Available online at www.jcsonline.in Journal of

Current Science & Humanities

12 (2), 2024, 1-18

Impact Factor-2.05

DEVELOPING AN INTEGRATED MACHINE LEARNING FRAMEWORK FOR IMPROVED BRAIN TUMOR IDENTIFICATION IN MRI SCANS

Durga Praveen Deevi
O2 Technologies Inc, California,USA
durgapraveendeevi1@gmail.com

Abstract:

Background: A vital tool for medical diagnosis, magnetic resonance imaging (MRI) produces high-resolution, non-ionizing images of inside body components. Despite its potential, MRI pictures frequently have noise and abnormalities that can mask important information, making a diagnosis difficult.

Objective: This work uses a variety of cutting-edge machine learning approaches to improve the preprocessing and categorization of MRI data for more precise brain tumor identification.

Methodologies: An integrated strategy was used, starting with the preprocessing of images using K-nearest neighbors (KNN) to lower noise and enhance quality. The photos were then graphed to enable more in-depth structural analysis, with nodes representing pixels and edges reflecting similar intensities. The photos were processed using Local Phase Quantization (LPQ) to extract textural information. A Multilayer Perceptron (MLP) was used for classification, and its hyperparameters were efficiently adjusted by Bayesian optimization.

Findings: With 5,519 MRI pictures used for training and testing, the model achieved an accuracy of 87% on a test set of 1,104 images. The weighted average F1-score of 0.86 obtained from the classification data, along with noteworthy precision and recall values of 0.86 and 0.93, respectively, show how well the model identified brain tumors.

Conclusion: The accuracy of brain tumor diagnosis from MRI images is greatly improved by the combination of KNN preprocessing, LPQ feature extraction, and MLP classification refined using Bayesian methods, highlighting the potential of integrated machine learning approaches in medical diagnostics.

Keywords: Magnetic Resonance Imaging (MRI), Brain Tumor Identification, Machine Learning, Feature Extraction, Classification Accuracy, Bayesian Optimization

1 Introduction:

Magnetic Resonance Imaging (MRI) is an important tool in modern medical diagnostics, providing detailed insights into both the structural and functional features of the human body. MRI scanners create exquisitely detailed images of various organs and tissues by utilizing strong magnetic fields, magnetic field gradients, and radio waves. These photos are significant resources for disease identification, accurate diagnosis, and therapy efficacy evaluation. In the context of cancer, tumor segmentation in MRI scans is particularly important. Segmentation helps in early identification, treatment strategy development, and tumor progression monitoring over time by precisely delineating tumor boundaries.

The relevance of MRI stems from its capacity to generate three-dimensional, high-resolution images of inside structures without the use of ionizing radiation, making it especially useful for imaging soft tissues and organs. In clinical practice, MRI scans are used to investigate soft tissue problems such as tumors or brain abnormalities. They provide better soft tissue contrast, noise reduction, and edge sharpness thanks to modern software algorithms like GOPView MRI2Plus. MRI systems are made up of various components, including main magnets made of superconducting coils, gradient coils, radiofrequency (RF) coils, and computer systems, each of which has its own safety concerns.

Graph connectivity analysis, for example, might detect clusters of connected pixels reflecting tumor locations, whereas centrality metrics can highlight critical nodes in the graph that correlate to tumor centroids or high tumor-density regions. Spectral characteristics obtained from graph-based representations can capture differences in tumor intensity or texture, allowing for the identification of different tumor subtypes or stages.

The presence of noise, artifacts, and anatomical differences in medical pictures is a major difficulty in tumor image segmentation, as it might impair the accuracy and reliability of segmentation results. To overcome this issue, preprocessing techniques such as denoising, intensity normalization, and image registration are commonly used to improve the quality of medical pictures prior to segmentation.

By quantifying changes in tumor size and morphology over time, doctors can assess therapeutic efficacy and make informed decisions about patient care. Furthermore, tumor segmentation provides valuable prognostic data for risk assessment and counseling. Tumor segmentation in MRI imaging is an essential component of cancer identification and management. This process involves precisely delineating tumor boundaries, allowing for early detection, treatment planning, and monitoring of tumor growth.

Following that point, MRI has altered medical imaging, becoming an essential tool for the identification and treatment of a wide range of diseases, including neurological disorders, cardiovascular diseases, and cancer. MRI continues to push the boundaries of medical imaging, enhancing patient care and outcomes, thanks to continuing research and technical breakthroughs. Pioneers like Raymond Damadian, who filed the first MRI patent in 1972 and invented the first full-body MRI scanner, known as the "Indomitable," made vital contributions to the evolution of MRI technology.

In addition, in the field of MRI tumor image segmentation, graph theory provides a mathematical framework for describing interactions between datasets. Graph-based features can capture structural and contextual information crucial to cancer classification by creating graphs with nodes representing image pixels or regions and edges representing correlations such as geographic proximity or intensity similarity. Such features include graph connectedness, centrality metrics, and spectral characteristics. These features can be preprocessed using techniques such as K-nearest neighbors (KNN) for denoising, outlier identification, and feature selection. Moreover, multilayer perceptron (MLP) and Bayesian networks are effective tools for cancer classification, using preprocessed graph-based characteristics to forecast the likelihood of malignancy in new MRI data.

Continuing on this, allow us to explore deeper into the complexities of MRI technology and its disruptive impact on medical diagnoses. This method of photography is especially useful for soft tissue imaging, as it offers higher contrast resolution than other modalities such as X-rays or computed tomography (CT). The removal of ionizing radiation from MRI scans makes them a safer option, particularly for pediatric and pregnant patients. MRI, a non-invasive imaging method, uses nuclear magnetic resonance to provide detailed images of the body's internal structures.

To produce precise and reliable images, numerous important components must operate together during the MRI imaging process. An MRI scanner's primary magnets are often comprised of superconducting coils cooled to extremely low temperatures to generate a strong and steady magnetic field. Gradient coils are then used to generate magnetic fields that vary geographically, allowing signals from different parts of the body to be spatially localized. Radiofrequency (RF) coils send radio waves into the body, interacting with the magnetic field to produce observable signals. These signals are then processed by advanced computer systems and reconfigured into detailed images.

