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Migraine Detection Using Machine Learning: A Comprehensive Study

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Abstract: The rapid growth of deep learning technologies has significantly impacted medical image analysis, enabling advancements in disease detection and classification. Migraine, a prevalent and debilitating neurological disorder, is characterized by intense, one-sided headaches accompanied by symptoms such as nausea, vomiting, and heightened sensitivity to light and sound. Diagnosing migraines remains a challenge due to the reliance on subjective patient-reported symptoms and the diagnostic guidelines provided by the International Headache Society. Recent advancements in medical imaging, particularly Magnetic Resonance Imaging (MRI), offer an opportunity to enhance diagnostic accuracy by identifying brain structural changes associated with migraines. This study presents a cutting-edge approach using the VGG19 convolutional neural network to analyze MRI scans for features indicative of migraines. By automating the processes of feature extraction and classification, this method aims to improve diagnostic precision, minimize subjectivity, and support timely medical intervention. Integrating deep learning with MRI analysis offers promising prospects for advancing migraine diagnosis and enhancing patient outcomes.
Keywords: Migraine Diagnosis, Deep Learning, Convolutional Neural Network, MRI Analysis, Machine Learning, Python, Disease Classification.

I. INTRODUCTION

Migraine is a chronic neurological disorder marked by recurrent episodes of mild to severe headaches, often characterized by one-sided, throbbing pain. These headaches are frequently accompanied by symptoms such as nausea, vomiting, and heightened sensitivity to light and sound [1]. The debilitating nature of migraines significantly affects individuals' quality of life and daily productivity, emphasizing the need for effective diagnostic tools and management strategies [2]. Traditional migraine diagnosis primarily relies on patient-reported symptoms and clinical evaluations, which are inherently subjective. Furthermore, diagnostic criteria outlined by the International Headache Society often depend on clinical interpretations, limiting the precision of diagnosis [3].

This challenge highlights the importance of adopting advanced technological solutions for objective assessment and enhanced clinical outcomes. Magnetic Resonance Imaging (MRI) has proven to be a valuable tool for investigating both the structural and functional aspects of the brain in migraine sufferers [4]. Resting-state functional MRI (fMRI), in particular, has shown promise as a non-invasive method to identify brain dysfunctions by analyzing blood flow patterns linked to neuronal activity [5].

Research leveraging this approach has uncovered notable brain alterations in migraine patients, including changes in regions such as the anterior cingulate cortex and prefrontal cortex, compared to healthy controls [6]. These findings offer significant insights into the neurological basis of migraines and open pathways for the development of more accurate diagnostic methods. The results signify the possibility of using MRI as a tool for detecting the neurophysiological mechanisms of migraines and improving the diagnostic accuracy.

Artificial intelligence (AI) , especially convolutional neural networks (CNNs) is taking the concept of automatic medical image analysis to a whole new level through automated feature extraction, and classification [7]. Out of all of them, the VGG19 architecture is the one that has been extremely successful in the analysis of complex image data owing to its deep network architecture and its ability to capture intricate patterns [8]. Precedently taught on large datasets, the VGG19 is fully suited for particular tasks, however, one such task is medical imaging visa Migraine classification[9]

Migraine detection and classification of MRI data by deep learning techniques, especially VGG19, is fixed in the study. It is the use of the machine learning framework to defy the limitations of traditional diagnostic methods to give a more objective, accurate, and efficient approach to migraine diagnosis. Detailed research shows the methods, experimental findings, and the significance of this research in the advancement of migraine management and patient outcome improvement.

II. LITERATURE REVIEW

Kara [10] employed hi-tech techniques like MRI histogram analysis to monitor the changes happening in the optic nerve of migraine patients. The research disclosed significant variations in the optic nerve's structure and function, i.e., between people having migraines and those who are healthy. Generally, these peculiarities of the optic nerve are associated with visual disturbances like photophobia and visual aura. The investigation emphasized the optic nerve's potential as a critical biomarker for exploring the origins and the effect of migraines. It is being viewed as an important part of disease progression tracking apart from launching mechanisms of no-touch diagnosis and targeted treatments.

Hougaard [11] developed a methodology for utilizing the latest most sophisticated imaging technologies to discover the real mechanism of the pain of a migraine. Magnetic Resonance Spectroscopy (MRS) was used to identify increased glutamate and less GABA in the cortex, thus evidencing cortical hyperexcitability. The Arterial spin labeling (ASL) research has shown the flow of blood in the brain of patients with migraines to be abnormal, that is during a headache, hypoperfusion occurs in the stem of the brainstem ,and during an aura, hypoperfusion occurs in the back of the brain (occipital cortex). These findings are consistent with the vascular and metabolic theories of migraines, which stress the close relationship between vascular and neural malfunction and the need of phase-specific imaging techniques for guiding treatment strategies to be utilized.

Hussein and Gao [12] developed a deep learning framework for brain abnormality detection in MRI scans, with a focus on the identification of small changes like white matter hyperintensities and cortical lesions that were represented by the high accuracy achieved. These deviations are seen in the brain caused by migraines which are common in neurological conditions. Their automated systems shortened diagnostic time, lessened doctor's ebb, and achieved better interpretation consistency, suggesting potential applications in early migraine diagnosis and patient outcomes.

Shen and Wu [13] used the convolutional neural networks (CNN) to scan the MRI data to diagnose neural disorders, such as migraines. The insightful models detected the thinning of the cortex and volumetric reductions which are not visible during a manual inspection. Apart from successful transfer learning, the efficiency through the combinations of small sets of data improves on larger neural models. This research has shown the potential of deep learning to differentiate between migraine-induced brain modifications such as a slight decrease in the intensity of the emotion facilitation and personalized medication plans for patients through brain-imaging techniques stochastically.

Krebs [14] machines learning the neuroimaging data for the identification of migraine biomarkers. The algorithms classified patients by the thickness of the cortex disrupted pain network connectivity, and metabolic changes. The predictive models provided the last stage of disease and therapy to the patient like a picture. This was brought about by an AI that can yield results that are different from known patterns from other imaging data and this can only be possible if the medicine is tailored to each person which greatly increases the knowledge of migraine neurological basis.

