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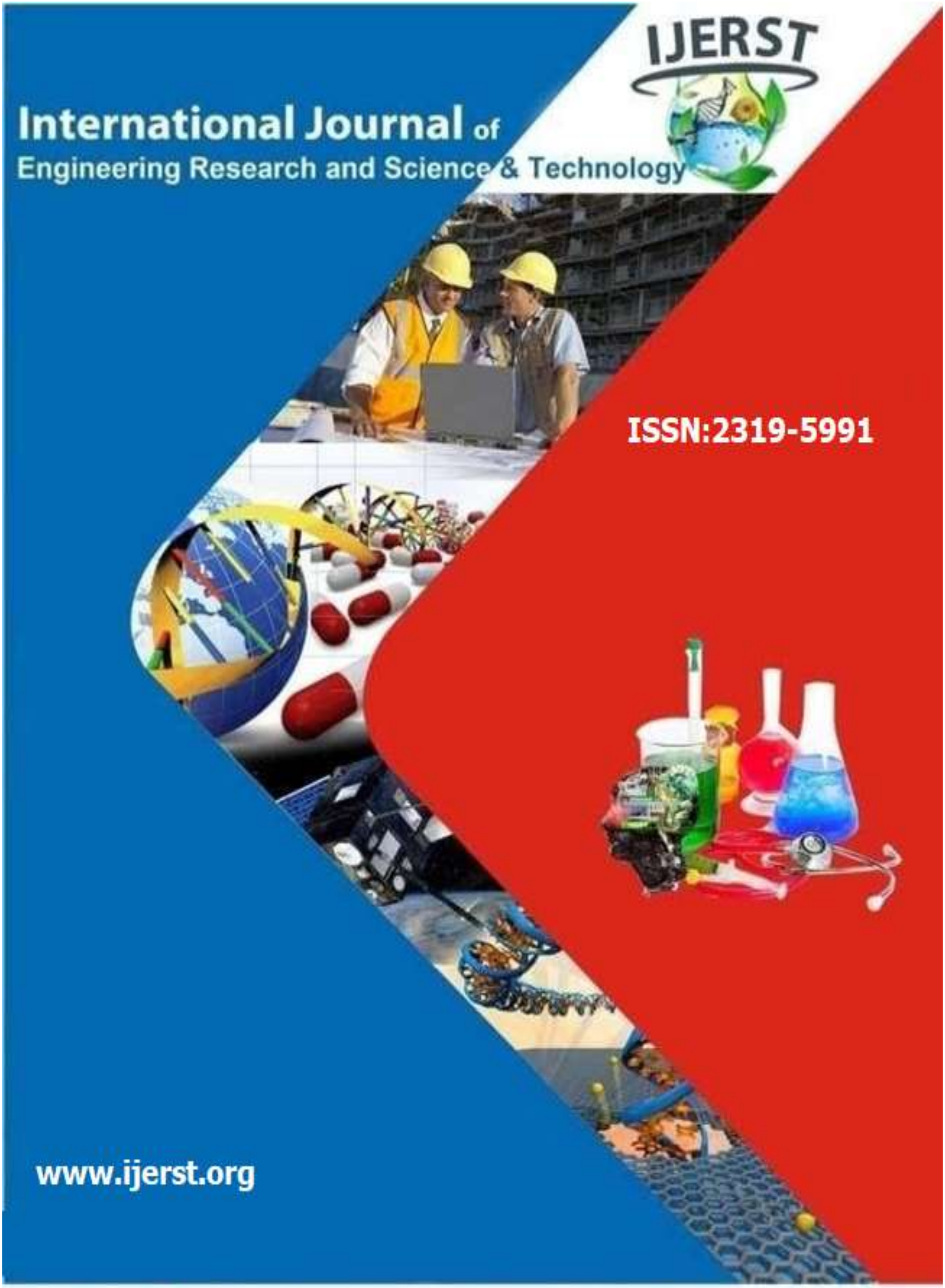