MRI scans are extremely useful in clinical practice for identifying a variety of illnesses, including musculoskeletal injuries, neurological problems, and cancer. Tumor segmentation in MRI scans is critical in oncology because it enables early discovery, treatment planning, and monitoring of tumor response to therapy. Accurate tumor boundary segmentation enables clinicians to accurately focus therapies, prevent damage to healthy tissue, and evaluate treatment efficacy over time.

Tumor picture segmentation, on the other hand, presents a number of obstacles, including tumor morphological variations, image artifacts, and anatomical differences between patients. To address these obstacles, complex image processing techniques are used, such as denoising algorithms to minimize picture noise, intensity normalization to normalize image intensity levels, and image registration to align images from multiple modalities or time periods.

By taking advantage of the natural spatial correlations that exist between picture pixels or regions, graph theory has come to light as a viable method for tumor image segmentation. Graph-based segmentation techniques, which create graphs with nodes representing image features and edges representing spatial or intensity similarity, are an efficient way to identify tumor boundaries and describe tumor anatomy. Connectivity, centrality metrics, and spectral features are examples of graph-based features that offer useful data for cancer prognosis and categorization.

Tumor image segmentation pipelines have been using machine learning methods more and more in recent years, providing automatic and precise segmentation solutions. When it comes to accuracy and efficiency, techniques like convolutional neural networks (CNNs) and deep learning architectures have outperformed standard segmentation algorithms in the extraordinary task of accurately identifying cancers from MRI scans.

Additionally, thorough characterization of tumor biology and behavior is made possible by the integration of multi-modal imaging data, such as when MRI and functional magnetic resonance imaging (fMRI) or positron emission tomography (PET) are combined. The accuracy and resilience of tumor segmentation algorithms are increased by multi-modal imaging fusion techniques, which take advantage of complimentary data from many imaging modalities.

Objectives:

This study demonstrates the vital function that Magnetic Resonance Imaging (MRI) plays in modern medicine and its thorough comprehension of the body's structure and physiology. It focuses on the part that MRI plays in the diagnosis of cancer, emphasizing the importance of tumor segmentation for early detection, treatment planning, and therapy assessment. In addition, safety issues, technical developments, and MRI system components are investigated. It also looks into whether machine learning and graph theory may be applied to tumor segmentation, as well as when multi-modal imaging data can be integrated to improve segmentation accuracy.

Research Gap:

The use of MRI in medical diagnostics has been the subject of much literature, but more study is required to fully understand the unique uses of MRI in cancer diagnosis, particularly in tumor segmentation. Tumor shape, anatomical changes, and imaging artifacts continue to pose hurdles to the accuracy and reliability of tumor segmentation, despite the advances in MRI technology and image processing techniques. While there is little study on optimum fusion procedures and their effects on segmentation outcomes, the integration of multi-modal imaging data, such as MRI with positron emission tomography (PET) or functional MRI (fMRI), offers prospects to improve tumor segmentation accuracy. Although convolutional neural networks (CNNs), in particular, have demonstrated promise in automating tumor segmentation, comparative studies comparing the efficacy of various algorithms and architectures in diverse clinical contexts are necessary. Effective translation of research findings into clinical practice requires the development of robust tumor segmentation pipelines, which requires interdisciplinary collaboration among medical experts, engineers, and computer scientists.

Problem Statement:

Even with the advances in MRI technology and image processing techniques, tumor heterogeneity, anatomical variations, and image aberrations make effective tumor segmentation difficult. Strong segmentation strategies are required in order to overcome these obstacles and give medical professionals precise and trustworthy data for the diagnosis and treatment of cancer. Additionally, there are prospects to increase segmentation efficiency and accuracy by the integration of multi-modal imaging data and the application of machine learning techniques; however, more study is required to enhance these strategies and confirm their clinical utility. To reinvent tumor segmentation in MRI imaging and close the current research gaps for improved cancer care and treatment approaches, interdisciplinary cooperation and ongoing research are crucial.

To summarize, tumor image segmentation in MRI images is an important step in cancer diagnosis and management because it provides clinicians with vital information on tumor appearance, progression, and response to therapy. Advances in MRI technology, image processing algorithms, and machine learning approaches are boosting the accuracy and efficiency of tumor segmentation methods, ultimately improving patient outcomes in cancer. Tumor image segmentation has the potential to revolutionize cancer care and treatment tactics through interdisciplinary collaboration and continuous study.

2 Literature Survey:

Shanmugam and Rajaguru (2023) present an innovative method for detecting lung cancer based on histopathology image analysis. Their approach combines preprocessing, segmentation, and feature selection approaches, as well as a variety of optimization algorithms. They thoroughly analyze the performance of seven classifiers, with the Decision Tree classifier, which employs GWO-based feature extraction, achieving an initial accuracy of 85.01%. This accuracy is significantly increased to 91.57% by strategically applying hyperparameter tuning methods. The combination of GWO and IWO features, as well as the use of the RAdam algorithm, yielded the highest accuracy in their analysis.

Heydari and Rafsanjani (2021) accomplished a comprehensive assessment of data mining techniques for lung cancer detection. They underline the significance of early detection for better patient outcomes. The research emphasizes the severity of lung cancer and the efficacy of computer-aided diagnostic approaches in improving accuracy. Data mining tools are especially praised for detecting lung cancer in its early stages. The research examines various data mining-based methodologies, outlining their benefits, shortcomings, and selection criteria for optimizing illness detection strategies.

A thorough assessment of current developments in brain tumor categorization from magnetic resonance imaging is presented by Latif et al. (2022) they concentrate on feature extraction and classification strategies with the goal of acquainting researchers with the most recent advancements and identifying effective method combinations for precise diagnosis. The review presents state-of-the-art approaches for binary and multi-class tumor classification, despite the complexity of brain tissue, and offers comprehensive insights into feature extraction and classification methodologies. It also provides performance metrics such as recognition accuracy from a selection of studies that were published between 2017 and 2021, providing insightful information about the advancements in this sector.