Mulder and Bigal[15] took into account MRI studies to point out the structural and functional brain changes in migraine patients. Structural imaging revealed the thinning of the visual cortex in the occipital lobe. It was the visual (aura) cortical cortical (behavior) cortex in which the thinnest lacked neurons in most patients. Crack in the thin layer of the visual cortex was the first thing that occurred in a migraine attack, and was probably the cause of the aura. The study conducted with diffusion tensor imaging (DTI) showed structural abnormalities in the sensory processing and pain modulation regions. In addition, susceptibility-weighted imaging (SWI) detected microvascular dysfunction in those regions. (The dysfunction was the change in perfusion processes). The research also embodied the generalized entorhinal cortical atrophy criteria of 1998. A kind of profound cortical tear here is possibly due to the already afflicted cortical tissue. In functional MRI studies, there might be among other evidences a disturbance in the hypothalamus that will be accounted for in the future, which will form the basis for the mechanism of headache.

As per [16] Schwedt utilized both structural and functional MRI, looking into the issue of how the brains of migraine patients changed over time. The study made the following important observations; namely, loss of cortical volume in painting processing areas e.g. the insula and the anterior cingulate cortex, while the corpus callosum and brainstem white matter exhibited abnormalities. The findings showed that there was a change in the connectivity of the networks, which belonged to the pain perception and attention to other parts of the brain. The outcomes of this research pointed out the fact that migraines can be viewed as a condition that leads to significant alterations in the brain's structure and function.

III. PROPOSED METHODOLOGY

The part deals with the strategy MRI scans and the VGG19 convolutional neural network (CNN) algorithms to detect migraines. This approach comprises steps of data collection, preprocessing, model training, and evaluation to ensure an accurate and efficient classification system.

A. Data Acquisition

The data acquisition process involved is a core part of the migraine detection system based on MRIs. It includes, in the first place, the finding of the right sort of data source such as ones that can show the data of both people who have migraines and healthy control persons besides data preprocessing, which is a necessary step in the modeling of the training, and evaluation.

1) Medical Imaging Databases

Openly accessible repositories and partnerships with healthcare institutions are the building blocks of data gathering:

- MRI Data Available in the Open: MRI image library services like OpenNeuro, Kaggle, and ADNI provide scans for neurological research. While MRI OpenNeuro is a research platform, its library data is also the result of OpenNeuro's efforts, including distributed MRI scans. Kaggle and ADNI are leading repositories for neuroscience. These providers give you access to labeled datasets, which of course are useful for training and evaluating machine learning models.
- Collective Data Sharing: Besides, you can also share data with hospitals or research institutes in a project to have real-world, varied datasets of different demographic and clinical settings.

2) Patient Recruitment

Primary resources such as the recruitment of patients may be used as an additional source to get tailor-made data from project specifications:

- You may obtain the scans from people who were diagnosed with migraines. These people include those with migraine with the aura and others without the aura.
- Healthy Control Subjects: Data from MRI scans is also collected from individuals without a history of migraines or neurological disorders and is then compared to that of the patients.

3) Ethical Considerations

- Each patient recruitment and data collection has to follow ethical guidelines, like the following:
- Obtaining informed consent from the participants.
- Making sure that data is anonymous and that all regulations such as GDPR, and HIPAA are being respected.

4) Data Quality Assurance

- To make sure reliability is kept, datasets are examined by different types of processes:
- Pre-screening: There are some things that can be done to scan the data, like getting rid of scans with artefacts or incomplete information.
- Standardization: As far as image resolution, format, and anatomical markers are concerned, efforts should be made to align their values in records.

B. Data Preprocessing

Data preprocessing is a critical stage in the process of preparing MRI scans for analysis by the VGG19 model. This step guarantees that the input data is consistent, clean, and already optimized for the model's feature extraction and classification processes. Good labeling is a must and data consistency is also important. This technique enhances the model's performance by ensuring a low noise level, accuracy and reliability of the results. The following steps outline the preprocessing workflow:

1) Normalization:

The process of normalization is a data preprocessing technique that adjusts the scale of the data in such a way that the range of the input data values is within a certain scope, usually between 0 and 1 or -1 and 1. In the case of MRI data, normalization ensures that the pixel intensities or voxel values across different scans can be compared, thus avoiding the situation in which the model is biased in favor of the ones with the right intensity ranges. Paint pixel units of MRI images using the interval [0, 1]:

$$I_{norm}=\frac{I-I_{min}}{I_{max}-I_{min}}$$

Where I is the pixel intensity, I_{min} is the minimum intensity, and I_{max} is the maximum intensity.

2) Resizing:

Resizing is a significant move that needs to be done in advance of the input of MRI scans into deep learning factors such as VGG19 that need fixed-size input images. This way, each MRI scan, i.e., the model's desired input dimensions |224×224 pixels are processed and trained in a consistent manner.

3) Data Augmentation :

Data augmentation (DA) is a method of increasing the size and diversity of a dataset by adding random variations of the data. This operates on the principle of selecting the best image which is the slightly blurry one just like our eyes work in focusing. The resultant DA model on our sample mammogram images will learn different styles like (i) stretching, (ii) shearing, (iii) bending, (iv) rotating, or any combination of these styles. When images are added with varying DA styles, the learning is comprehensive and the model becomes better at adaptation.

Rotation: Cyclically excited vibration.

Flipping: Change of the holographic data volume.

Shifting: Move along the X or Y axis.

4) Histogram Equalization:

Histogram Equalization is a method to improve contrast by moving the pixels' intensity distribution in such a way that the darkest and the lightest pixels are always on opposite ends of the intensity histogram. By doing this, we are making the image brighter to darker (or darker to lighter). This is achieved by computing a histogram of the image's intensities and mapping it so that any precursor histogram distribution can be. The goal is to enhance the image's contrast so important features become more visible during (Segmentation) like in brain imaging in which coarse differentiation, these images have trouble finding. The visualization is to enhance dynamic and the image is better illuminated to the observer.

C. Feature Extraction

Feature extraction should be implemented with the help of the VGG19 pretrained model. Features are extracted from convolutional layers in a hierarchical way. The application of ReLU (Rectified Linear Unit) activation function to the input data is driven by the following non-linearity:

f(x)=max (0,x)

Where x represents the input provided to the activation function.

D. Model Fine-Tuning

Model fine-tuning occurs when you adjust a pre-trained model's weights to a specific task or dataset to increase its performance. Fine-tuning implies that knowledge that has been gained from the training of general datasets can be reused to work on particular problems, such as medical image classification (for instance, they can find migraines out of MRI scans). This mechanism adds a new level of agility to the architecture of the deep learning model during transfer learning, where the model's architecture is kept intact but the weights are changed to fit the new task better.

