*Research Journal of Engineering Technology and Medical Sciences (ISSN: 2582-6212), Volume 06, Issue 02, June-2023*
*Available at www.rjetm.in/*

# A Review on Multimodal Brain Abnormality Detection Using Deep Learning

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**Abstract:** *Clinical diagnosis has become very significant in today's health system. The most serious disease and the leading cause of mortality globally is considering brain abnormality are brain cancer, tumors, and other disorders which is a key research topic in the field of medical imaging. The examination and prognosis of this abnormalities can be improved by an early and precise diagnosis based on magnetic resonance imaging. For computer-aided diagnosis methods to assist radiologists in the proper detection of brain abnormalities, medical imagery must be detected, segmented, and classified. Manual brain abnormality detection is a monotonous and error-prone procedure for radiologists; hence, it is very important to implement an automated method. As a result, the precise brain abnormalities detection and classification method is presented. Therefore, this work analyze multiple types of data from the brain, such as magnetic resonance imaging (MRI), positron emission tomography (PET), electroencephalography (EEG), and other modalities. By combining information from various modalities, deep learning models aim to improve the accuracy and efficiency of detecting and diagnosing brain abnormalities, such as tumors, lesions, neurodegenerative diseases, or epileptic activity. Our proposed work has an accuracy of 98 % and 93 % for different datasets. Multimodal brain abnormality detection using deep learning has the potential to improve diagnostic accuracy, reduce human error, and provide valuable insights into complex brain disorders. However, it requires large and diverse datasets, expertise in multimodal data processing, and careful validation to ensure its effectiveness and generalizability in real-world clinical settings.*

**Keywords:** *Medical Diagnosis, Brain Abnormality, Machine Learning, Deep Learning, Multi-modal.*

## 1. Introduction

The human brain is a vital organ that controls various functions such as thoughts, memory, emotions, motor skills, vision, and breathing. It is composed of billions of neurons and trillions of synapses, forming complex connections at different spatial and temporal scales[1]. Understanding the neural mechanisms underlying brain activities is of great importance for researchers due to the intricacies involved. Neurological and mental disorders impact the central or peripheral nervous system[2]. The causes of brain diseases are diverse, including genetic, epigenetic, and external factors such as trauma, infection, and environmental influences. Some notable brain disorders[3] include multiple sclerosis (MS), Alzheimer's disease (AD), Parkinson's disease (PD), cerebral palsy, autism spectrum disorder (ASD), amyotrophic lateral sclerosis (ALS), myasthenia gravis (MG), traumatic brain injury, and epilepsy. Neuroimaging plays a crucial role in diagnosing and identifying brain diseases. It allows for the visualization of the brain's structural form and functional behavior [4]. Neuroimaging modalities are categorized into structural and functional modalities. Structural neuroimaging techniques provide insights into the anatomical structure of the brain and aid in diagnosing neurological disorders associated with structural changes. Common structural modalities include computerized tomography (CT), structural magnetic resonance imaging (sMRI), and diffusion tensor imaging (DTI). On the other hand, functional neuroimaging techniques assess the brain's behavior and metabolism during specific tasks like sensory, motor, and cognitive activities. Functional modalities include positron emission tomography (PET), functional magnetic resonance imaging (fMRI), single-photon emission computed tomography (SPECT), and magnetoencephalography (MEG) [5]-[10].

The Fig. 1 describes the progression of Medical image processing. The first step is to collect the image from the database available. In this case images from different modalities are to be comsidered. The second step is to apply the contrast adjustment and histogram equalization which is the preprocessing of the image [11][12]. The third step is to find out the particular ROI. The fourth step is to apply the different patterns for the feature extraction. The final step is to classify the texture from the image to find out the existence of normal and abnormal images [13].

By utilizing these neuroimaging modalities, researchers gain valuable insights into brain abnormalities and diseases. Structural imaging helps detect structural changes associated with disorders, while functional imaging provides information about brain activity and metabolic processes. These techniques aid in the diagnosis, understanding, and treatment of various brain disorders, leading to advancements in neuroscience and clinical practice. Despite its advantages, neuroimaging methods have certain limitations [14].