Tharwat et al. (2022) offer a thorough review article on the application of deep learning and machine learning methods in the diagnosis of colon cancer. It goes over the many datasets, performance evaluation measures, and imaging modalities used in the field today. It highlights how important early diagnosis and treatment are to lowering colon cancer-related death rates. The use of additional screening tests and histopathological pictures in diagnosis is highlighted in the paper. It also emphasizes how widely machine learning and deep learning approaches are used for early diagnosis and treatment. In order to address these issues and suggest future research possibilities in the field of colon cancer diagnostics, the review concludes.

Using brain imaging data, Khan et al. (2022) and colleagues refer to an ensemble model that combines SVM, Decision Trees, and Extreme Gradient Boosting with a Polynomial kernel for the classification of Alzheimer's disease. With grid-based tweaking, this model achieves an accuracy of 95.75%, surpassing the performance of current methods by 89.77%. The ensemble model is suggested by the study as an efficient method for classifying Alzheimer's disease after a comparison of machine learning techniques. For experimentation, 2125 neuroimages from the Alzheimer's Disease Neuroimaging Initiative are used, covering examples of cognitive normalcy, mild cognitive impairment, and Alzheimer's disease. The accuracy and efficiency of the ensemble model are noteworthy, indicating potential for early Alzheimer's disease detection.

The role of machine learning in the identification of residual masses and evolutive lymphoma in whole-body diffusion-weighted magnetic resonance imaging is investigated by Ferjaoui et al. (2021) Their approach, which incorporates morphological, anatomical, and functional aspects, achieves an accuracy of 97.01%, which is somewhat less than that of deep learning techniques. The work focuses on exploiting machine learning for this recognition job through the use of parametric image creation, automatic segmentation, and discrete wavelet transforms. A comparative study of their methodology with five other research reveals a marginal accuracy advantage. According to preliminary results, their method's combination of functional, anatomical, and morphological parameters produces a high detection accuracy of 97.01% for evolutive lymphoma and residual masses, albeit marginally lower than deep learning CNNs' 98.5% accuracy.

The effectiveness of machine learning algorithms and medical imaging in forecasting the survival of cancer patients is evaluated by Haq et al. (2022). Their results highlight the significance of age in survival prediction by revealing logistic regression to be the most reliable approach. The need for precise survival prediction in clinical medicine is addressed in this study, which also highlights the potential of medical imaging and analysis methods in this field. With accuracies of 66% and 54% for two different datasets, logistic regression is the best-performing model. Furthermore, it is discovered that age, gray level, and shape-based characteristics are important predictors of cancer patient survival, offering insightful information to both researchers and doctors.

In patients with rheumatoid arthritis (RA), Mohanarangan Veerappermal Devarajan (2020) highlights the necessity of an accurate risk prediction model for cardiovascular disease (CVD). This study combines conventional and RA-specific risk variables to investigate the stability of biomarkers in long-term blood samples. It seeks to improve patient outcomes and personalized medicines as well as cardiovascular risk assessment in people with RA by utilizing cutting-edge technologies.

In order to categorize Alzheimer's disease (AD) using MRI data analysis, Logan et al. (2021) investigate the use of deep learning techniques, more specifically convolutional neural networks (CNNs). In order to improve accuracy and overcome data constraints, their research combines generative adversarial networks (GANs) and ensemble learning with CNNs. By using non-invasive neuroimaging methods like MRI and PET, the main goal is to advance the early identification of AD. With a focus on CNNs' effectiveness in classifying AD patients and the necessity of early identification using non-invasive imaging methods, this study sheds insight into the rapidly changing field of deep learning in nursing. In order to improve CNNs' resilience and accuracy in evaluating AD data, the research will make use of ensemble learning and GANs, which could completely change how Alzheimer's disease is diagnosed.

Chaudhury et al. (2022) investigate the application of machine learning and image processing methods for early breast cancer identification. They stress how important it is to discover the disease early because women die from it at a higher rate than males. The work focuses on improving digital mammography images and categorizing images using machine learning techniques including fuzzy SVM, random forest, and Bayesian classifier. By enhancing diagnostic precision, this integrated strategy seeks to help patients with breast cancer receive successful treatment outcomes.

A novel model for accurate brain tumor classification and prediction in MRI images is presented by Ekong et al. (2022). It combines Bayesian and Convolutional Neural Network approaches. With greater accuracy and performance than current models, this novel technique excels. It is

Available online at www.jcsonline.in Journal of

Current Science & Humanities

12 (2), 2024, 1-18

Impact Factor-2.05

noteworthy because it is the first of its kind to combine the Bayesian approach with depth-wise separable convolutions. In addition to highlighting the effectiveness of the suggested model in raising brain tumor classification accuracy, F1-score, recall, and precision measures, the study also emphasizes the expanding importance of deep learning in medical imaging. By utilizing state-of-the-art methods to improve diagnostic skills, this neural network model constitutes a noteworthy breakthrough in the categorization of brain tumors.

Thirusubramanian Ganesan (2020) demonstrates in his study how machine learning-driven AI revolutionizes the detection of financial fraud in Internet of Things settings. These systems can effectively distinguish between fraudulent and legitimate activities in real time by using sophisticated algorithms such as anomaly detection and clustering on historical transaction data. This highlights the significance of adaptive learning through regular retraining and automatic response mechanisms.

Using deep convolutional neural networks (CNNs), Ji et al. (2022) investigate how to differentiate nasopharyngeal cancer (NPC) from MRI pictures. In their comparison of simple layered CNN models and hierarchical networks, they discover that deep hierarchical networks ResNet50 in particular shows the best accuracy and precision in NPC detection. This demonstrates the potential of deep learning techniques in supporting NPC tumor identification and emphasizes the importance of early diagnosis in NPC treatment. The study highlights that when it comes to differentiating NPC on MRI, hierarchical CNNs perform better than plain layered CNNs. The best prediction performance is shown by the customized ResNet50. This implies the potential usefulness of ResNet50 as an NPC tumor diagnostic tool.