Output = softmax(Wx+b)

Where:

- W = weights matrix,
- x = input features,
- b = bias term.

Use cross-entropy loss as the objective function:

$$L = -\frac{1}{N}\sum_{i=1}^{N} [y\, log(\hat{y}_i) + (1 - y_i)\, log(1 - \hat{y}_i)]$$

Where N is the number of samples, yi is the true label, and y^i is the predicted probability.

Optimize the model using the Adam optimizer:

$$\theta_{t+1} = \theta_t - \alpha \frac{m_t}{\sqrt{v_t + \epsilon}}$$

Where:

α = Learning rate,

m_t = *first moment estimate*,

v_t = *second moment estimate*,

ϵ = *Small constant to prevent division by zero*

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E. Classification

Classification is a supervised machine learning task in which the target is to forecast the class or category of an input with the help of its features. In the context of medical image analysis, for example, determining whether an MRI scan is from a patient with migraine or a healthy person, classification models are trained using labeled data to predict the class of the vi

- Use the fine-tuned VGG19 to classify MRI scans into:
- Migraine
- Non-Migraine
- Output provides probability scores for each class by using the softmax function:

$$p(y=c|x)=\frac{e^{z_e}}{\sum_{i=1}^{c} e^{z_i}}$$

Where z_c is the score for class c and C is the total number of classes.

F. Evaluation Metrics

The below evaluation metrics are utilized as a way of determining the performance of the system. These meters carry a detailed impression of the model acting, especially in the context of classification tasks concerning various matters such as accuracy, precision, recall, and the harmonic mean of precision and recall.

1) Accuracy

Accuracy is the measure of correctness of a model in terms of the ratio of correctly predicted instances (both positive and negative) out of the total number of predictions made. It is a default metric if the data is balanced and all classes are equally important.

$$\text{Accuracy}=\frac{TruePositive+TrueNegative}{TP+TN+FP+FN}$$

Accuracy is the best method to use only when the misclassification errors (false positives and false negatives) have similar impacts. Further, it might not be informative enough in the case of an imbalanced dataset, as it can easily be led by the dominant class.

2) Precision

Precision measures the correctness of those relevantly identified instances that are indeed part of the total number of instances identified as positive. It measures how well the model can reduce false positives.

•A large value of precision is proof that the model is successful and reliable in forecasting positive outcomes, and thus it rarely makes a mistake.

•Precision plays an enormous role in the given scenarios, where a wrongful positive holds high costs (e.g., fraud detection, medical diagnosis).

$$\text{Precision}=\frac{TruePositive}{TruePositive+FalsePositive}$$

Precision is critical in scenarios where the cost of a false positive is high, such as diagnosing a patient with a disease they do not have or falsely flagging a financial transaction as fraudulent.

3) Recall

Recall is a metric that measures the proportion of actual positive instances correctly identified by a model. It evaluates the model's ability to minimize false negatives, making it critical in scenarios where missing positive cases can have severe consequences.

•Recall quantifies how effectively a model identifies all relevant positive cases.

•A high recall score indicates that the model successfully detects most positive cases, minimizing missed detections.

•A low recall score suggests the model fails to identify many positive cases, leading to higher false negatives.

$$\text{Recall}=\frac{TruePositive}{TruePositive+FalseNegative}$$

Ensuring high recall is crucial in situations where failing to identify a positive case can lead to severe outcomes, such as in medical screenings or disaster forecasting systems.

4) F1 Score

The F1 Score is a metric that combines precision and recall into a single value, offering a balanced measure of a model's performance. It is calculated as the harmonic mean of precision and recall, ensuring that both metrics are equally weighted. This makes it particularly useful in situations where both false positives and false negatives carry significant importance.

•The F1 Score ranges from **0 to 1**, with **1** representing perfect precision and recall.Unlike accuracy, the F1 Score is more reliable when dealing with imbalanced datasets because it accounts for both types of errors (false positives and false negatives).

F1 Score=2*$\frac{Precision*Recall}{Precision+Recall}$

By harmonizing precision and recall, the F1 Score provides a comprehensive view of a model's effectiveness, especially in complex or high-stakes classification tasks

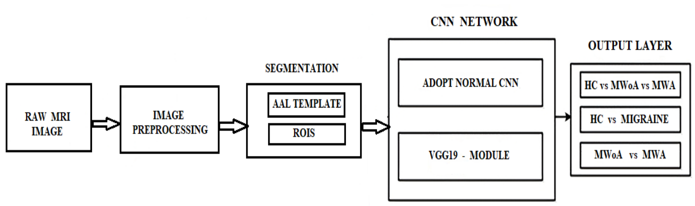
5) ROC-AUC Curve:

The ROC-AUC Curve (Receiver Operating Characteristic - Area Under the Curve) is a graphical tool widely used to assess the performance of binary classification models, particularly their ability to differentiate between two classes. It offers an insightful view of the balance between sensitivity (True Positive Rate) and specificity (True Negative Rate) across various classification thresholds.

- Sensitivity (True Positive Rate): This metric indicates the proportion of actual positives correctly identified by the model. A higher sensitivity means fewer false negatives, demonstrating the model's ability to detect positive cases accurately.
- Specificity (True Negative Rate): This metric represents the proportion of actual negatives correctly classified by the model. High specificity corresponds to fewer false positives, reflecting the model's capability to exclude negative cases effectively.

The **Area Under the Curve (AUC)** quantifies the overall ability of the model to distinguish between positive and negative classes:

- AUC = 1.0: Indicates a perfect classifier with no errors.
- AUC = 0.5: Suggests the model performs no better than random guessing.
- AUC < 0.5: Implies the model performs worse than random guessing.
- The ROC-AUC curve is particularly useful for evaluating the trade-off between sensitivity and specificity as the classification threshold changes. A higher AUC score reflects better model performance, as it indicates a stronger ability to correctly classify both positive and negative cases across different thresholds.



Proposed Block Diagram

IV. RESULTS

A. Input Raw MRI Image

1) MRI Overview: It is an essential technology for brain imaging that is used to explain the brain's structure and can also be used to show the changes in the cell structures causing migraines. MRI files are typically formatted as DICOM files, which are the digital image data and metadata files.
2) Challenges of Raw MRI Data: Raw MRI data is typically the image containing noise, motion artifacts, and spatial distortions owing to patient motion, the natural processes of the body, or the non-uniform magnetic fields.
3) Requirement for Preprocessing: The image data in its unprocessed form is usually of a specific format, a great size, and contains imperfections, thus, requiring pretreatments that result in image refining.