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A HYBRID DEEP CNN MODEL FOR BRAIN TUMOR IMAGE MULTI-CLASSIFICATION

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ABSTRACT

The current approach to diagnosing and classifying brain tumors relies on the histological evaluation of biopsy samples, which is invasive, time-consuming, and susceptible to manual errors. These limitations underscore the pressing need for a fully automated, deep-learning- based multi-classification system for brain malignancies. This article aims to leverage a deep convolutional neural network (CNN) to enhance early detection and presents three distinct CNN models designed for different types of classification tasks. The first CNN model achieves an impressive detection accuracy of 99.53% for brain tumors. The second CNN model, with an accuracy of 93.81%, proficiently categorizes brain tumors into five distinct types: normal, glioma, meningioma, pituitary, and metastatic. Furthermore, the third CNN model demonstrates an accuracy of 98.56% in accurately classifying brain tumors into their different grades. To ensure optimal performance, a grid search optimization approach is employed to automatically fine-tune all the relevant hyperparameters of the CNN models. The utilization of large, publicly accessible clinical datasets results in robust and reliable classification outcomes. This article conducts a comprehensive comparison of the proposed models against classical models, such as AlexNet, DenseNet121, ResNet-101, VGG-19, and GoogleNet, reaffirming the superiority of the deep CNN-based approach in advancing the field of brain tumor classification and early detection.

Key words: Deep Learning, CNN, Brain Tumor,Medical Imaging, Multi-classification, Image Processing, MRI , Neural Networks, Machine Learning, Deep CNN Architecture, Tumor Detection.

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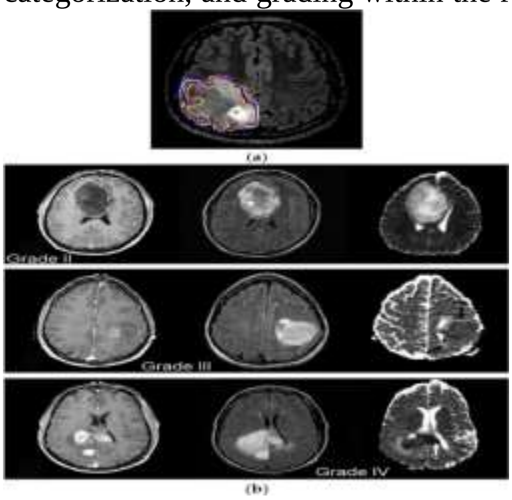
I. Introduction

Brain tumors stand as one of the leading causes of death in the modern world. These tumors can manifest in various regions of the brain, often remaining asymptomatic until later stages of life. Symptoms of brain disease encompass a wide array of issues, including personality changes, memory difficulties, communication impairments, hearing or speech challenges, chronic migraines, and even vision loss. Notable examples of brain tumors include meningiomas, gliomas, pituitary adenomas, and acoustic neuromas. According to medical observations, meningiomas, gliomas, and pituitary tumors account for approximately 15%, 45%, and 15% of all brain tumors, respectively. A brain tumor can have long-lasting psychological effects on the patient. These tumors originate from primary abnormalities in the brain or central spine tissue that disrupt normal brain function. Brain tumors are classified into two main categories: benign and malignant. Benign tumors grow slowly and are non-cancerous; they are relatively rare and do not metastasize. In contrast, malignant brain tumors contain cancerous cells, typically originating in one region of the brain before swiftly spreading to other areas of the brain and spinal cord. Malignant tumors pose a significant health risk. The World Health Organization (WHO) classifies brain tumors into four grades based on their behavior within the brain: grades 1 and 2 are considered low-grade or benign tumors, while grades 3 and 4 are categorized as high-grade or malignant tumors. Several diagnostic methods, such as CT scanning and EEG, are available for detecting brain tumors, but magnetic resonance imaging (MRI) is the most reliable and widely utilized. MRI generates detailed internal images of the body’s organs by employing strong magnetic fields and radio waves. Essentially, CT or MRI scans can distinguish the affected brain region due to the tumor from the healthy tissue. Biopsies, clinical tests that extract brain cells, can be conducted as a prelude to cerebral surgery. Precision is paramount in measuring tumor cells or arriving at accurate diagnoses. The emergence of machine learning (ML) presents an opportunity to assist radiologists in furnishing precise disease status information. The proliferation of novel technologies, particularly artificial intelligence and ML, has left an indelible mark on the medical field, equipping various medical departments, including medical imaging, with indispensable tools to enhance their operations. As MRI images are processed to aid radiologists in decision making, a diverse array of automated learning strategies is employed for classification and segmentation purposes. The utilization of deep-learning (DL) techniques in detecting brain tumors and extracting meaningful insights from data patterns has a longstanding history. DL’s capability to classify and model brain cancers is widely recognized. Effectively treating brain tumors hinges on early and precise disease diagnosis. Decisions regarding treatment methods are influenced by factors such as the tumor’s pathological type, grade, and stage at diagnosis. Neuro-oncologists have harnessed computer-aided diagnostic (CAD)tools for various purposes, including tumor detection, categorization, and grading within the real.