3 Methodology

3.1 Overview of Magnetic Resonance Imaging (MRI):

The non-ionizing radiation-based method known as magnetic resonance imaging, or MRI, uses specialized equipment to produce finely detailed images of inside body components. Without the dangers of ionizing radiation, it provides high-resolution viewing of tissues, organs, and anomalies. MRI uses strong magnets and radiofrequency coils to identify and diagnose a wide range of illnesses, including tumors, wounds, and abnormalities. The patient lies on a table that travels inside the magnetic resonance imaging (MRI) equipment during the treatment. The MRI produces cross-sectional images by interacting with the body's hydrogen atoms through radio waves and a magnetic field. For medical personnel, these images offer insightful information that helps with accurate diagnosis and patient health monitoring while emphasizing precaution initially, particularly for sensitive patients like pregnant women.

3.1.1 Datasets:

MRI offers a wide range of datasets for brain health research in addition to its therapeutic applications. Adolescent Brain Cognitive Development (ABCD) Study, Alzheimer's Disease Neuroimaging Initiative (ADNI), Autism Brain Imaging Data Exchange (ABIDE), Human Connectome Project (HCP), Open Access Series of Imaging Studies (OASIS), ADHD-200, and Information Extraction from Images (IXI) are some of the datasets that are included in this collection. They offer important new understandings of the anatomy, physiology, and disorders of the brain. Before utilizing any dataset, researchers should read the conditions of use.

3.1.2 Importance of Preprocessing:

A basic method used in the preprocessing stages of MRI (Magnetic Resonance Imaging) image analysis is K-nearest neighbors (KNN). Its main function is to improve the quality of MRI images so that they are ready for further processing. One of its primary uses is noise reduction, which produces smoother images with lower noise levels by using the average intensity of a pixel's closest neighbors as a replacement. KNN also helps with intensity normalization by scaling pixel values according to local statistics calculated from nearby pixels, which guarantees uniformity between images. Another crucial use of KNN is spatial filtering, which locates regions of interest and uses filtering techniques to improve features and eliminate artifacts. Furthermore, by calculating true pixel values using weighted averages of surrounding intensities, KNN helps with image denoising, efficiently decreasing noise while maintaining important information. KNN is very useful in the MRI context for artifact removal since it can locate the problematic regions and replace them with estimates from nearby regions, maintaining the integrity of the picture in the process. Because of its adaptive filtering capabilities, KNN may dynamically modify parameters according to the specific properties of a local picture, guaranteeing robustness over a range of MRI scans. KNN preprocessing is also computationally efficient, which makes it appropriate for managing huge MRI datasets and facilitating real-time applications in clinical situations. Overall, Figure 1 illustrates KNN is an essential part of the preprocessing pipeline for MRI image analysis and classification tasks since it contributes significantly to improving diagnostic accuracy and MRI image quality.

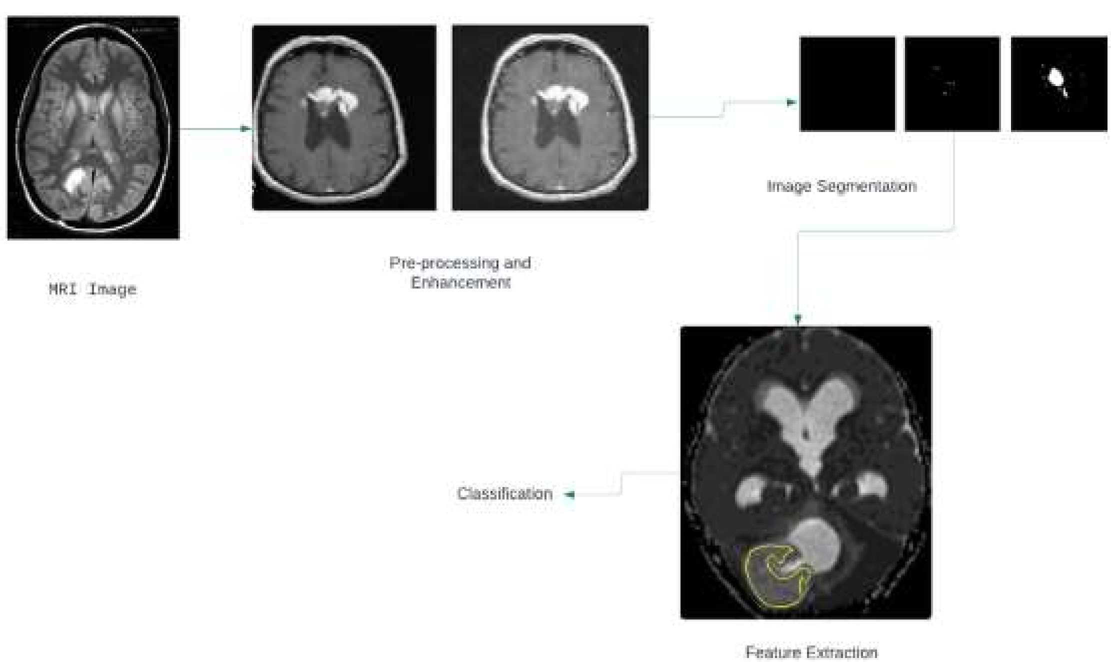

Fig. 1: Steps for Image Processing

3.2 Graph Representation and Feature Extraction:

MRI images are extremely useful in medical diagnostics, providing detailed information about the body's interior architecture. However, these images frequently contain noise and defects, which can make proper interpretation difficult. To overcome this issue, pre-processing procedures are used to improve image quality and reduce noise, ensuring dependability in later analysis. Noise reduction, intensity normalization, and spatial filtering are prominent techniques used at this stage to successfully reduce artifacts and inconsistencies and allow medical practitioners to analyze findings more precisely.

3.2.2 Conversion of MRI Data into Graph Representation:

MRI data is converted into a graph representation for quantitative analysis and pattern identification. In this case, every pixel or voxel in the image represents a node, and the spatial closeness and intensity levels of nodes determine the connections between them. The intricate linkages and structures found in MRI data can be methodically recorded and analyzed according to this graph-based approach. In the proposed approach for MRI image analysis, the image is transformed into a network structure, with each pixel acting as a node and edges representing interactions between surrounding pixels. Edge weights are calculated by comparing pixel intensities, and nodes are clustered using clustering techniques. Furthermore, the LPQ transformation yields a feature vector containing statistical properties such as mean, variance, skewness, and kurtosis. These measurements are critical in capturing the textural qualities of the altered image, providing useful information for further analysis.