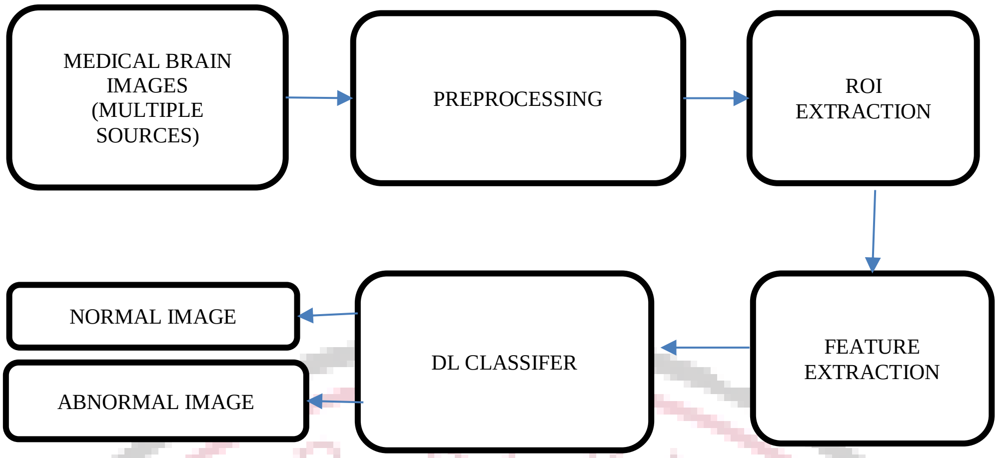


**Fig. 1.** Flow Diagram of Multimodal Brain Abnormality detection using DL

For instance, CT imaging has drawbacks such as limited tissue characterization, exposure to X-rays, high costs, and substantial radiation doses per examination. PET combines nuclear medicine with biochemical analysis, allowing the detection of biochemical changes associated with diseases before anatomical changes become visible through other imaging techniques. PET offers benefits like high sensitivity, deeper penetration, and the ability to visualize physiological and biochemical processes. However, PET has limitations such as limited resolution, radiation exposure, high costs, motion artifacts, image interpretation challenges, and the use of radioactive materials. SPECT, a nuclear medicine tomographic imaging technique, uses gamma rays to provide accurate 3D information. While it shares similarities with conventional gamma camera imaging, SPECT suffers from blurring effects, limited resolution, radiation exposure, and high costs. However, it offers advantages like sensitivity, deeper penetration, and absence of background interference in the images. MRI is a popular imaging technique that enables the visualization of anatomical structures, physiological functions, and molecular composition of tissues. MRI offers high-contrast presentation of brain tissue, high-resolution imaging with voxel sizes as small as 1 mm, good signal-to-noise ratio, and no radiation exposure. However, drawbacks of MRI include longer scanning times compared to CT and the complexity involved in image analysis by physicians. Despite these limitations, neuroimaging techniques continue to be invaluable tools in the diagnosis and understanding of brain disorders [15]. This neuroimaging techniques poses several technical challenges, including differences in brightness, resolution, noise presence, varying image modalities, limited availability of images in each modality, increased imaging costs, and computational complexity. To address these challenges, extensive research has been conducted in recent years in the field of diagnosing brain disorders using AI techniques and multimodality imaging. AI techniques can be categorized into machine learning (ML) and deep learning (DL) methods [16]. ML, a subset of AI, enables systems to learn from data, recognize patterns, and make decisions without explicit coding. Evaluating and selecting ML algorithms for disease diagnosis often involve trial and error, which can be challenging. Machine learning methods especially neural-network based algorithms have shown huge success in medical image analysis for variety of tasks including the detection, segmentation and classification of brain tumors and Ischemic stroke. Usually, these models address one problem at a time which is considered as Artificial Weak Intelligence (AWI). There is the need to develop methods that can push the research towards a goal where a model can solve multiple tasks [17].

DL models, on the other hand, have the capability to automatically learn representations from raw data and optimize them. These models exhibit robustness against natural variations in data and generally perform better with larger training datasets. Furthermore, DL models can learn from unstructured data, allowing the utilization of diverse data formats. Labeling data can be costly and time-consuming, but certain DL models can process non-labeled data. The fundamental concept behind DL and multimodality image segmentation, explain various DL architectures, analyze different Neuroimaging techniques, compare their results, and conclude with perspectives on future research. These advancements in DL-based multimodality imaging hold promise for enhancing the diagnosis and understanding of brain disorders. Therefore, this work proposed deep learning based multimodal brain abnormality detection.