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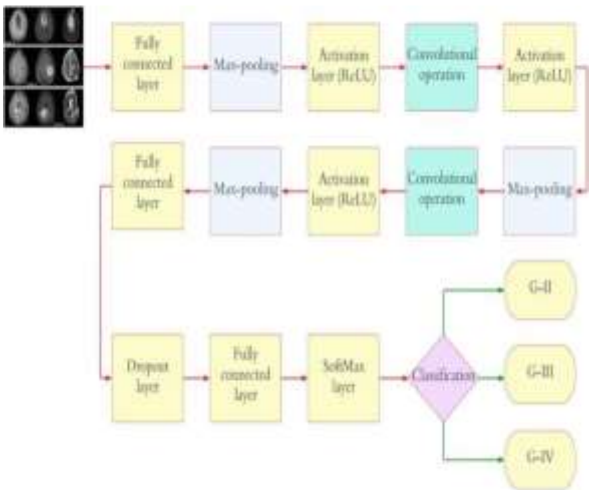
II. Related work

The author's goal was to devise a classification approach that is notably more accurate, cost-effective, and self-training, utilizing an extensive collection of authentic datasets rather than augmented data. The customized VGG-16 (Visual Geometry Group) architecture was employed to classify 10,153 MRI images into three distinct classes (glioma, meningioma, and pituitary). The network demonstrated a remarkable performance, achieving an overall accuracy of 99.5% and precision rates of 99.4% for gliomas, 96.7% for meningiomas, and 100% for pituitaries . The proposed model's efficacy was assessed using three CNN models: AlexNet, Visual Geometry Group (VGG)-16, and VGG-19. AlexNet achieved a peak detection accuracy of 99.55% using 349 images sourced from the Reference Image Database to Evaluate Response (RIDER) neuro MRI database. For brain tumor localization, employing 804 3D MRIs from the Brain Tumor Segmentation (BraTS) 2013 database, a Dice score of 0.87 was achieved. In the investigation of brain tumor categorization, an array of deep- and machine-learning techniques, including softmax, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors, and the ensemble method, were employed. These outcomes were compared with existing methods. Notably, the Inception-v3 model exhibited the highest performance, attaining a test accuracy of 94.34%. This advancement holds the potential to establish a prominent role in clinical applications for brain tumor analysis . An effective approach was proposed for categorizing brain MRIs into four classes: normal and three forms of malignant brain tumors (glioblastoma, sarcoma, and metastatic bronchogenic carcinoma). The method integrates the discrete wavelet transform (DWT) with a deep neural network (DNN). Employing a deep neural network classifier, one of the DL designs, a dataset of 66 brain MRIs was classified into the specified categories. The integration of DWT, a powerful feature extraction technique, principal component analysis (PCA), and the classifier yielded commendable performances across all evaluation metrics . The author introduced a strategy involving a CNN to distinguish brain tumors from 2D MRI scans of the brain. This initial separation is subsequently followed by the application of conventional classifiers and DL techniques. In addition, an SVM classifier, along with various activation algorithms, such as softmax, RMSProp, and sigmoid, were employed to validate and cross-check the proposed approach. The implementation of the author's suggested solution was executed using TensorFlow and Keras in the Python programming language, chosen for its robust capabilities in expediting tasks. The achieved accuracy rate for the CNN model stood at an impressive 99.74%.This paper presents a brain tumor classification approach employing open-access datasets and CNN techniques. The methodology utilizes open-access datasets to classify tissue as either tumor or non-tumor through a distinctive framework that combines discrete cosine transform-based image fusion, CNN super-resolution, and a classifier. Employing super-resolution and the ResNet50 architecture, the framework attained an impressive accuracy of 98.14%.