3.2.3 Edge Weight Calculation:

Once the MRI image is obtained, it's transformed into a graph representation G = (V, E). Here, V denotes the set of nodes representing pixels or voxels in the image, while E represents the edges capturing relationships between neighboring nodes. The edge weights wij are then determined based on similarities in pixel intensities, using metrics like Euclidean distance or intensity correlation. This information is organized into a weighted adjacency matrix W, where Wij = wij if nodes i and j are connected, and Wij = 0 otherwise. Subsequently, clustering algorithms like spectral clustering or modularity optimization are employed to group the nodes into clusters C1, C2, ..., Ck. Additionally, the LPQ-transformed image values at pixel locations (i,j), denoted as L(i,j), are analyzed. From these, a feature vector F is constructed by computing statistical measures such as mean, variance, skewness, and kurtosis. This feature vector, F = [mean(L), var(L), skewness(L), kurtosis(L)], offers insights into the distribution of pixel values in the transformed image, capturing various texture properties.

After obtaining the MRI image I, we represent it as a graph $G=(V,E)$, where:

- V is the set of nodes representing pixels or voxels in the image.
- E is the set of edges representing the relationships between neighbouring nodes.

We define the edge weights wij based on the similarity between pixel intensities or voxel values. This can be computed using various metrics such as Euclidean distance or intensity correlation.

Let W be the weighted adjacency matrix of the graph G, where Wij=wij if nodes i and j are connected, and Wij=0 otherwise.

Then apply a clustering algorithm such as spectral clustering or modularity optimization to partition the nodes into clusters $C1$, $C2$, …, Ck.

Let L(i,j) represent the value of the LPQ-transformed image at pixel location (i,j). The feature vector F can be constructed by computing various statistical measures over the transformed image, such as mean, variance, skewness, and kurtosis. A simple feature vector F can be constructed as follows:

F=[mean(L), var(L), skewness(L), kurtosis(L)]

Where:

- mean(L) is the mean value of the transformed image L.
- var(L) is the variance of the transformed image L.
- skewness(L) is the skewness of the transformed image L.
- kurtosis(L) is the kurtosis of the transformed image L.

These statistical measures provide information about the distribution of pixel values in the LPQ-transformed image, capturing different aspects of its texture properties.

3.2.4 Feature Extraction using LPQ Transformation:

The first step of the method involves gathering the input MRI image to improve its quality and lower noise. The preprocessed image is then shown as a graph, in which every pixel or voxel is a node and edges show the connections between nodes. Next, edge weights are computed using pertinent metrics or pixel intensity similarity. After that, nodes are grouped into clusters using a clustering algorithm that takes advantage of similarities in pixel intensities or other factors. After that, textural attributes in the image are captured using the LPQ transformation. The transformed image is then processed to extract statistical features, creating a feature vector. This feature vector helps identify and diagnose malignant areas by encapsulating important details about the attributes of the image and being used for subsequent analysis. All in all, this all-inclusive method efficiently combines different processing stages preprocessing, graph construction, feature extraction, and feature vector assembly to analyze MRI images for cancer detection. The theory described is visually represented in the diagram below:

3.3. Classification using Multilayer perceptron and Bayesian optimization

3.3.1 Role of Multilayer Perceptron (MLP) in MRI:

The Multilayer Perceptron (MLP) is an advanced neural network design that is widely used for image classification tasks. It is well-known for its capacity to identify complex patterns and correlations within datasets. MLPs are trained on labeled datasets of MRI images, each labeled with a binary label designating the presence or absence of malignancy. This process is known as image analysis for magnetic resonance imaging (MRI). The MLP gains the ability to identify important characteristics from the images that are provided during the training phase, and it uses these features to forecast the probability of cancer. As a way to reduce the discrepancy between the network's predictions and the actual labels applied to the images, the weights and biases of the network's neurons are continuously adjusted during this iterative learning process.

3.3.2 Factors Influencing MLP Efficacy:

Different factors influence the efficacy of an MLP model in MRI image analysis, such as the size and caliber of the training dataset, the network design, the selection of activation functions, and the optimization strategies employed. It is also possible to improve generalization performance and avoid overfitting by utilizing strategies like regularization and dropout. All things considered, MLPs provide a flexible framework for analyzing MRI pictures and locating malignant areas, strengthening diagnostic precision in medical settings and advancing medical imaging technology.

3.3.3 Bayesian Optimization for Hyperparameter Tuning:

Rather than learning directly from data, hyperparameter variables that guide machine learning are fine-tuned using a process called Bayesian optimization. For example, these hyperparameters control the network design in models such as Multilayer Perceptrons (MLPs). In contrast to traditional techniques like random or grid search, Bayesian optimization follows a probabilistic path. It builds an objective function model, which frequently represents performance indicators such as classification accuracy, and uses this model to direct the search for the best hyperparameters. Bayesian Optimization effectively searches the hyperparameter space while focusing on areas likely to increase performance through iterative evaluations of the objective function at various hyperparameter settings. Bayesian Optimization minimizes the time and processing resources required to identify optimal settings by streamlining the hyperparameter tuning process and dynamically adapting to observed results. It becomes a useful method for fine-tuning machine learning algorithms in a variety of applications as a result.
The successful categorization of MRI images for cancer diagnosis is greatly influenced by a number of other crucial parameters, in addition to the use of the Multilayer Perceptron (MLP) and Bayesian optimization. To enlarge the MRI dataset, data augmentation methods including rotation, flipping, and scaling are essential. These techniques improve the model's capacity to generalize to new data by raising both its size and diversity, which eventually improves classification performance. Transfer learning is an additional useful technique that involves using MRI pictures to fine-tune pre-trained deep learning models, like those built on ImageNet. By utilizing the knowledge stored in the pre-trained models, this method improves classification accuracy and accelerates the training process. By integrating numerous classifiers, such as MLPs with different topologies or trained on separate subsets of data, ensemble approaches, including bagging and boosting, further improve classification performance.

