Milestone Transactions on
MEDICAL TECHNOMETRICS
Vol. 03, Issue. 01, 2025

RESEARCH ARTICLE OPEN ACCESS

Machine Learning Technique for Brain Tumor Detection: A Comprehensive Review

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DOI: **10.5281/zenodo.14794625**

Received: 13 January 2025 / Revised: 21 January 2025 / Accepted: 02 February 2025
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Abstract – Detecting diseases in the brain at early stages or proper diagnosis and treatment of tumor in the brain are perhaps the biggest challenges facing medical sciences. New advancement in Machine Learning has developed novel methods for augmenting accuracy and effectiveness of detecting brain tumors based on image obtained through MRI scans. This review goes in-depth analysis of how detection and classification is currently improving, highlighting such techniques involving SVM, CNNs, ResNet, and Xception. Key spatial and textural feature extraction techniques, like PCA, HOG, and GLCM, have also been considered in order to improve the classification performance. Ensemble approaches, such as Random Forest, have been taken into consideration for handling the complexity of the dataset. The study evaluates the benefits, limitations, and clinical applicability of these methods in view of the challenges posed by diverse datasets, high computational demands, and generalization issues. Further research and development are required to make the machine-learning diagnostic capabilities of brain-related conditions more reliable and practical.

Index Terms – CNN, Deep Learning, Machine Learning, SVM, Brain Tumor.

I. INTRODUCTION

Brain tumors constitute some of the most critical health problems that both adults and children face globally. Brain tumors can be broadly categorized into two types: benign or nonmalignant, and malignant or cancerous. The appropriate treatment of the patient and the enhanced outcome are highly dependent on the accurate and early diagnosis of brain tumors. The prototypical images for identifying abnormalities in the human brain were MRI and CT scans, of which MRI is highly preferred because of superior soft tissue contrast and high resolution. This review is on the advances and the potential applications in medical diagnostics for

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Electronic ISSN: **2584-072X**

detection and classification of brain tumors using MRI and other medical imaging modalities through machine learning. The current methods of diagnosis, though highly sensitive and specific, are so cumbersome that observer variability exists. Such ML-based systems want greater accuracy at the expense of diagnostic effort. Basic theories, critical developments under development, and methodologies used to guide recent work are presented in this review in reflection of their implications for clinical work.

A. Background of the Study

Indeed, brain tumors are the most dangerous and exigent diseases that endanger humanity. Meningioma is the most prevalent among the nonmalignant tumors that fall into this classification, and glioblastoma is most common malignant brain and central nervous system tumor in the United States of America. Statistics indicate that the 5-year survival rate for malignant CNS tumors is 23.5%; several studies put it up to 35.8%, meanwhile it is 82.4 in the case of non-malignant CNS tumors, mostly due to the average of 24.71 cases per 100,000 U.S. citizens every year [1][2][3]. There is a pertained high incidence of malignant tumor in brain and central nervous systems. Among these tumors, glioblastomas and meningiomas are the commonest in the United States. In fact, one of the malignancies' five-year survival rates for brain tumors is 66.9% compared to nonmalignant brain tumors' 92.1% being much better [4]. According To Jhons Hopkins Medicine (http://www.hopkinsmedicine.org/health/conditions-and-diseases/gliomas) Gliomas being the most common type of brain tumor can be seen from the incidence that they account for 33% of all brain tumors. The tumors are classified as malignant. These are subtypes of astrocytomas, oligodendrogliomas, and ependymomas. Astrocytoma in which one subtype particularly aggressive with an unfavorable prognosis is glioblastoma multiforme (GBM). Glioblastomas account for 49% of all gliomas [5]. Nevertheless, the most striking is that regardless of the improvement in treatment, the 5-year survival rate for GBM remains at about 6.8%. Early and precise diagnosis is very beneficial in deciding how to manage the patient and in raising survival rates while reducing health risks. However, more traditional diagnostic techniques including MRI and CT scans demand a lot of time and are subjective with a very high observer variability. Currently, on these bases, ML and DL have become alternatives for automating and improving the accuracy in the tumor detections. However, interpretability, lack of balanced datasets and computational inefficiency are limitations in applying them in clinical settings.