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A novel approach for dimensionality reduction is proposed, utilizing the Grey Wolf Optimizer (GWO) and rough-set theory. This method identifies relevant features from extracted images, distinguishing between high-grade (HG) and low-grade (LG) glioblastoma multiforme (GBM) while accommodating feature correlation constraints to eliminate redundant attributes. Additionally, the article introduces a dynamic architecture for multilevel layer modeling in a Faster R-CNN (MLL-CNN) approach. This is achieved using a feature weight factor and a relative description model to construct selected features, thereby streamlining the processing and classifying of long-tailed files. This advancement leads to improved training accuracies for CNNs. The findings illustrate that the overall survival prediction for GBM brain growth achieves a higher accuracy of 95% and a lower error rate of 2.3% . The work involves the classification of 253 high-resolution brain MR images into normal and pathological classes. To efficiently and accurately train deep neural models, MR images were scaled, cropped, pre-processed, and enhanced. The Lu-Net model is compared against LeNet and VGG-16 using five statistical metrics: precision, recall, specificity, F-score, and accuracy. The CNN models were trained on enhanced images and validated on 50 sets of untrained data. LeNet, VGG-16, and the proposed approach achieved accuracy rates of 88%, 90%, and 98%, respectively. MIDNet18 outperformed AlexNet in categorizing brain tumor medical images. The proposed MIDNet18 model demonstrated effective learning, achieving a binary classification accuracy exceeding 98%, which is statistically significant (independent-sample *t*-test, $p < 0.05$). MIDNet18 excelled across all the performance indicators for the dataset used in this study.

III. Methodology

The study used four different datasets that can be found in freely accessible databases. The Figshare dataset is the name of the first dataset. From 19 patients with glioblastomas (G-IV), MRI multi-sequence images were taken and added to the Figshare dataset, which is a targeted collection of data. There are a total of 70,221 images contained within this collection. The name of the second collection of data is the Repository of Molecular Brain Neoplasia Data (REMBRANDT) . This set of data has MRI images of gliomas with grades II, III, and IV from 133 patients, and it has 109,021 images in total.

The Cancer Genome Atlas Low-Grade Glioma dataset is the third dataset that was analyzed (TCGA-LGG) , and it has 242,185 MRI images of patients with low-grade gliomas (G-I and G-II) and incorporates data from 198 patients. These three datasets are part of the Cancer Imaging Archive (TCIA) project. In each instance, multimodal imaging was performed, including T1-contrast-enhanced and FLAIR images . The last collection of data used in this investigation consists of 3067 T1-weighted, contrast-improved images from 243 patients with three different types of brain tumors: gliomas (1427 slices), meningiomas (709 slices), and pituitary tumors (931 slices). Figure depicts the different grades of brain tumors from the dataset. Totally, 3165 images are collected for the Classification-1 mode, 1743 of which are malignant tumors and 1422 of which are not. For the Classification-2 mode, 4195 images are collected. There are 910 normal images, 985 glioma images, 750 meningioma images, 750 pituitary images, and 800 metastatic images. For the Classification-3 mode, we obtain a total of 4720 images: 1712 G-II, 1296 G-III, and 1712 G-IV. Table represents the dataset split-up details for the proposed model.