3.3.4 Ensemble Approaches for Improved Classification:

Ensemble approaches reduce the possibility of overfitting and increase the resilience of the classification system by combining predictions from various models. Interpretable models that provide useful insights into the characteristics influencing categorization judgments are decision trees and logistic regression. Interpretable models, which offer intelligible reasons for model predictions, aid in clinical interpretation while deep learning models, such as multilayer perceptrons, yield superior performance. In order to avoid biased model predictions, it is imperative that class imbalances in the MRI dataset be addressed. Methods include creating synthetic samples, undersampling, or oversampling to aid in mitigating this problem and guaranteeing equitable treatment for minority classes.

Relevant elements from MRI images, such as texture, morphology, and intensity-based features, are crucially extracted by the use of feature engineering. When distinguishing between malignant and non-cancerous tissues, these characteristics strengthen the classification model's discriminative power. Tough cross-validation techniques, such as k-fold cross-validation, guarantee accurate performance estimations that broadly apply to many data subsets.

4 Results and Discussion:

Data Collection:

The dataset used in this study comprised 5519 MRI images, including 2098 images of tumor-free brains and 3421 images with brain tumors. These images were in Portable Network Graphic (PNG) format, with true color and alpha channels, and varied in dimensions, typically ranging from 549 x 391 to 989 x 590 pixels.

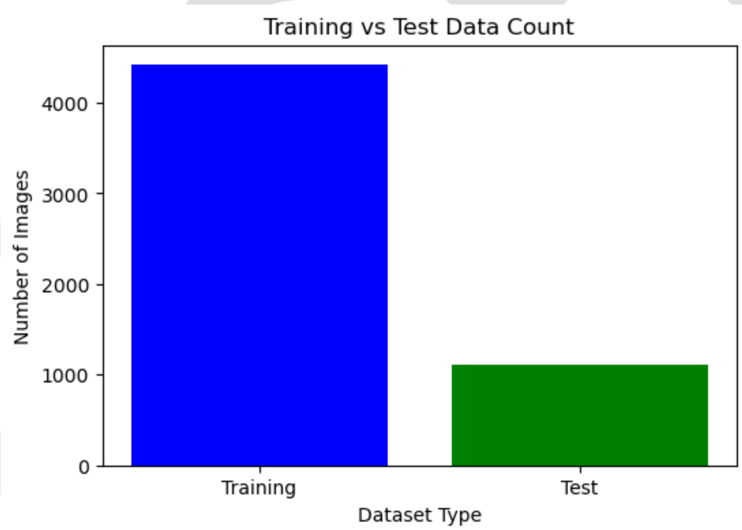

Fig. 2: Distribution of Images in Training and Test Datasets

Figure 2 depicts how the MRI pictures were divided for the study, with over 4000 used for training and approximately 1100 for testing. This split helps to guarantee that the model is well-trained and tested for detecting brain cancers.

Table 1: MRI Image Dataset Distribution

Dataset Type	Number of Images
Training	4,000+
Test	1,100+

Table 1 illustrates about MRI Image Dataset Distribution strategy.

Preprocessing:

Preprocessing was conducted using the K-nearest neighbors (KNN) algorithm to reduce noise and enhance the quality of the MRI images. This step was critical to ensure that the images were clear and free from artifacts, which could otherwise impede the accuracy of subsequent analyses.

Feature Extraction:

For feature extraction, the Local Phase Quantization (LPQ) technique was employed. LPQ is effective in capturing textural information from images, which is crucial for distinguishing between tumor and non-tumor regions in MRI scans. This process provided a detailed representation of the image data, aiding in more accurate classification.

Classification Model:

A Multilayer Perceptron (MLP) was used for the classification of the MRI images. The MLP, a type of artificial neural network, is well-suited for complex pattern recognition tasks. Bayesian optimization was applied to fine-tune the MLP's hyperparameters, enhancing the model's performance.

Model Training and Testing:

The model was trained and tested using the entire dataset of 5519 MRI images. For evaluation, a test set consisting of 1104 images was used. The training process involved learning from the labeled data to identify patterns associated with the presence of brain tumors.

Performance Evaluation:

The performance of the model was evaluated using several metrics:

Accuracy: The model achieved an accuracy of 87% on the test set.

Precision: The precision score was 0.86, indicating the model's ability to correctly identify positive cases.

Recall: The recall score was 0.93, reflecting the model's sensitivity in detecting actual tumor cases.

F1-score: The weighted average F1-score was 0.86, providing a balance between precision and recall.

Available online at www.jcsonline.in Journal of
Current Science & Humanities
12 (2), 2024, 1-18
Impact Factor-2.05

