existing data. This approach helps improve the generalization and robustness of machine learning models by exposing them to different variations of the input data during training.

D. Splitting Samples : This stage involves splitting the pre-processed data into three sets: a training set, a validation set and a test set. The training set is used to train the CNN classifier, and the test set is used to evaluate the performance of the classifier.

E. Glioma : Glioma is a type of brain tumor that originates in the glial cells, which are supportive cells in the brain and spinal cord. These tumors can occur in various parts of the brain and can be either benign (non-cancerous) or malignant (cancerous).

F. Meningioma : Meningioma is a type of tumor that arises from the meninges, the protective membranes that surround the brain and spinal cord. These tumors are typically slow-growing and are usually benign (non-cancerous), although they can occasionally be malignant (cancerous).

G. Pituitary : The pituitary gland, often referred to as the ”master gland,” is a small, pea-sized gland located at the base of the brain, just below the hypothalamus. Despite its small size, it plays a crucial role in regulating various bodily functions by producing and releasing hormones that control growth, metabolism, reproduction, stress response, and other essential processes.

H. No tumor : ”No tumor” simply means that there is an absence of a tumor or abnormal growth in the area being examined. It indicates that no pathological mass or lesion was detected during medical evaluation or imaging studies such as MRI or CT scans. This is generally considered a normal or healthy finding, suggesting that there are no concerning abnormalities in the tissue or organ being assessed.

I. Model Selection: An effective model for Brain tumor detection is Convolutional Neural Networks (CNNs) due to their well-established track record in image evaluation tasks. Here we have used ADNet model(proposed CNN model).

J. Training CNN Classifier : This stage involves training the CNN classifier on the training dataset. The CNN classifier is a type of deep learning model that is specifically designed to analyze image data. During training, the CNN classifier learns to identify patterns in the MRI scans that are associated with different types of dementia.

K. Segmentation : Segmentation in medical imaging involves partitioning an image into distinct regions or objects of interest, like organs or lesions, for detailed analysis. It aids in precise delineation and measurement of structures, facilitating accurate diagnosis and treatment planning. Advanced algorithms, including deep learning methods, are commonly used for automated segmentation, improving efficiency and consistency in medical image analysis
L. Algorithms used: We are using the state-of the-art deep learning models on the MRI images of brain which were taken from kaggle. These State-of the-art deep learning models include Hybrid VGG-RNN, VGG16, EfficientNetB7, CNN. These models were chosen because of less number of parameters to train which results in less computation power and less training time.

IV. DATASETS USED

- This dataset contains 7022 images of human brain MRI images which are classified into 4 classes: glioma - meningioma - no tumor and pituitary.
- No tumor class images were taken from the Br35H dataset.
- The Dataset is taken from kaggle and it consists of Preprocessed MRI (Magnetic Resonance Imaging) Images.
- All the images are resized into 224 x 224 pixels.The Dataset has four classes of images.The Dataset is consists of total 7022 MRI images.

V. RESULT ANALYSIS

- The performance analysis of the CNN model for brain tumor detection revealed promising results. The model achieved a training accuracy of 99.42\%, a test accuracy of 96.18\%, and a validation accuracy of 96.488%. The high accuracy scores demonstrate the model's ability to effectively classify brain tumor images.
- Furthermore, various metrics such as precision, recall, and F1 score were used to evaluate the model's performance comprehensively. These metrics provide insights into the model's ability to correctly classify positive and negative instances, with the F1 score representing the harmonic mean of precision and recall.
- The confusion matrix provided additional insights into the model's performance for each class of brain tumors.While the model exhibited high accuracy for classes such as glioma and meningioma, it faced challenges in accurately predicting notumor and pituitary cases. Adjustments to parameters and feature selection could potentially improve the model's performance for these classes.
- Comparing the CNN model with established models such as VGG16,Hybrid VGG-RNN, and EfficientNetB7 highlighted the superior accuracy of the proposed model. Despite the high performance of these models, the CNN model outperformed them, achieving an accuracy rate of 96.18%. This suggests that the CNN model has better discriminatory ability and precision in making predictions.

VI. CONCLUSION

In conclusion, the literature review highlights the significant advancements achieved in utilizing deep learning methods, particularly Convolutional Neural Networks (CNNs), for brain tumor detection from MRI data. CNNs demonstrate exceptional accuracy, exceeding 96 percentage, offering promise for early and precise tumor identification crucial for timely interventions. Transfer learning and data augmentation techniques effectively address dataset limitations, while the integration of multi-modal data enhances diagnostic precision by providing a comprehensive understanding of tumor characteristics. Despite challenges such as ethical considerations, dataset reliance, and model interpretability, continued research efforts focused on refining deep learning architectures, innovating data augmentation methods, and addressing ethical concerns are essential for responsible and effective clinical implementation. Ultimately, the transformative potential of deep learning in brain tumor detection underscores its significance in advancing healthcare, emphasizing the importance of ongoing vigilance and collaboration to overcome challenges and fully realize its clinical potential.

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