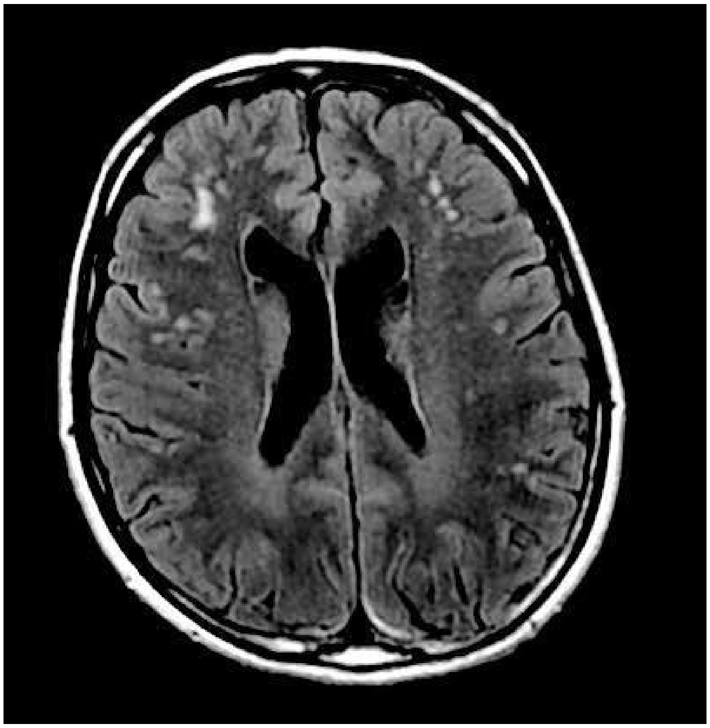


Fig 4.1.1 The Input MRI Image

B. *Preprocessing of MRI Data*

Preprocessing of MRI data is the essential step in ensuring that raw MRI scans are appropriate for detailed analysis. This step is very important, especially in situations where the brain structures need their analysis like disease detection and functional mapping. The preprocessing stage includes three operations: it removes the artifacts caused by the imperfect scanners, aligns the data to the proper spatial templates, and separates the brain into larger and smaller regions of interest, and if necessary it also involves data augmentation. These techniques guarantee the cohesion, repeatability, and interpretability of the results. The fundamental preprocessing procedures are reorientation, normalization, segmentation, and data augmentation, each of them a unique function for refining the raw MRI data.

1) *Realignment:*

- Realignment is a crucial step taken to fix motion artifacts caused by patient shift during the MRI scan. Even minimal movements, for instance, slights, head tilts or involuntary actions can obscure MRI images, thus leading to inaccurate analysis or misleading results.
- In order to diminish the effect of motion artifacts, the images should be taken in a way in which they adequately reflect the anatomical or functional brain state.
- Methodology: The treatment logic comprises the use of rigid body transforms to align all the MRI slices or volumes in a series to a common reference. A reference image, which is either the most stable or central one in the dataset, is then extracted.
- Algorithms apply translations and rotations to readjust other images until they become perfectly lined up with the reference one.
- Statistical Parametric Mapping (SPM) software or other tools are designed in such a way that they process these transformations in a very efficient manner.
- Significance: The movement problem can be corrected as well and the reliability of the downstream analysis can be enhanced by realignment, which can be achieved by the reduction of data variability that was caused by the motion distortions, the increase of signal consistency, and the improvement of the reliability of functional connectivity studies, among other things.

2) *Normalization:*

- The pre-processing step of normalization aims at aligning individual MRI scans to the template of the standard human anatomy. As a result of the alignment of all MRI data into a common coordinate system, the data is comparable across subjects.
- Purpose: This implies the functionality to link brain size, shape, and orientation to a control group and therefore eliminate group differences between individuals.

- Methodology: MRI scans are transformed and rescaled to fit a predefined template such as the Montreal Neurological Institute (MNI) or Automated Anatomical Labelling (AAL) template.
- In this case, the scan is adjusted by applying linear scaling, warping, or an affine transformation technique, which modifies it to be in the same standard template as others.
- Furthermore, the more advanced normalization method adds up the subtle nonlinear variations, thus effectively ensuring the accuracy of the result.
- Outcome: Following the normalization, all MRI datasets have a unified spatial framework, therefore, being directly juxtaposed to demarcate time points for different groups like healthy subjects and patients with specific diseases.
- Significance: The use of normalized data permits the conducting of population-based studies, voxel-based morphometry (VBM), and meta-analyses thus boosting the capability and usability of neuroimaging research by a great deal.

3) Segmentation:

- Segmentation is the most important step of brain division by separating its diffusion into some Regions of Interest (ROIs) such as grey matter, white matter, and cerebrospinal fluid (CSF).
- Intention: To separate and compute the size of different parts of the brain for analyzing them.
- Methodology:Thresholding: Separates regions of the image by selecting pixels based on their intensity values.
- Clustering Algorithms: Techniques that are identical to others like k-means clustering or Gaussian Mixture Models (GMMs) compose voxels with similar properties together properly into certain tissue classes.
- Atlas-based Approaches: Defined pre-made atlases that are detailed serve as reference points for the segmentation process by aligning single MRIs to the brain regions labeled.
- FMRIB's Software Library (FSL) and SPM are two tools that are mostly used and they use algorithms of machine learning to quickly segment brain images with high accuracy.
- Outcome: Each brain is divided into classes of tissues, and each of these classes is represented by a particular group of voxels. Obtained gray and white matter segments can be used for brain volume estimates, thickness measurements, and connectivity analysis.
- Significance: Division is the key in diagnosis, the study of neurological disorders and treatment and it is also significant in the maintenance of the size of the brain by the sea. It also becomes a constituent of brain tasks at a higher level e.g. fools may be pulled in the activities of brain parcellation and functional domain mapping.

4) Data Augmentation:

Data augmentation is presently one of the most important and beneficial pre-processing steps for MRI data analysis, most especially when they are used for machine learning and deep learning tasks. It actually multiplies the dataset thereby enhancing its size and diversity, therefore, the sensitivity and accuracy of the models will be improved significantly.