## 2. Literature Review

In their study, Khan et al. [18] introduced a deep learning-based automated multimodal classification method for classifying brain tumor types. The method comprised five main steps. Firstly, they employed linear contrast stretching using edge-based histogram equalization and discrete cosine transform (DCT). Secondly, deep learning feature extraction was performed by utilizing transfer learning with two pre-trained convolutional neural network (CNN) models, VGG16 and VGG19. In the third step, a correntropy-based joint learning approach was implemented along with the extreme learning machine (ELM) to select the best features. The fourth step involved fusing the robust covariant features based on partial least square (PLS) into one matrix. This combined matrix was then fed to the ELM for final classification. The proposed method was evaluated on the BraTS datasets, achieving high accuracy rates of 97.8%, 96.9%, and 92.5% for BraTs2015, BraTs2017, and BraTs2018, respectively.

Sappagh et al. [19] developed a precise and interpretable model for diagnosing and detecting the progression of Alzheimer's disease (AD). The model incorporated 11 modalities from the Alzheimer's Disease Neuroimaging Initiative (ADNI) real-world dataset, consisting of 1048 subjects, including cognitively normal individuals, stable and progressive mild cognitive impairment (MCI), and AD patients. The model was designed as a two-layer architecture, utilizing a random forest (RF) classifier algorithm. In the first layer, the model performed multi-class classification for early AD diagnosis, while the second layer employed binary classification to detect possible progression from MCI to AD within three years of baseline diagnosis. The model's performance was optimized using key markers selected from a large set of biological and clinical measures. To enhance explainability, the authors provided global and instance-based explanations of the RF classifier for each layer using the SHapley Additive exPlanations (SHAP) feature attribution framework. They also implemented 22 explainers based on decision trees and fuzzy rule-based systems, presenting explanations in natural language form to aid physicians' understanding of predictions. The model achieved a cross-validation accuracy of 93.95% and an F1-score of 93.94% in the first layer, while attaining a cross-validation accuracy of 87.08% and an F1-score of 87.09% in the second layer. The resulting system not only demonstrated high accuracy but also provided trustworthy, accountable, and medically applicable explanations that were consistent with the AD medical literature, contributing to a better understanding of AD diagnosis and progression processes.

Rahaman et al. [20] proposed a multi-modal deep learning framework to capture the interaction between latent features and evaluate their complementary information for schizophrenia characterization. Their framework incorporated data from different modalities, including structural MRI, functional MRI, and genome-wide polymorphism data, for the classification task. The model consisted of a multi-layer feed-forward network, an encoder, and a long short-term memory (LSTM) unit with attention mechanism to learn latent features. A joint training scheme was employed to capture synergies between the modalities, while different regularizers addressed overfitting and modality-specific bias in the multi-modal setup. The learned features were analyzed using a saliency model. Integrating multiple modalities improved the classifier's performance, achieving an accuracy of 88% ($P < 0.0001$) on a dataset of 437 subjects.

Anand et al. [21] proposed a multimodal approach combining machine learning techniques and medical assistance for brain tumor segmentation and classification. To address the noise present in MRI images, they applied a geometric mean filter during picture preprocessing. The fuzzy c-means algorithm was utilized for image segmentation, dividing the image into smaller parts. Segmentation facilitated the identification of a region of interest. For dimension reduction, the GLCM (Grey-level co-occurrence matrix) algorithm was employed. Features were extracted from the images using the GLCM algorithm, and various machine learning methods such as SVM, RBF, ANN, and AdaBoost were used for image classification. The SVM RBF algorithm demonstrated superior performance in brain tumor classification and detection, achieving an accuracy, sensitivity, and specificity of 99%, 98%, and 99%, respectively.

Maqsood et al. [22] proposed a method for brain tumor detection and classification consisting of five steps. Firstly, a linear contrast stretching technique was utilized to identify edges in the source image. Secondly, a custom 17-layered deep neural network architecture was developed for brain tumor segmentation. In the third step, a modified MobileNetV2 architecture was employed for feature extraction, trained using transfer learning. The fourth step involved an entropy-based controlled method and a multiclass support vector machine (M-SVM) for feature selection. Finally, M-SVM was used for brain tumor classification, specifically identifying meningioma, glioma, and pituitary images. The proposed method was evaluated on the BraTS 2018 and Figshare datasets, outperforming other methods both visually and quantitatively, achieving accuracy rates of 97.47% and 98.92%, respectively. The results were explained using the eXplainable Artificial Intelligence (XAI) method, providing insights into the improved accuracy of the proposed approach.