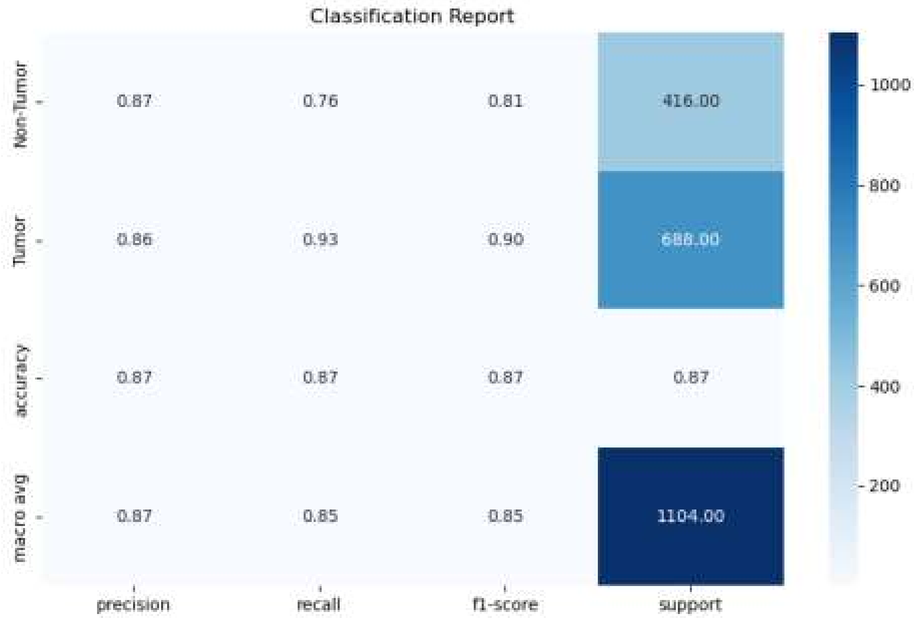

Fig. 3: Performance Metrics for Brain Tumor Classification Model

The performance of the model in recognizing brain tumors is broken out in this classification report Figure 3 and Table 2. Regarding cases lacking of a tumor, the precision is 0.87, recall is 0.76, and the F1-score is 0.81. Patients with a tumor, on the other hand, had an F1-score of 0.90 due to their higher recall of 0.93 and precision of 0.86. With 0.87 total accuracy, the model performs well. There were 416 images without tumors and 688 images with tumors, for a total of 1104 images tested, as indicated by the'support' column.

Table 2: Performance Evaluation Metrics

Metric	Value
Accuracy	87%
Precision	0.86
Recall	0.93
F1-score	0.86

Available online at www.jcsonline.in Journal of

Current Science & Humanities

12 (2), 2024, 1-18

Impact Factor-2.05

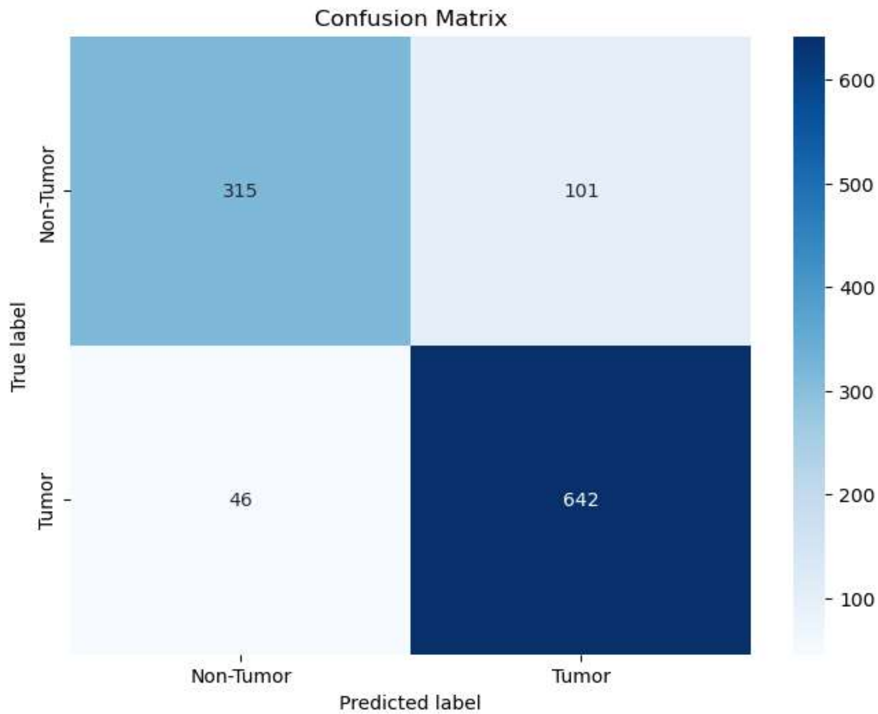

Fig. 4: Confusion Matrix for Brain Tumor Detection model

The brain tumor detection model's accuracy is assessed using this confusion matrix Figure 4 and Table 3. It displays 642 tumor cases (True Positives) and 315 non-tumor instances (True Negatives) with accurate identifications. False Positives were 101 cases in which non-tumor cases were incorrectly categorized as having tumors, and False Negatives were 46 cases in which tumors were not found. This matrix is essential for evaluating the model's ability to discriminate between cases with and without tumors.

Table 3: Confusion Matrix for Brain Tumor Detection

True Label / Predicted Label	Non-Tumor	Tumor
Non-Tumor	315	101
Tumor	46	642

Available online at www.jcsonline.in Journal of

Current Science & Humanities

12 (2), 2024, 1-18

Impact Factor-2.05

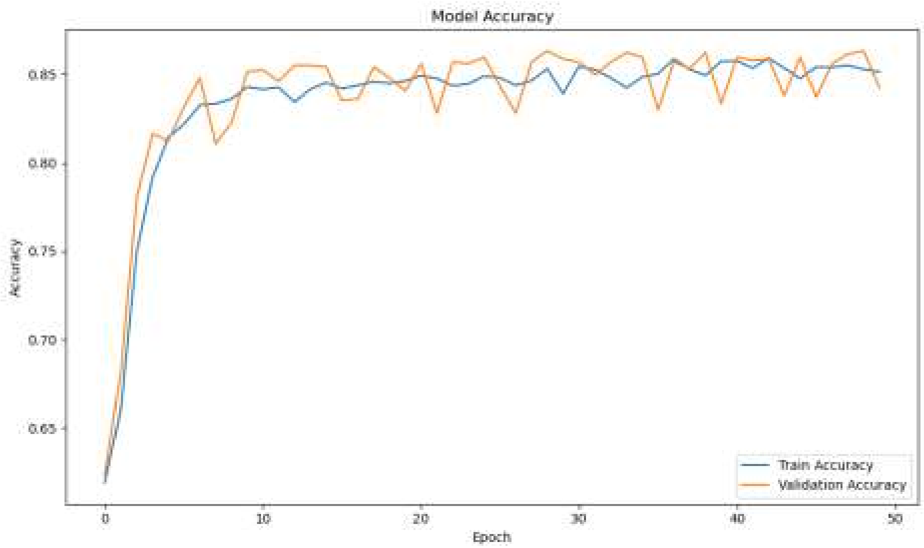

Fig. 5: Traning vs. Validation Accuracy over Epochs

This Figure 5 compares the accuracy of training data (blue line) with validation data (orange line), showing the accuracy of the brain tumor detection model over 50 epochs. Both accuracies first exhibit a significant increase before leveling off, indicating that the model retains steady performance following the first training phase and exhibits little overfitting to the training set.