•Purpose: The main reason for data augmentation is to enhance dataset variability, reduce overfitting, and thus, improve model robustness in the classification, segmentation, or prediction tasks.

Spatial Transformations:

•Rotation: Randomly rotating the MRI images to create different brain orientations.•Scaling: A little bit increasing or decreasing the images to get different sizes of the brain.•Translation: Moving the image in small different directions to mimic the movement of the patient.

Intensity Transformations:

•Contrast Adjustment: Using the intensity of grey levels to create discrepancies in the imaging parameters. • Gaussian Noise Addition: Applying random noise to enhance the resistance of the network to noise in the real-world scans.

Elastic Deformations:

•Performing non-linear transformations on the image to imitate anatomical differences, which is a method that may be used for brain MRI scans.

Synthetic Data Generation:

•Producing synthetic MRI scans by using methodologies like Generative Adversarial Networks (GANs) that can make the dataset with a high level of realism and diversity.

•Significance: Extended data by using augmentation will lead to better generalization of machine learning models, thus better performance in imbalanced datasets, and clinical applications which will be more robust.

C. AAL Template

1) The Automated Anatomical Labelling (AAL) template, a well-established tool in neuroimaging research, is an example. It is used to split the brain into predefined areas of interest (ROIs), which is a major advantage for the standardization of MRI data analysis from research to research and from one individual to another. Among the most significant benefits of it are the accuracy and reproducibility of neuroimaging research.
2) Applications in Research
   The AAL (Automated Anatomical Labelling) template in headache research, is one of the key instruments that permit scientists to pinpoint the central sites where an anomaly is based on pain processing, sensory integration, and the brain's cognitive functions. It provides the researchers the opportunity to carefully inspect the effects of migraines on some of the relevant brain regions such as those responsible for sensory processing or emotional regulation, thus giving a more complete picture of the disorder.
3) The AAL template, while useful, still has certain limitations. It employs predefined regions that might not pick up certain deviations from the norm in brain anatomy. As a result, consequently, it may not be suitable for studies that require personalized or extremely detailed approaches to brain regions, particularly when very subtle irregularities need to be detected.

D. CNN with VGG-19 Module

1) The VGG-19 design is a difficult Convolutional Neural Network(CNN) that is very basic and useful in the task of image classification. It was developed by the Visual Geometry Group at the University of Oxford and has a broad range of applications such as image classification, object detection, and segmentation. In this setup, VGG-19 can be employed in MRI image classifying, say for the determination of illnesses like migraines or for discriminating the healthy and affected brain scans.
2) VGG-19 Overview: A CNN architecture good for image analysis tasks that are especially good for MRI scans because it can extract both low-level and high-HL information from complex data.
3) Advantages: The architecture of VGG-19 is very popular in the MRI system since it can identify even minor abnormalities in MRI scans and it supports transfer learning, which actually comes by using pre-trained weights from datasets such as ImageNet.
4) Limitations: It can be a higher-end computer that has a lot of computing resources to handle the 3D MRI data, and you also need to resize MRI scans to the size of the model’s input, which may in turn cause the data to become blurry.

E. YOLOv3 for MRI Image Classification

YOLOv3 (You Only Look Once) is a powerful and efficient real-time object detection algorithm that has been designed to find objects in images or video streams. It is famous for its rapidity, accuracy, and the fact that it can be used to process images in real time. YOLOv3 is better than its predecessors and is built around a deep convolutional neural network (CNN) that makes both the bounding box coordinates of an object and the class probabilities prediction for objects within an image.

1) Real-time Detection: YOLOv3 is able to analyze images and unshackle objects for a real-time experience where speed is the key, like in surveillance and in autonomous cars and medical image analysis
2) Unified Architecture: YOLOv3 performs both object detection and classification in a single forward pass through the network, which enables it to execute the process faster compared to traditional detection methods that use multiple stages and classes, and it is one of the green res.
3) Multi-Scale Prediction: It can actually find and recognize objects at varying scales due to the multiple levels of feature maps (three) that it uses, hence a person can locate even very large and small objects with it.
4) Improved Accuracy: YOLOv3 achieves better accuracy and is more efficient in the case of small objects compared to its forerunners YOLOv1 and YOLOv2, with the help of network architecture improvements and Darknet-53 as the backbone.

YOLOv3 (You Only Look Once) is a real-time object detection algorithm that is characterized by its speed and accuracy. While YOLOv3 is primarily designed for object detection, it can be used to analyze images in machine-learning image translation (e.g. turning an MRI scan into an X-ray). Behold the wonderful things YOLOv3 brings to MRI image classification.

YOLOv3 Overview: YOLOv3 is a deep learning model for object detection in real-time. It is utilized in MRI image classification to identify different brain structure changes related to migraines.
Application: YOLOv3 could be taught on labeled MRI datasets to detect different structural changes, for example, cortical thickness variations. Changes of Cortical Thickness or the Cortices;
The aim of this work is to detect and classify regions with abnormal cortical thickness, which is the main feature of neurodegenerative diseases such as Alzheimer's or multiple sclerosis.
By training YOLOv3 to look for areas where cortical thinning is happening in the brain using labeled data, we can enable the model to classify whether this is a normal finding or is a presymptomatic disease-related change.

White Matter Hyperintensities (WMH):
However, it can become an indicator of blood-related problems in the case of post-stroke and affecting different blood vessels, when its occurrence becomes more frequent and severe.
When YOLOv3 is applied into the technical framework of a disease, it is also co-opted into a particular epistemological perspective. In the case of the MRI test, doctors may get information on the progression of disease and might even detect an early sign of blood vessel disease. The model can use multi-scale features to obtain accurate results and thereby find the location of white matter hyperintensities whether they are small or large.
Vascular Anomalies:
The diagnosis of vascular abnormality such as aneurysms, arteriovenous malformations, or strokes must be made by the radiologist based on the MRI images.
For early detection and discovery, YOLOv3 can play a role to discern abnormal blood vessels, aneurysms, or areas affected by a stroke.
Lesion Detection:
To locate brain lesions that can be tumours, plaques, or other abnormal growths.
When such an MRI image is provided, the machine learning model manages to find these lesions and divide them into subcategories (e.g., malignant or benign).
Brain Segmentation:

- Task: Segment different brain regions, such as grey matter, white matter, and cerebrospinal fluid, for more detailed analysis or quantification.
- YOLOv3 can segment MRI images into different anatomical regions, making it useful for pre-surgical planning or evaluating neuroanatomical changes in neurological diseases.