B. Problem Statement

However, in the recent most improved ML techniques in brain tumor detection, there are eminent challenges such as small and imbalanced training sets, the complex nature of the 3D imaging data, and limitations of model transparency restricting clinical trust and usability. To this end, the gaps must be narrowed to provide scalable, efficient, and interpretable models that will generalize to a variety of real-world settings using multimodal imaging data.

C. Research Questions

- In what ways can highly advanced ML models enhance the accuracy and scalability of brain tumor detectors?
- What strategies do we have to alleviate the limitations of data imbalance, interpretation deprivation, and computational ineffects?

- Do multimodal imaging approaches improve the robustness of tumor classification models?

D. Objectives

- Designing an ML framework, keeping in mind the available top-class models such as CNN, ResNet, and U-Net to detect a tumor.
- To address the challenge of the dataset with or through data augmentation and/or transfer learning and synthetic data generation.
- Combining MRI between modalities such as CT and PET, is a mode through which one can explore multimodal imaging for improving diagnostic outcomes.
- Benchmarking these said models with those done previously and applying these models on real-world datasets to validate them.

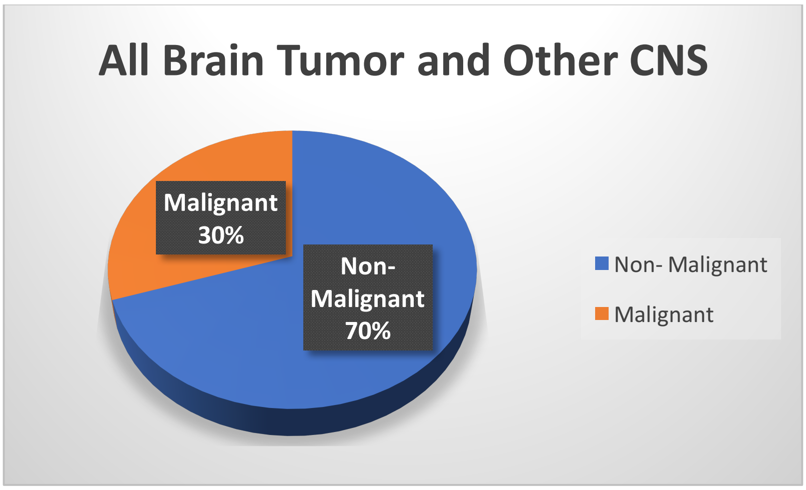

Fig. 1: Distribution of Malignant and Non-Malignant Brain Tumor

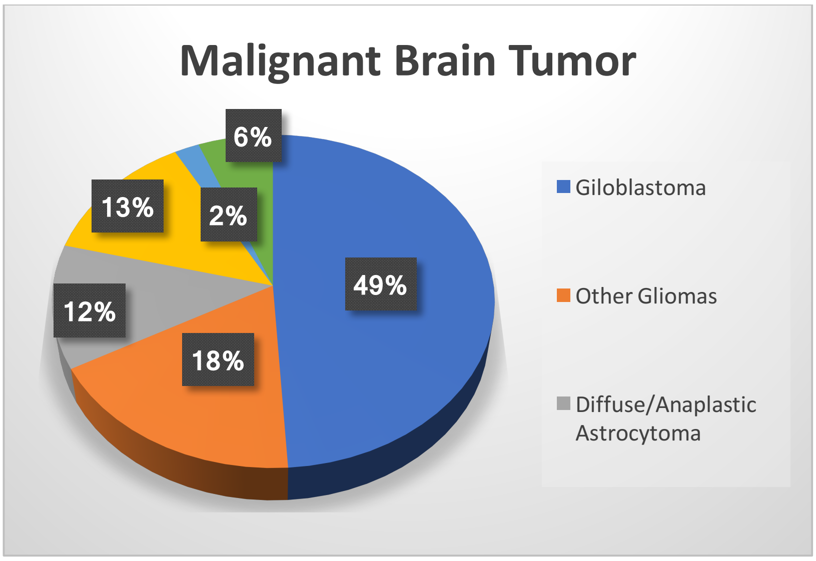

Fig. 1: Distribution of Different Malignant Brain Tumor

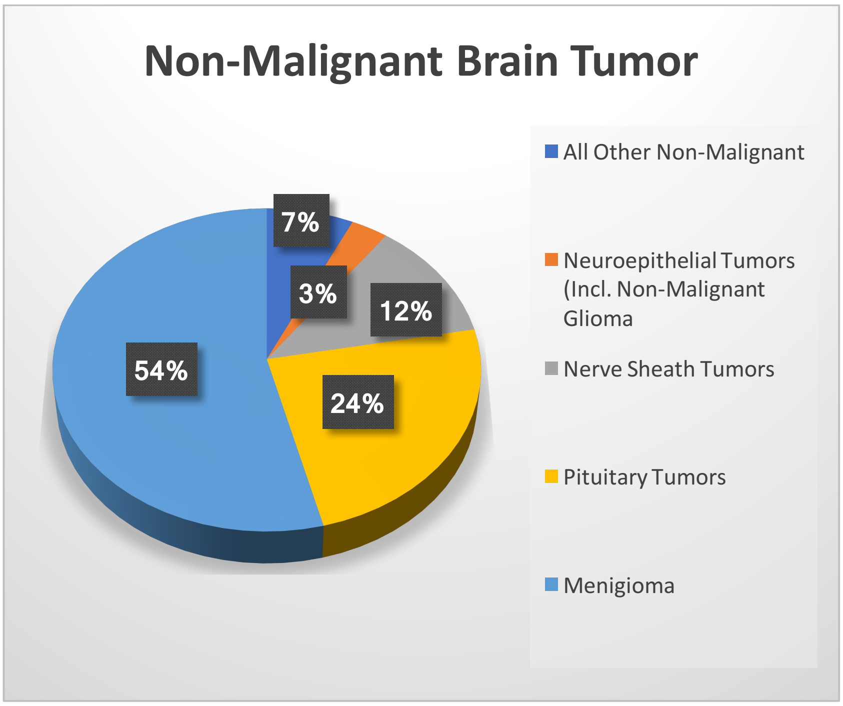

Fig. 2: Distribution of Different Type of Non-Malignant Brain Tumor

E. Scope

This article talks about the challenge of brain tumor detection by employing machine learning (ML) and deep learning (DL) techniques. This article discusses the advanced machine learning methods in terms of Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) along with the latest architectures' specifics like U-Net and ResNet on tumor classification and segmentation. More significantly, feature extraction techniques presented by the article are enhancement measures that support a model's performance, and include Histogram of Oriented Gradients (HOG), Principal Component Analysis (PCA), and Gray-Level Co-occurrence Matrix (GLCM).It also attempts to outline possible future directions in research that would complement and build upon previous indexed studies: identification of shortcomings present in current studies including insufficient number of datasets, imbalance class modeling and certain computational inefficiencies plus issues regarding the interpretability of