Dwivedi et al. [23] introduced a novel multimodal fusion-based method for the accurate diagnosis of Alzheimer's disease (AD). Instead of using single modality data like MRI or PET, the authors fused metabolic and structural data to obtain a holistic view of AD-staging analysis. The fusion was achieved by leveraging the demon algorithm and discrete wavelet transform for optimal fusion of MRI and PET images. The fused image features were then extracted using ResNet-50, and a robust energy least square twin support vector machine (SVM) classifier was utilized for classification. Experimental results on the AD neuroimaging initiative dataset demonstrated the effectiveness of the proposed model, achieving high accuracies of 97%, 94%, and 97.5% for distinguishing cognitive normal (CN) versus AD, CN versus mild cognitive impairment (MCI), and AD versus MCI, respectively. This proposed model holds promise for accurate early-stage AD diagnosis.

Liu et al. [24] presented an efficient multimodality fusion framework for identifying multiple mental disorders based on functional and structural magnetic resonance imaging (MRI). To address the scarcity of multimodal data, a multioutput conditional generative adversarial network (GAN) was developed for data augmentation. Based on the augmented training data, a multiheaded gating fusion model was proposed to extract complementary features across different modalities for classification. The experiments demonstrated robust accuracies of $75.1 \pm 1.5\%$, $72.9 \pm 1.1\%$, and $87.2 \pm 1.5\%$ for autism spectrum disorder (ASD), attention deficit/hyperactivity disorder, and schizophrenia, respectively. The interpretability of the model was emphasized, as it enables the identification of neuropathology diagnostic biomarkers, facilitating informed therapeutic decisions.

Khan et al. [25] proposed an automated system for brain tumor detection and classification using a saliency map and deep learning feature optimization. The framework consisted of multiple stages, starting with a fusion-based contrast enhancement technique. Next, a tumor segmentation technique based on saliency maps was introduced, followed by mapping the segmentations onto the original images using active contour. A pre-trained CNN model called EfficientNetB0 was fine-tuned and trained on enhanced and tumor localization images using deep transfer learning. Deep learning features were fused using an improved fusion approach called Entropy Serial Fusion. The best features were selected using an improved dragonfly optimization algorithm, and classification was performed using an extreme learning machine (ELM). The proposed framework was evaluated on three publicly available datasets, achieving improved accuracy rates of 95.14%, 94.89%, and 95.94% respectively, outperforming several neural nets.

Yousaf et al. [26] developed a convolutional neural network (CNN) based integrated model for the simultaneous detection and classification of two brain diseases: tumors and ischemic stroke. A new dataset was created by merging the BRATS 2015 and ISLES 2015 datasets. The designed network was an enhanced version of the encoder-decoder architecture based UNET, incorporating feature map fusion to preserve fine-grained information and distinguish overlapping features during the encoding process. The dataset was partitioned into training and validation sets, addressing the class imbalance issue by including a proportional number of images in each training batch. The proposed model achieved high average accuracy of 99.56%, 99.99% specificity, 99.59% precision, and an F1-score of 99.57%. These performance scores demonstrated the effectiveness of the proposed feature fusion mechanism for multi-disease detection.

Meshram and Rambola [27] presented a novel approach for a convolutional neural network (CNN) model that analyzed facial images from recorded interview sessions to detect facial patterns indicative of depression levels. The model aimed to predict the depression scale and differentiate depression from other mental disorders using the patient's psychiatric illness history and dynamic textual descriptions extracted from user inputs. The dynamic textual descriptors were subjected to linguistic analysis using the k-nearest neighbor algorithm to classify mental illnesses into different classes. Dimensionality reduction and regression were performed using the Random Forest algorithm to predict the depression scale. The proposed framework extended pre-existing frameworks by replacing handcrafted feature extraction techniques with deep feature extraction. The model achieved a 2.7% improvement over existing frameworks in facial detection and feature extraction.