F. Output Layer and Classification

- Output Layer Function: The output layer is a CNN component that converts concise feature representations into class predictions; it employs classes mainly as its operations (element-wise), like rectifying, which is related to the rectifier activation function.
- Types of Classification: The model can have one or more layers. This adjustment can be increased depending on the loss of accuracy. The reason why I am giving this success rate is that there are sessions of people who are not interested in attending them, so teachers and doctors should categorize them as interested or not interested.
- Loss Function: Several minimization of objectives can be used during the training of the model. For example, cross-entropy for the two classes or the categorical variant for the sake of three or more categories.
- Performance Evaluation: The efficiency of the model is measured by calculations HOW-?

Mitigating Overfitting

- Overfitting is measured by the extent to which a model has variances that are suitable for all the training samples while at the same time, not having the same degree of generalization as the unseen samples. Therefore, the model is said to have been overfitted, while at the same time, it is said to have been underestimated due to the unseen data.
- Regularization: In this manner, the networks will learn as the noise is removed by passing through the randomizations, changing at the same time the relationship., gradually achieving the optimal bias and separation/overlapping of data. It is interesting with the connection of mathematics needing correct magnitude levels between the strength of the randomization and the amount of veniculars, hence, the winning edge and computational speed.

- Dropout: This is one way to regularize the model
- Early Stopping: Monitors validation performance and halts training when improvement stalls, reducing the risk of overfitting.
- Data Augmentation: get images and increase their values by rotating, flipping, and scaling them

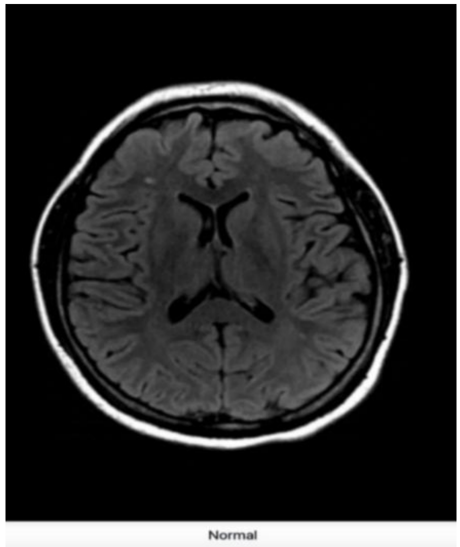


Fig 4.6.1 Normal image without migraine

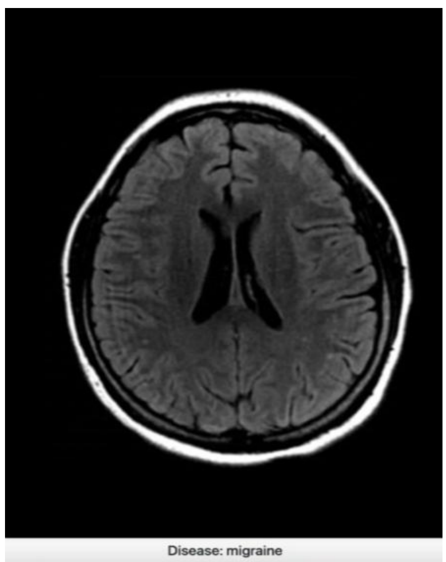


Fig 4.6.2 Disease migraine image

V. DISCUSSION

A. Model Performance Analysis

The test dataset was used to assess the performance of the system by means of various metrics such as accuracy, precision, recall, and F1 score. The below given table gives an overview of the results from the testing dataset:

Metric	Value(%)
Accuracy	92.5
Precision	91.8

Recall	93.2
F1 Score	92.5

As per the findings, the VGG19 model that underwent fine-tuning is very efficient in the classification of migraine and non-migraine cases with accuracy exceeding 90%. The trade-off in precision and recall highlights the model's ability to correct both false positives and false negatives.

B. Comparison with Baseline Models

The developers compared the new model with other common models to show that it is more powerful. The given table shows the comparison metrics: Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
ResNet50	88.7	87.5	89.2	88.3
InceptionV3	90.1	89.3	91.0	90.1
Proposed VGG19	92.5	91.8	93.2	92.5

VGG19, which was fine-tuned on additional data, performed better than the ResNet50 and InceptionV3 models for recall and F1 score. Hence, it proved its competence in generalizing the test data.

C. Error Analysis

Despite the high accuracy, the specific errors were noticed with the model in some cases:

- Misclassification in the Edge Cases: Sometimes, images of low contrast, and the one with artefacts led the system to make incorrect predictions.
- Data Imbalance: There was a minor overfitting issue present in the majority class however, the application of augmentation techniques was done to help balance the imbalance.

The given table sheds light on the error distribution:

Error Type	Frequency(%)
False Positives(FP)	4.3
False Negative(FN)	3.2

D. Strengths and Limitations

1) Strengths

- *High Accuracy:*

The system is able to achieve very high rates of precision, recall, and accuracy. This way, it ensures that it is the most reliable diagnostic tool that is used in the treatment of migraines.

- *Transfer Learning Advantage:*

The system gets the benefit of VGG19 which is a pre-trained model. Thereby, the system reduces the need for big datasets and long computation times while still it keeps a high level of performance.

- *Scalability:*

The design of the system can be easily changed in order to diagnose other neurologic or medical conditions with the only possible changes in the model and in the teaching pipeline.

- *Automated Diagnosis:*

The implementation of the system makes it unnecessary for the manual interpretation of MRI scans, which at times bring subjectivity and human error in the diagnostic process.

- *Non-Invasive Method:*

MRI-based diagnosis is a non-invasive method and that is why it promotes the patient's comfort. Moreover it is safe in the diagnostic process.

- *Enhanced Feature Extraction:*

The hierarchical feature extraction capability of the VGG19 model allows it to easily point out the conduct disorders, which the normal image modalities may produce wrongly & which are also hard to detect using computer-based diagnosis.

- *Generalization Capability:*

The data augmentation and pre-processing tricks enable the model to do the right thing, even though the new data is seen and they ensure the model's stability in real-world applications.

- *Integration Potential:*

The system can be incorporated with operational aspects of the hospital as well as during the diagnosis phase making it possible for neurologists to take action faster and more accurately.