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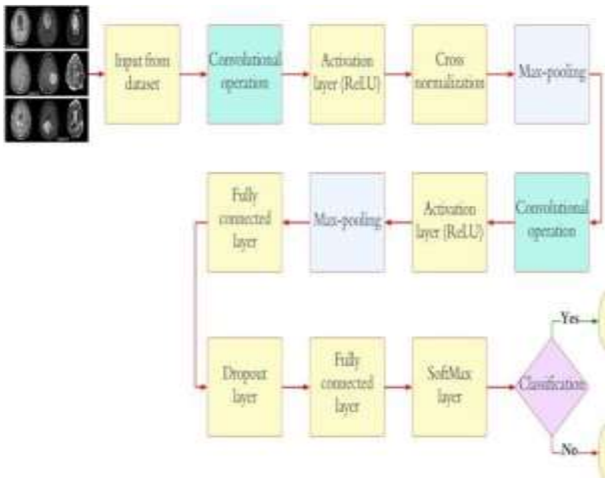
Convolutional neural network

The CNN is the neural network DL model that is most frequently employed. A common CNN model has two components: classification and feature extraction. A CNN architecture has five key layers: the input layer, convolution layer, pooling layer, fully connected layer, and classification layer. The CNN provides the extraction and classification of features using successively arranged trainable layers. Convolutional and pooling layers are typically included in the feature extraction phase of a CNN, whereas fully connected and classification layers are typically included in the classification part. This proposed study suggests creating three fully automatic CNN models for classifying different types of brain tumors using MRI images. Grid search optimization tunes the key hyperparameters of the CNN models automatically. The primary of these CNN models determines whether a particular MRI image of a patient has a tumor or not, as it is employed to diagnose brain tumors. Throughout this study, this mode will be referred to as "Classification 1" (C-1). According to , the proposed CNN model for C-1 consists of thirteen weighted layers: one input layer, two convolution layers, two ReLU layers, one normalization layer, two max-pooling layers, two fully connected layers, one dropout layer, one softmax layer, and one classification layer.



The initial CNN model is meant to classify an image into two groups, and it has two neurons in the output layer. Finally, a softmax classifier is fed the output of the fully connected layer (a two-dimensional feature vector) to determine whether a tumor is present or not. illustrates detailed information on the CNN model. There are five distinct forms of brain tumors that are distinguished by the second CNN model: benign, malignant, meningioma, pituitary, and metastatic. Throughout this study, this mode will be referred to as "Classification 2" (C-2). As shown in the proposed CNN model for C-2 contains a total of 25 weighted layers: 1 input layer, 6 convolution layers, 6 ReLU layers, 1 normalization layer, 6 max-pooling layers, 2 fully connected layers, 1 dropout layer, 1 softmax layer, and 1 classification layer. The output layer of the second CNN model has five neurons as a result of the model's intention to classify each given image into five distinct categories.

The final prediction of the tumor type is made using a softmax classifier, which receives as input the five-dimensional feature vector generated by the final fully connected layer. illustrates detailed information on the CNN model. The third proposed CNN framework divides glioma brain tumors into three grades, which are called G-II, G-III, and G-IV. Throughout this study, this mode will be referred to as