## 3. Future Research Directions

Based on the provided research articles, we can identify several research gaps and future research scope in the field of automated classification and diagnosis of brain tumors and mental disorders using multimodal data and deep learning techniques. Here are some potential research gaps and future research directions:

- Improved Performance: While the proposed methods in the articles achieved high accuracy rates in brain tumor classification and mental disorder diagnosis, there is still room for improvement. Future research can focus on developing more advanced and sophisticated deep learning models, exploring different network architectures, and optimizing the fusion of multimodal data to further enhance the performance and accuracy of these systems.
- Generalizability and External Validation: Most of the studies mentioned the evaluation of their proposed methods on specific datasets. To ensure the generalizability and applicability of these techniques in real-world clinical settings, future research should focus on conducting external validation and testing the proposed methods on diverse and larger datasets, including data from multiple institutions or sources.
- Interpretability and Explainability: As deep learning models become more complex, interpretability and explainability become crucial in the medical domain. Future research should focus on developing techniques and methods that provide meaningful explanations for the decisions made by the deep learning models. This can help clinicians and medical professionals understand and trust the predictions made by these models, ultimately improving their adoption in clinical practice.
- Robustness and Transferability: It is important to ensure that the developed models are robust and can handle variations in data acquisition protocols, imaging devices, and patient demographics. Future research should investigate techniques for domain adaptation, transfer learning, and data augmentation to improve the robustness and generalization capabilities of the models across different datasets and clinical settings.
- Integration of Clinical Data: While some of the articles mentioned the inclusion of clinical and biological measures alongside imaging data, there is still room to explore the integration of additional clinical data, such as demographic information, genetic data, cognitive assessments, and other biomarkers. The integration of these data modalities can potentially improve the accuracy and reliability of the classification and diagnosis models.
- Real-time and Point-of-Care Applications: Most of the proposed methods are offline approaches that require pre-processing and analysis of the entire dataset. Future research can focus on developing real-time or point-of-care systems that can analyze medical images and make predictions in real-time. This would enable faster decision-making and facilitate the integration of these models into clinical workflows.
- Validation on Prospective Cohorts: While some of the studies utilized retrospective datasets, future research should consider conducting prospective studies on cohorts of patients. This would provide valuable insights into the clinical utility of the proposed methods in real-time scenarios and allow for the evaluation of their impact on patient outcomes.
- Ethical Considerations and Bias Mitigation: As these automated systems become more integrated into clinical practice, it is crucial to address ethical considerations, potential biases, and unintended consequences. Future research should focus on developing methods to mitigate biases in data collection, algorithm development, and decision-making processes to ensure fair and equitable outcomes for patients from diverse populations.
- Integration with Clinical Workflows: Successful implementation of these automated systems requires seamless integration with existing clinical workflows and electronic health record systems. Future research should explore ways

to integrate these models into clinical decision support systems, radiology reporting systems, or other relevant healthcare platforms to facilitate their adoption and usage by healthcare professionals.

- Longitudinal Analysis and Disease Progression: While some studies focused on disease classification, future research can explore methods for longitudinal analysis and disease progression prediction. This can help in monitoring disease evolution over time, tracking treatment response, and providing personalized prognostic information for patients.

By addressing these research gaps and exploring the future research scope, the field of automated classification and diagnosis of brain tumors and mental disorders can advance further, leading to more accurate, reliable, and clinically applicable systems with the potential to improve patient care and outcomes.

## 4. Conclusion

In conclusion, paper explored several research articles in the field of automated classification and diagnosis of brain tumors and mental disorders using multimodal data and deep learning techniques. The reviewed studies showcased various approaches and methodologies, highlighting their strengths, limitations, and achieved results. The surveyed articles demonstrated the potential of deep learning models in accurately classifying brain tumor types and diagnosing mental disorders. The integration of different modalities, such as structural and functional MRI, genetic data, and clinical measures, proved beneficial in improving classification accuracy and understanding disease progression. The use of transfer learning, feature selection, and fusion techniques further enhanced the performance of the models. However, despite the promising results, there are several research gaps and areas for future exploration. These include improving model performance, ensuring generalizability and external validation, enhancing interpretability and explainability, addressing robustness and transferability, integrating clinical data, developing real-time and point-of-care applications, validating on prospective cohorts, considering ethical considerations and bias mitigation, and integrating the models with clinical workflows. Addressing these research gaps and pursuing the future research scope outlined in this paper will advance the field and contribute to the development of more accurate, reliable, and clinically applicable automated classification and diagnosis systems.

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