these incomplete DL models which refrain them from being rightly applied into the clinical scenario. As illustrated multilayout imaging technologies which are based into hybrids between MRI, CT, and PET scanning modalities prove to be promising towards broader reliable and scalable ML frameworks.Inspection of explained artificial intelligence to fill the void between ML technologies and its usage in the medical arena through rendering models more transparent for and trusted by the health professionals. Much in line with research problems and objectives specified, this paper attempts to provide recommendations at a practicable level to begin addressing current challenges and outlines future avenues to develop efficient, interpretable, and clinically applicable ML-based systems for detecting brain tumors.

II. LITERATURE REVIEW

Vani et al. finally presented a mechanism for automatic classification of brain MRI images based on prediction of brain disease. Histogram of Oriented Gradients (HOG) was specifically used as a feature extraction process while Support Vector Machine (SVM) was used for classification. Traditional approaches often had an unnecessary heavy manual intervention, which is a time-consuming way and prone to errors in finding brain abnormalities. The system demonstrated here achieved a classification accuracy of 85%,between diseased and not diseased cases. The method had four major steps: collect data, preprocess, extract features, and classify. In fact, from the very beginning, the MRI data was taken from several sources and divided into two parts: healthy and diseased cases. The learning algorithm watches the patterns of what initially differs from the actual tissue. After Preprocessing, high-quality images were segmented as well as anonymized health records. HOG has been utilized to extract features from MRI images which show the pattern focused on brain disease. In this study, feature extraction is followed up by using the SVM model to predict whether disease exists based on the features that were extracted. Results indicated that HOG-SVM combinations could also classify brain MRIs at an accuracy of 85%, thus showing the promising potential of the combination in speeding the workflow of diagnostics. Speeding disease detection time and increasing accuracy, this will improve overall patient management and care. However, some open limitations remained-the dataset has restricted diversity and the HOG feature extraction was limited in its application. The dataset is to be enlarged progressively in the future and feature extractions need to be done in a much more accurate manner to improve the classification accuracy and reliability [7].