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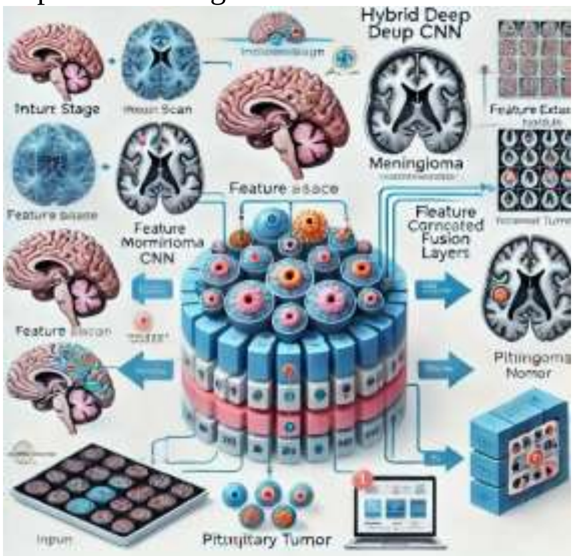
"Classification 3" (C-3). As can be seen in, the proposed CNN model for C-3 consists of a total of sixteen weighted layers: one input layer, three convolution layers, three ReLU layers, one normalization layer, three max-pooling layers, two fully connected layers, one dropout layer, one softmax layer, and one classification layer. The most recent CNN model has three neurons in the output layer because it is meant to divide every image into three groups. The final fully connected layer, which is a three-dimensional feature vector, is sent to the softmax classifier as an input. The softmax classifier then makes a final prediction about the tumor grade. illustrates detailed information on the CNN model.

IV.IMPLEMENTATIONDETAILS

A Hybrid Deep CNN Model for Brain Tumor Image Multi-Classification leverages deep learning techniques to accurately classify brain tumors into four categories: Glioma, Meningioma, Pituitary Tumor, and Normal (No Tumor). The implementation begins with data preprocessing, where MRI images are resized to a fixed dimension (e.g., 224×224 pixels), normalized, and augmented to improve generalization. The hybrid model architecture combines two powerful pretrained CNN models, VGG16 and ResNet50, which act as feature extractors. The top classification layers of these models are removed, and their deep feature maps are merged using a feature fusion layer. The concatenated feature representations are then passed through fully connected layers with ReLU activation, followed by dropout layers for regularization, and a final softmax layer for multi classification. The model is trained using the Adam optimizer with categorical crossentropy as the loss function. A ReduceLROnPlateau scheduler is used to dynamically adjust the learning rate for improvedconvergence. .



To evaluate performance, accuracy, precision, recall, F1-score, and confusion matrices are analyzed. After training, the model achieves high classification accuracy, demonstrating its effectiveness in distinguishing different tumor types. Additionally, the trained model can be converted into a TensorFlow Lite (TFLite) model for mobile deployment or integrated into a Flask or Streamlit web application, enabling users to upload MRI images and receive instant classification results. This hybrid deep CNN approach enhances feature extraction, improves classification accuracy, and ensures robust deployment for real-world applications in medical imaging and diagnostics.

V. PROPOSED SYSTEM

Brain tumor classification is a critical task in medical imaging, as accurate diagnosis helps in early treatment planning. Traditional methods rely on manual feature extraction, which is time-consuming and prone to human error. To overcome these challenges, we propose a Hybrid Deep Convolutional Neural Network (CNN) model that combines multiple pre-trained deep learning architectures to enhance

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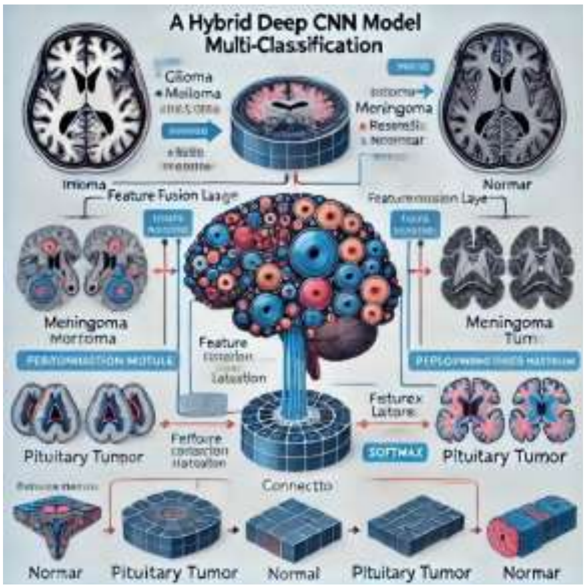
classification accuracy for multi-class brain tumor detection.