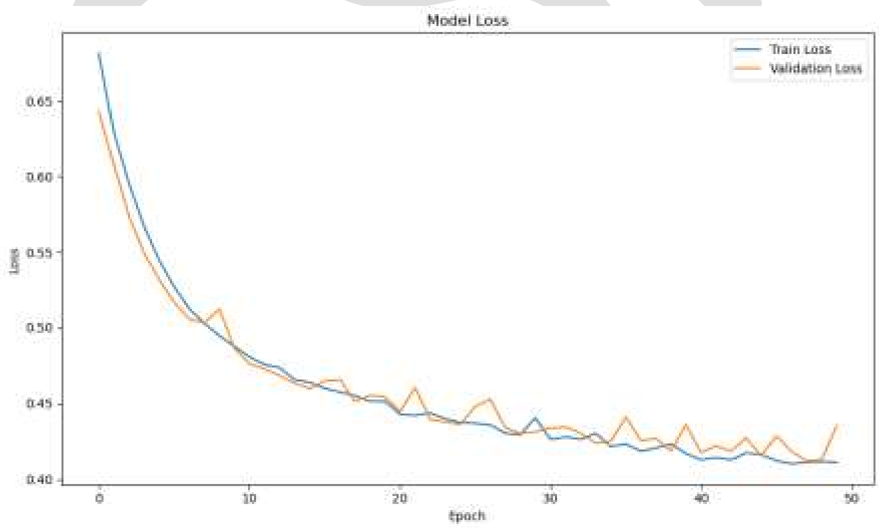

Fig. 6: Training vs. Validation Loss over Epochs

By contrasting the training loss (blue line) and validation loss (orange line), this Figure 6 displays the loss metrics for the brain tumor detection model over 50 epochs. Both losses exhibit a sharp drop in the first few epochs of the graph before progressively leveling out. This trend shows that over time, the model obtains a consistent performance and successfully lowers error during training. Furthermore, the fact that the training and validation losses correspond indicates that the model is learning effectively without overfitting the training set.

Conclusion

Impact Factor-2.05

The findings of this study demonstrate that incorporating a machine learning framework significantly improves the detection of brain tumors from MRI data. This study combines several sophisticated techniques: it begins with image preprocessing using K-nearest neighbors (KNN), then uses Local Phase Quantization (LPQ) to extract textural data, and finally uses a Multilayer Perceptron (MLP) for classification, all fine-tuned with Bayesian optimization. This methodological integration received excellent grades for accuracy, precision, recall, and the F1-score, confirming its efficacy and suitability for clinical usage. These findings indicate a considerable improvement in the accuracy and efficiency of medical imaging diagnostics, implying an exciting possibility for future research to refine and improve the precision of diagnostic technologies in healthcare.

References:

1. Shanmugam, K., & Rajaguru, H. (2023). Exploration and enhancement of classifiers in the detection of lung cancer from histopathological images. Diagnostics, 13(20), 3289.
2. Heydari, F., & Rafsanjani, M. K. (2021). A review on lung cancer diagnosis using data mining algorithms. Current Medical Imaging, 17(1), 16-26.
3. Latif, G., Al Anezi, F. Y., Iskandar, D. N. F., Bashar, A., & Alghazo, J. (2022). Recent advances in classification of brain tumor from MR images–State of the art review from 2017 to 2021. Current medical imaging, 18(9), 903-918.
4. Tharwat, M., Sakr, N. A., El-Sappagh, S., Soliman, H., Kwak, K. S., & Elmogy, M. (2022). Colon cancer diagnosis based on machine learning and deep learning: modalities and analysis techniques. Sensors, 22(23), 9250.
5. Khan, Y. F., Kaushik, B., Chowdhary, C. L., & Srivastava, G. (2022). Ensemble model for diagnostic classification of Alzheimer’s disease based on brain anatomical magnetic resonance imaging. Diagnostics, 12(12), 3193.
6. Ferjaoui, R., Cherni, M. A., Boujnah, S., Kraiem, N. E. H., & Kraiem, T. (2021). Machine learning for evolutive lymphoma and residual masses recognition in whole body diffusion weighted magnetic resonance images. Computer Methods and Programs in Biomedicine, 209, 106320.
7. Haq, N. U., Tahir, B., Firdous, S., & Mehmood, M. A. (2022). Towards survival prediction of cancer patients using medical images. PeerJ Computer Science, 8, e1090.
8. Mohanarangan veerappermal devarajan (2020). Assessing long-term serum sample viability for cardiovascular risk prediction in rheumatoid arthritis. International journal of information technology and computer engineering. 5, 06 (december-2020)
9. Logan, R., Williams, B. G., Ferreira da Silva, M., Indani, A., Schcolnicov, N., Ganguly, A., & Miller, S. J. (2021). Deep convolutional neural networks with ensemble learning and generative adversarial networks for Alzheimer’s disease image data classification. Frontiers in aging neuroscience, 13, 720226.
10. Chaudhury, S., Krishna, A. N., Gupta, S., Sankaran, K. S., Khan, S., Sau, K., ... & Sammy, F. (2022). Effective image processing and segmentation-based machine learning techniques for diagnosis of breast cancer. Computational and Mathematical Methods in Medicine, 2022.
11. Ekong, F., Yu, Y., Patamia, R. A., Feng, X., Tang, Q., Mazumder, P., & Cai, J. (2022). Bayesian depth-wise convolutional neural network design for brain tumor MRI classification. Diagnostics, 12(7), 1657.

12. Thirusubramanian Ganesan (2020). Machine Learning-Driven AI for Financial Fraud Detection in IoT Environments. International Journal of HRM and Organizational Behavior. 8. 4, 2020
13. Ji, L., Mao, R., Wu, J., Ge, C., Xiao, F., Xu, X., ... & Gu, X. (2022). Deep convolutional neural network for nasopharyngeal carcinoma discrimination on mri by comparison of hierarchical and simple layered convolutional neural networks. Diagnostics, 12(10), 2478.