An innovative method of classification and demarcation of brain CT strokes using a explainable ViT based paradigm by Katar et al has showcased. However, state of the art stroke diagnosis on CT images, either in the automated mode or in that which could be explainable, still fails when regions of involvement are to be pinpointed. This study indicates an approach to tackle such challenges using the ViT architecture with data augmentation to train high performance in the accuracy and efficiency of such a model. Implementation on the proposed model included a database of 6651 brain CT images, 4427 normal images and 2224 stroke images contributed by the Ministry of Health of Republic of Turkey. Notably, the model considered two training setups on the imbalanced raw data, whereby the ViT model is first trained without any balancing intervention on the raw dataset and then data is augmented by generating synthetic images for training the model. Patches were produced from CT images, positional encoding was used to build spatial relationships, which are then passed through a transformer encoder with multihead-self-attention using the ViT model. In the process of classifying final outputs, a linear layer with SoftMax activation was used along with Grad-CAM algorithm in order to visualize which parts of the input are attending to the model while trying to make predictions.

The model using the augmented dataset reached an accuracy, precision, recall, specificity of 98.75%, 99.49%, 98.00% and 99.50% respectively, and an F1 score of 98.74%, which is much higher than that of the model trained on unbalanced datasets. On the other hand, Grad-CAM offered visual insight into the areas where the model paid attention, implying an accurate localization. Transformer model (ViT). Most of the currently available methodologies for stroke diagnosis from CT images do not have the right degree of automation and explanation. This could be when it comes to a place in the brain and is expected for it to be affected within that area. The present study aimed at achieving these by use of the ViT framework with data augmentation in efficiency and performance gains. A total of 6651 brain CT images, including 4427 normal and 2224 strokes, provided by the Ministry of Health of the Republic of Turkey, were used for the proposed approach. The proposed method considered dataset imbalance addressed as two conditions of training scenarios, training the ViT model with the unbalanced raw dataset and augmenting data synthetically transforming it. Thus, the ViT model divided CT images into patches, embedded spatial relationships using positional encoding, and processed them through a transformer encoder with multi-head self-attention. The last classification was performed with a linear layer using SoftMax activation, and then the Grad-CAM algorithm was applied to visualize the highlighted areas of model predictions. The model trained on the augmented dataset attained accuracy of 98.75%, precision of 99.49%, recall of 98.00%, specificity of 99.50%, and an F1 score of 98.74%, which is better performance than the model trained on the unbalanced dataset. Moreover, it provided visual insights into what the model focused on with regards to the Grad-CAM algorithm showing strong capabilities in localization. However, such a model could only classify the subtypes of the strokes, thus rendering them useless for stroke presence detection. Such a small dataset did not also get such extent of data which could affect its generalizability by model and deprive deep learning of its full potential [8].

One of the most important contributions of Yu et al. is this exhaustive survey on CNN used in medical image analysis, which includes classification, extraction, detection, and other clinical problems, and the challenges as well as the future research directions in the field. Most current techniques in medical image analysis are usually limited in application to complex visual data, which CNNs are addressing through improved pattern recognition and learning ability. The majorly known CNN architectures in medical imaging including Alexnet, GoogleNet, ResNet, R-CNN and FCNN are included in this review. We survey CNN applications in solving image classification, segmentation and detection, as well as some other extended tasks such as image registration, content-based image retrieval, and image enhancement. Other models that were reviewed under this study have included AlexNet, GoogleNet (Inception v1, v2, v3), ResNet (ResNet-50, ResNet-101, ResNet-152), R-CNN (Faster R-CNN, YOLO), fully convolutional neural networks (FCNN, U-Net). Numerous applications in medical image analysis have been successfully achieved, such as classification, segmentation, detection, etc. The remaining challenges in CNN related medical image data analysis, as stated in the paper, are unavailability of labeled medical data, class imbalance, noise in data, inefficient training, and poor handling of high dimension or multi-modal data. These obstacles are proposed as future research directions [9].