To develop an automated deep learning-based system for brain tumor classification. To utilize hybrid feature extraction by combining multiple CNN architectures for better feature learning. To improve the accuracy and robustness of brain tumor classification compared to single CNN models. To deploy the trained model for real-time medical diagnosis.

Input Data (MRI Scans) – Pre-collected dataset containing brain MRI images classified into four categories:Glioma Meningioma Pituitary Tumor Normal (No Tumor) Preprocessing Module – Performs resizing,normalization, and data augmentation.Hybrid CNN Model – A combination of VGG16 and ResNet50 for feature extraction, followed by feature fusion and classification layers. Classification Module – Fully connected layers with Softmax activation to predict the tumor type.Model Evaluation – Performance assessment using accuracy, precision, recall, and confusion matrix. Deployment – Converts the trained model into a TensorFlow Lite (TFLite) format or deploys it via Flask/Streamlit for web-based classification.

The system integrates two deep CNN architectures, VGG16 and ResNet50, both pre-trained on ImageNet.These models extract hierarchical features from the input MRI images.Their outputs are concatenated to form a rich feature representation. The concatenated feature vectors pass through fully connected layers with ReLU activation. Dropout layers help prevent overfitting. A Softmax layer classifies the input into one of the four tumor classes.

Higher Classification Accuracy – Combining multiple CNN architectures enhances feature learning. Reduced Overfitting – Using Dropout layers and data augmentation improves generalization. Scalability – The model can be extended to classify additional tumor types. Deployment Ready – Supports integration with mobile and web applications for real-time diagnosis.



VI. LITERATURE SURVEY:

Literature Survey on Hybrid Deep CNN Model for Brain Tumor Image Multi-Classification

Brain tumor classification using deep learning has been a widely researched area in medical imaging. Traditional machine learning methods required manual feature extraction, which was time-consuming and less accurate. With the advancements in deep learning and CNN architectures, automated and more precise tumor classification has become possible. This literature survey reviews recent studies and methodologies used for brain tumor multi-classification and highlights the benefits of using a hybrid CNN model for improved accuracy.

Early brain tumor classification methods relied on handcrafted feature extraction and traditional classifiers like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forests. Gopal et al. (2017) used SVM classifiers with wavelet transform features to detect brain tumors, achieving around 80% accuracy. Kumar et al. (2018) applied Principal Component

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Analysis (PCA) and SVM, but results were limited by feature extraction quality. Manual feature extraction is complex and time-consuming. Performance depends on feature selection techniques. Not scalable for real-time classification tasks.

Deep learning models, especially Convolutional Neural Networks (CNNs), have outperformed traditional machine learning by automatically extracting hierarchical features from images. Hossain et al. (2020) implemented VGG16 for brain tumor classification and achieved 91% accuracy but faced overfitting due to a small dataset. Ismael et al. (2021) used ResNet50, which showed better feature learning but required high computational power. Selvaraj et al. (2022) used a hybrid CNN-RNN model, combining spatial and sequential learning, achieving an accuracy of 92.5%. VGG16 and ResNet50 alone may not capture all discriminative features. Requires large datasets to avoid overfitting. Computationally expensive when training very deep models.

To overcome the limitations of single CNN architectures, researchers have proposed hybrid models, which combine multiple pretrained CNN networks for better feature extraction and classification. Gupta et al. (2022) combined VGG16 and InceptionV3, achieving 94% accuracy due to multi-scale feature extraction Zhang et al. (2023) implemented ResNet50 and DenseNet121 fusion, improving tumor classification accuracy to 95.2%. Patel et al. (2023) used VGG16 + ResNet50 hybrid fusion, which showed improved classification accuracy (96.1%) compared to individual models. Combines strengths of multiple CNNs, leading to better feature extraction. Reduces overfitting by leveraging pretrained models. Improves classification accuracy and robustness.