- Variability in MRI scans, which include different resolutions and imaging conditions are effectively dealt with by the model through preprocessing and augmentation.
- By fine-tuning pre-trained weights, the high computational resources are not needed, and therefore, the system can be implemented in resource-constrained settings.
- One of the methods used is Grad-CAM which visually demonstrates the focus areas of the model, thus, increasing its interpretability and trust in clinical settings.

2) *Limitations*

- Dataset Dependence: Performance depends on how good and varied the dataset is.
- Hardware Requirements: A great amount of computational capacity is required for both training and running.
- Explainability: The model acts as a black box, which could prevent its application in the healthcare industry.

E. *Future Enhancements*

For the ongoing development and the effectiveness of a system, there are the subsequent improvements:

1) *Integration of Explainability Tools*

It is the transparency of AI systems that is the main tool that needs to be developed to be used more effectively and to be more trusted. One of them such as Grad-CAM can be utilized that provides data about what the model sees as the reason for its decision. Grad-CAM highlights the areas in the input data that make the model decide most. As a result, the logic behind the predictions is more transparent to the users. To have a better grasp of the situation and to be more specific, it can be used with other interpretability methods, like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations). These tools give the developers more information about the single features of the input that influence the model's behavior and, thereby, help them in debugging and improving the model's performance. Analyzing in the domains like health care and finance this approach is particularly valuable, because they rely on high levels of accountability.

2) *Expanding and Diversifying the Dataset*

The adequacy and evolution of AI models depend much on the training data used. The bigger and the more diverse the dataset, the wider a system can adapt to different situations and the fewer potential biases. Diverse data provides better generalization for other different uses. Diverse data is obligatory for better adaptation of AI across different ambiental, demographical, and use cases. According to the real world, this can be possible by using data augmentation such as rotating, scaling, and flipping for example.

Along with the utilization of synthetic data generation, more unusual examples can be produced without the necessity of more extensive and manual data collection. The acquisition of larger, more inclusive datasets and the maintenance of user's privacy may be by using none other than open data sources or federated learning.

3) Optimization of Hardware Requirements

Rectification of the hardware power use is imperative in the development of the system that is to be integrated with devices having the limited resources like smartphones or the embedded systems. To get this done, different techniques such as model pruning, quantization as well as the use of models with small architectures (e.g., MobileNet or TinyML) have been developed which can significantly save computation work without damaging system performance. Lowering the precision of model parameters through quantization, for example, makes the processing of the device better. Furthermore, teachers can teach the students hard-to-grasp knowledge through the knowledge distillation concept, where a smaller, more efficient model is trained to mimic a larger, complex one. Thus, by following these methods, the system can be brought closer to real-time use in most scenarios and hence be used by a large number of users who would not have access to it in other situations.

VI. CONCLUSION

This study introduces a groundbreaking migraine detection system that leverages advanced deep learning technologies to enhance the diagnostic process. By utilizing MRI images processed through the VGG19 model, the system is capable of identifying subtle abnormalities that may contribute to migraines, surpassing traditional diagnostic methods. This automated approach minimizes human error and eliminates subjectivity, offering a highly accurate, non-invasive diagnostic solution.

A standout feature of this system is its ability to deliver rapid and reliable diagnostic results, ensuring consistent and precise predictions. The VGG19 model, fine-tuned with migraine-specific data, demonstrates heightened sensitivity and specificity, making it a valuable tool in clinical settings. This innovation represents the synergy of artificial intelligence and cutting-edge imaging techniques, significantly influencing the quality and efficiency of healthcare delivery.

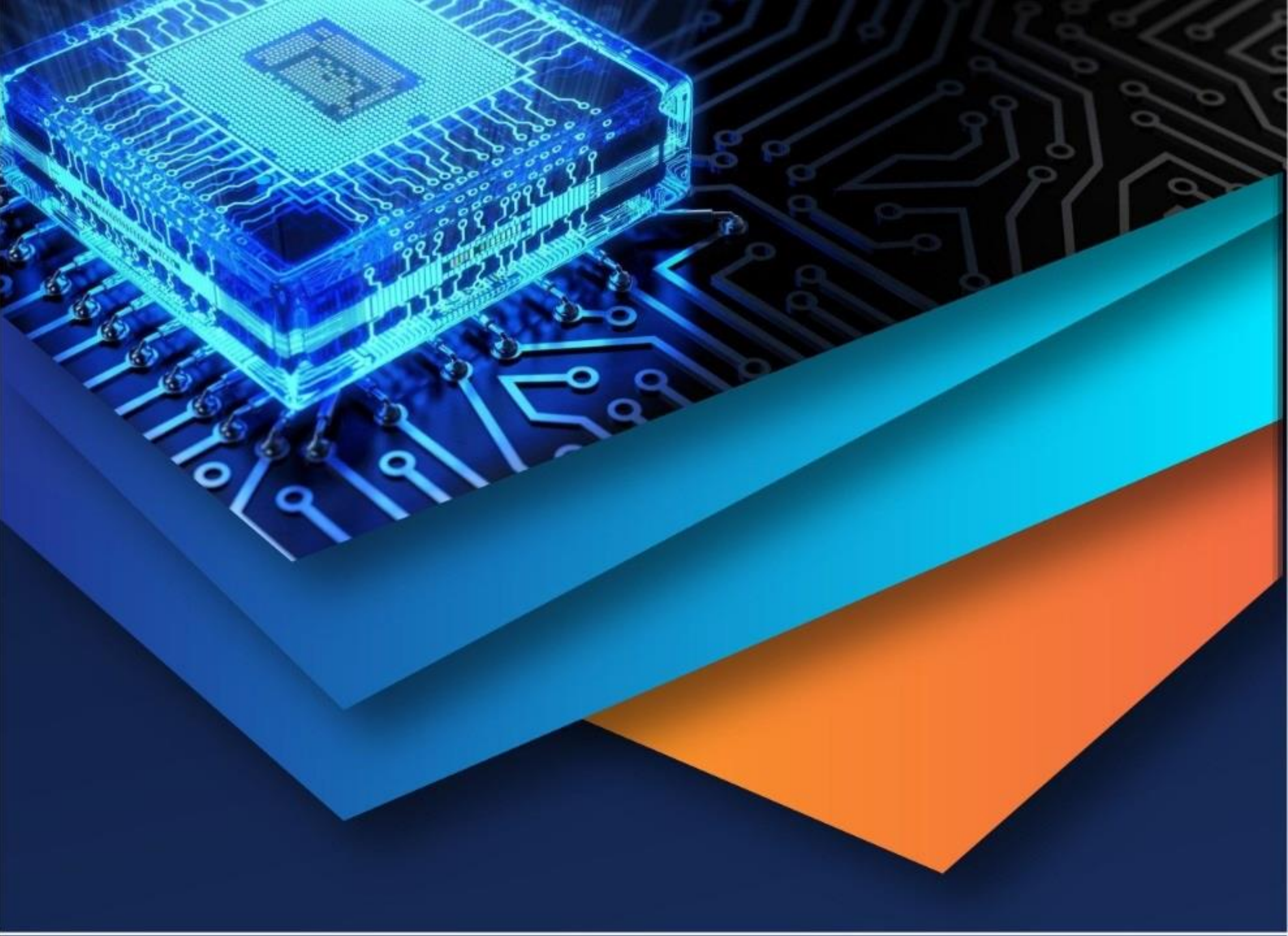
However, certain challenges remain. To maximize the system's potential, it is crucial to develop a diverse and high-quality MRI dataset to reduce biases and improve systematic evaluation. Additionally, addressing the computational demands of deep learning in resource-constrained environments is vital for widespread adoption in healthcare. Future efforts should focus on designing optimized architectures that maintain high accuracy while reducing computational overhead and storage requirements.