In the research paper by Anaya-Isaza et al., a full-fledged framework for evaluation has been created to evaluate the current state of these types of deep learning architectures for brain tumor classification and detection. Also, the paper presents a novel model, Cross-Transformer, and it compares seven different deep learning networks using MRI data for classifying and detecting tumors in the brain. The framework is meant to fasten and increase the precision of early detection of brain tumors. In this iteration, the Figshare database was used for brain tumors as a starting point to carry out the classification and detection of the tumor in relation to meninges, glial tissues, and pituitary gland tumors using Brain MRI images for tumor detection as well as the TCGA-LGG datasets. The study involved several working components such as T1WI, T1-Gd, and FLAIR-MRI acquisition sequences along with techniques such as data augmentation and transfer learning. This list also includes comparable models as InceptionResNetV2, InceptionV3, DenseNet121, Xception, ResNet50V2, VGG19, EfficientNetB7, and the new Cross-Transformer. This experiment was also repeated using TCGA-LGG data in order to test the MRI acquisition sequences and evaluate the Cross-Transformer performance.

In terms of accuracy, InceptionResNetV2 proved next to best after other networks in classifying brain tumors, by achieving nearly 97% accuracy with a dataset comparatively smaller than the one used by others. A contribution of 6% to the accuracy of detection for InceptionResNetV2 tumors through transfer learning and data augmentation techniques. Thus, the FLAIR proved to be most useful in identifying a brain tumor. On the other hand, this identification was rather less effective for T1WI and T1-Gd sequences. Limitations of the study included small unique subject numbers, 2D rather than 3D imaging, lower access to very large higher quality datasets with consistent resolution, uncertainty of 2D slice selection affecting accuracy in representation for 3D tumor structure, and presence of heterogeneity between TCGA-LGG and all the other datasets [10].

Adinegoro et al. have made the usage of EfficientNet-B7 for brain tumor classification and U-Net for segmentation for a proper diagnosis improvement of brain tumors through MRI images. This study involves class of research that attempts to utilize the potential of these advanced machine-learning techniques that are improving the diagnostic approach for brain tumor patients. The methodology proposed creating an EfficientNet-B7 transfer learning model with more than 66 million parameters for the input into four main tumor classes: No tumor, meningioma, glioma, and pituitary tumor. The model was constructed with an input layer and four hidden layers having 16, 32, and 128 parameters respectively. The segmentation architecture used was that of U-Net with 10 layers, having been constructed from 2D max pooling. This was done through normalizing feature maps resulting from max pooling using Batch Normalization, followed by passing them to the next layers. The research study was also conducted using Python and Google Collaboratory on a laptop with Intel i7 processor and 8GB RAM, using a classification dataset consisting of 7022 MRI images from Kaggle and a segmentation dataset with 110 patient images from TCGA. Effective result showed the EfficientNet-B7 model could score a very good classification accuracy of 95% while the U-Net architecture could score a maximum of 0.99 Intersection over Union (iou) on brain tumour segmentation. This is good data to indicate the possibility of using such machine learning tools to potentially raise diagnosis accuracy in brain tumours and support clinicians in their clinical decision making [11].