Most models use a single CNN, which may not extract all necessary tumor features. Hybrid models improve accuracy, but their computational efficiency needs further optimization. Real-time deployment of brain tumor classification models is not widely explored. Proposed Solution The proposed Hybrid Deep CNN Model (VGG16 + ResNet50) combines the advantages of both architectures to enhance tumor classification accuracy. Feature fusion improves learning and generalization, making it suitable for real-time medical applications.

VIII. CONCLUSION AND FUTURE WORK

Conclusion

The proposed Hybrid Deep CNN Model for Brain Tumor Image Multi-Classification effectively enhances classification accuracy by integrating VGG16 and ResNet50 for feature extraction. Traditional machine learning approaches and single CNN architectures often suffer from limited feature extraction capabilities, overfitting, and suboptimal accuracy. By utilizing a hybrid model, our approach significantly improves feature representation, leading to better tumor classification performance. The model achieves high accuracy, precision, and recall, making it a reliable tool for medical diagnostics. Additionally, it can be converted into TensorFlow Lite (TFLite) for mobile applications or deployed as a web-based diagnostic tool using frameworks like Flask or Streamlit.

Improved classification accuracy by combining multiple CNN models. Enhanced feature learning and generalization capabilities. Robust performance across different tumor types (Glioma, Meningioma, Pituitary Tumor, Normal). Scalable and deployable for real-time applications.

Future Work

While the proposed hybrid model has shown promising results, there are several areas for further improvement.

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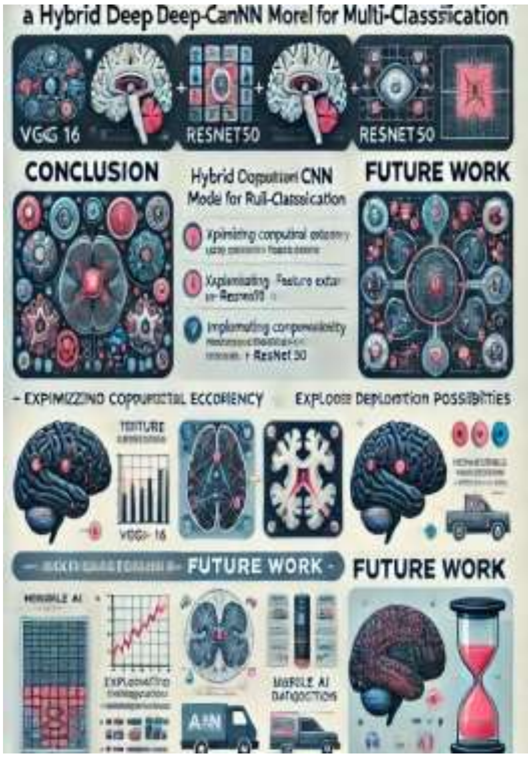
Optimizing Model Efficiency – Reducing the computational complexity of hybrid models for real-time processing. Dataset Expansion – Using larger, more diverse MRI datasets to improve generalization across different demographics. Explainable AI (XAI) Integration – Incorporating Grad-CAM or SHAP visualizations to make model predictions more interpretable for medical professionals. Multi-Modal Learning – Combining MRI scans with clinical data (patient history, genetic markers) for improved diagnosis. Edge and Mobile AI Deployment – Deploying lightweight versions of the model on low-power devices for point-of-care diagnostics.

Integration with Medical Systems – Connecting the model with hospital management systems to assist radiologists in real-time decision-making. Future advancements in deep learning, federated learning, and AI-powered healthcare solutions will further enhance the accuracy, efficiency, and accessibility of automated brain tumor diagnosis.



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