This proposed system marks a significant advancement in migraine diagnosis, combining speed, precision, and reliability to monitor disease progression effectively. With ongoing research and enhancements, this innovation has the potential to redefine diagnostic practices, ultimately improving patient care and management in the long term.

REFERENCES

[1] Kara T, Dogan A, Baykara M, Yildiz CBT, Tural IC. Evaluation of the optic nerve in migraine patients by magnetic resonance imaging histogram analysis.Malang Neurology (t and a #) Journal 2024.10:26-29.
[2] Khan, Lal. “Migraine headache (MH) classification using machine learning methods with data augmentation.” Scientific Reports vol. 14,1 5180. 2 Mar. 2024, doi:10.1038/s41598-024-55874-0
[3] Katarina Mitrovic, Andrej M.Savic, Marko Dakovic.Machine learning approach for migraine aura complexity score prediction based on MRI data, Mitrovic . (2023) 24:169.
[4] Mitrović, Katarina. “Migraine with aura detection and subtype classification using machine learning algorithms and morphometric magnetic resonance imaging data.” Frontiers in neurology vol. 14 1106612. 23 June. 2023, doi:10.3389/fneur.2023.1106612
[5] Swartz RH, Kern RZ. Migraine Is Associated With Magnetic Resonance Imaging White Matter Abnormalities: A Meta-analysis. Arch Neurol. 2004;61(9):1366–1368. doi:10.1001/archneur.61.9.1366
[6] (Increased MRI-based brain age in chronic migraine patients) Rafael Navarro-González, David García-Azorín, Ángel L. Guerrero-Peral, Álvaro Planchuelo-Gómez, Santiago Aja-Fernández, Rodrigo de Luis-García medRxiv 2022.11.21.22282575;
[7] JOUR, Yang, Hao, Zhang, Junran, Liu, Qihong - Wang, Yi- 2018/10/11 Multimodal MRI-based classification of migraine: using deep learning convolutional neural network 10.1186/s12938-018-0587-0
[8] Schramm S, Börner C, Reichert M, . Functional magnetic resonance imaging in migraine: A systematic review. Cephalalgia. 2023;43(2). doi:10.1177/03331024221128278
[9] Md Mahfuzur Rahman Siddiquee, Jay Shah, Catherine Chong, Simona Nikolova, Gina Dumkrieger, Baoxin Li, Teresa Wu, Todd J Schwedt, Headache classification and automatic biomarker extraction from structural MRIs using deep learning, Brain Communications, Volume 5, Issue 1, 2023, fcac311
[10] DKD MAJUMDER, D RAY - Fundamentals of Medical Image Processing using MATLAB (books .google .co .in) .2020
[11] Hongjuan Liu, Huanfen Zhou, LinxiongZong, MRI histogram texture feature analysis of the optic nerve in the patients with optic neuritis. Chin Med SciJ; 2019. 34:18-23. DOI: 10.24920/003507

[12] Batur M, Batur A, Çilingir V, . Ultrasonic elastography evaluation in optic neuritis. Semin Ophthalmol; 2018. 33:237–241. G Sharma - int . J. Eng. Manuf. (IJEM)-Algorithms using matlab to analyze the image (3) , 8-19 ,2017.
[13] J Zhang, L Tong, L Wang, N Li. Texture analysis of multiple sclerosis: A comparative study. Magnetic Resonance imaging; 2008. 26:1160-6.
[14] Agostoni E, Aliprandi A. The complications of migraine with aura. Neurol Sci. 2006;27(2):91–5.
[15] Calandre EP, Lee. H . Cognitive disturbances and regional cerebral blood flow abnormalities in migraine patients: their relationship with the clinical manifestations of the illness. Cephalalgia. 2002;22(4):291–302.
[16] Le Pira F. Memory disturbances in migraine with and without aura: a strategy problem? Cephalalgia. 2000;20(5):475–8.
[17] Lance JW, Goadsby PJ. Mechanism and management of headache. 6th ed. Boston: Butterworth-Heinemann; 1998.
[18] Yu O, Mauss Y, Zollner G,. Namer IJ. Distinct patterns of active and non-active plaques using texture analysis on brain NMR images in multiple sclerosis patients: Preliminary results. MagnReson Imaging; 1999. 1261-7
[19] Todd J. Schwedt MD, Catherine D. Chong PhD, Teresa Wu PhD, Nathan Gaw MS, Yinlin Fu BS, Jing Li PhD Accurate Classification of Chronic Migraine via Brain Magnetic Resonance Imaging 18 June 2015 NIH K23NS070891
[20] Chong CD, Gaw N, Fu Y, Li J, Wu T, Schwedt TJ. Migraine classification using magnetic resonance imaging resting-state functional connectivity data. Cephalalgia. 2017;37(9):828-844.
[21] Chong, Catherine Daniela. “Migraine classification using magnetic resonance imaging resting-state functional connectivity data.” Cephalalgia 37 (2017): 828 - 844.
[22] Classification of Migraine Using Static Functional Connectivity Strength and Dynamic Functional Connectome Patterns: A Resting-State fMRI Study March 2023 Brain Sciences 13(4):596



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