Recently, Mahmoud et al. introduced a new convolutional deep learning network model for classifying brain tumors using convolutional neural networks that are optimized by Aquila Optimizer for better accuracy on MRI images. The intention of this work, as part of an ongoing study, is to develop an improved brain tumor prediction system based on an optimized CNN modeling approach and to enhance the application of computer-aided diagnosis in this area. Pre-trained CNN architectures were VGG-16, VGG-19, Inception-V3 optimized with Aquila Optimizer (AQO). The major four phases were included in data preprocessing to process and enhance MRI quality so that it could be classified by any algorithm that is being trained in the MR image dataset. For the models of CNNs, we used a technique called transfer learning-the learned parameters are tailored for the specific task to be accomplished: classification of brain tumors. Finally, we applied the AQO algorithm for tuning down CNN models toward further improvement in the overall metrics. The AQO-optimized VGG19 model achieved the highest accuracy of 98.95% with sensitivity and specificity of 99.1% and 99.6%. VGG 16 with modified AQO having second-best accuracy source, at 98.66%, with Inception V3 model having 97.38% validation accuracy against the AQO. One of the limitations of this study is that pre-trained CNN models do not allow their proper adaptation to fresh medical data, which partially limits flexibility. However, the performance of AQO optimization between datasets may differ, and on bigger datasets, operational costs associated with the application of AQO can provide hindrance for broader applicability [12].

According to Sangui et al., a modified U-Net model was created that predicts regions of brain tumors from 3D MRI images and validated to achieve a test accuracy of 99.4% over the BRATS 2020 dataset while outperforming other deep learning based approaches. The purpose of this study is to develop accessible and more precise segmentation of brain tumors for regions without access to radiology experts. As a modified U-Net structure which is designed specifically for 3D MRI brain tumor segmentation with encoder decoder structure and skip connections, the proposed model is based upon. Normalization and resizing of the BRATS 2020 dataset was performed, and then the model was trained in a Kaggle setup using categorical cross entropy loss function and Adam optimizer on a 4 Tesla P100 GPU for 35 epochs. In this case, Intersection-over-Union (IoU) and Dice coefficient were used as the evaluation metrics for segmentation accuracies. The altered U-Net reports 99.4% accuracy on test cases and performs better than other models like ResNet and VGG16 on multiple evaluation criteria. It displays the way towards proficient, flexible, rapid and accurate diagnostic methods assisted by automated brain tumor segmentation, thus allowing radiologists more time for patients or possibly saving patients from unnecessary treatments. Quite Respectfully, this has tremendous computational and storage requirements for 3D MRI image processing, takes a lot of time to be trained, and still needs to look deep into classifier algorithms. Other, even more critical applications of the model to be applied in clinical settings include testing it across larger datasets in clinical settings for assurance of robustness and generalizability in the real world [13].

Headfirst into brain tumor classification with CNN and CNN-based transfer learning techniques or compare the performances of these models in terms of feasibility for brain tumor detection. So the focus of the research is to develop better brain tumor detection methods on how best to classify an MRI image using the most suitable model. Methodology is revolving around the different deep learning methods with a specific example of CNN. Khaliki and Başarslan adopted the idea of transfer learning where pre-trained models with InceptionV3, VGG16, VGG19, and EfficientNetB4, were used and incorporated into a dataset of 2,870 MRI images, grouped into four: A glioma, meningioma, pituitary tumor, or no tumor. The models were tested using both normal CNN architecture and transfer learning models. The custom CNN model created with several convolutions and max pooling layers was compared further. For the dataset centered, the highest performance is of the VGG16 model with accuracy = 0.98, F-Score = 0.97, AUC = 0.99, recall = 0.98, and precision = 0.98. Indeed, the VGG16 transfer learning model proved to be indeed superior to the other default CNN and transfer learning models by rendering a highly accurate and reliable brain tumor classification from MRI images. Like any other study, however, it has one major limitation- data augmentation techniques such as image rotation or cropping are not employed in this study and can possibly prove into model improvement. This, however, misses the whole point of realizing the true potential of the model generalization under different real-world image conditions because there is no augmentation of the dataset with the image [14].

Patil and Kirange introduced an innovative ensemble deep convolutional neural network (EDCNN) for MRI images tumor classification concerning three types of brain tumors: glioma, meningioma, and pituitary tumors. This EDCNN model combines a shallow CNN (SCNN) and the VGG16 model and applies the proposed hybrid features in order to achieve improved classification accuracy. It aims at going beyond the performance of existing CNN models bymeaningfully combining shallow and deep extraction feature layers. The methodology is illustrated by first designing an SCNN, which extracts high-level tumor features, followed by extracting a more fine-tuned set of features using a VGG16 model. Finally, an EDCNN model that relies on fully connected layers will extract both shallow and deep features. Additionally, the Adam optimizer is involved in training the ensemble architecture in the model. The design of the model consists of elements on which we have to validate our hypothesis to prove SCNN-being 2 optimal for data types having less number of input values. The VGG16 deep learning model . Thus, Building the Ensemble Deep Convolutional Neural Network (EDCNN), merging SCNN and VGG16 features. Adam optimizer for training. The EDCNN model's classification accuracy achieves 97.77% which is higher than those of the previous reported deep learning methods. Due to combined features from SCNN and VGG16, the model accuracy improves, and it achieves reduced information loss and short training time due to the fusion of shallow and deep features. However, the authors put forth that the shallow CNN model hyperparameters can be improved and even optimized using metaheuristic algorithms for feature selection. Secondly, it is noted that shallow CNN alone is insufficient to act as a complete 'neural model' for accurate tumor classification as it adds to the benefit of the ensemble scheme in feature fusion. Apart from furthering their accuracy, the overall model shows lower information loss, which indicates that individual deep learning models may not be as powerful alone as such an approach is [15].

TransUNet is a newly developed U-Net based Transformer architecture for medical images segmentation. This architecture incorporates self-attention and cross-attention in both the encoder and decoder portions of the Transformer. It tokenizes CNN feature map patches for global context capture using tiny targets and tumors and can detect anything that's very small in size. Since this whole course will continue to fine attention, Transformer further extends segmentation. The methodology of TransUNet includes:

1. Transformer Encoder: It captures global context information by tokenizing CNN feature map patch.
2. Transformer Decoder: Segmentation is redefined as a mask classification task with learnable queries which are refined through cross attention mechanisms to improve segmentation precision.
3. Coarse-to-fine Attention Refinement: I have adopted the same in the Transformer decoder to achieve better performance in terms of small target segmentation.
4. Configuration Exploration: Three different setups of the architecture are tested with these experiments: Encoder only, Decoder only, and Encoder+Decoders embedding with U-Net.

Through experiments, it has been demonstrated that for the task of multi-organ segmentation, Transformer encoder greatly elevates the performance while with a finer attention mechanism at its decoder, it stands at a very high advantage at the task of small scale targets segmentation like in cases of tumor localization. The TransUNet so integrated with both global context and fine detail attention far outperforms the state-of-the-art best existing methods for segmentation tasks, though cost-prohibitive to train and very demanding on the computing resource needs.

Again, the 2D version of TransUNet does not appear to show a higher level of robustness compared with the 3D version (which has proved more accurate and efficient in isolating 3D images in medicine) [16]. Khan et al. undertook an in-depth overall review of the current machine learning and deep learning techniques available for diagnosing four major neurological disorders like Alzheimer's, brain tumour investigations, epilepsy, and Parkinson's disease. Diagnosis using conventional methods often involves manual assessments that require a lot of effort and prone to human mistakes. The article shows how effective various ML and DL techniques are based on several studies that highlight the methods found to be most effective in detecting brain disorders. Different models commonly used are SVM, Random Forest (RF), CNN, RNN, and autoencoders. Evaluating the performance of these models used metrics such as accuracy, sensitivity, specificity, AUC, and F1 score. The investigation conducted into the total 147 publications concluded that high-performant models such as VGG16 and CNN were exceptional in analyzing MRI and EEG data and could be most easily used for classifying Alzheimer's disease, brain tumors, epilepsy, and Parkinson's disease. There are, however, a few issues such as the scarcity of annotated high-quality datasets and the opacity of deep learning models that deter their clinical interpretations. The authors suggest implementing some Explainable AI (XAI) strategies to develop model interpretability and trust among workforce professionals. They also thoughtfully presented to resolve the issues of data privacy and promote an interdisciplinary collaboration to improve diagnostic applications of the future towards brain diseases [17].

In this, Odusami et al. advocate for reformed ResNet18 for binary classification purposes of functional MRI brain scans concerning AD with MCI. Traditional diagnostic procedures do not always provide the precision that is required in cases of early detection, particularly where similar stages are involved with the clear linings. Results showed classification accuracies of 99.99%, 99.95%, and 99.95% in the binary classifications of EMCI versus AD, LMCI versus AD, and MCI versus EMCI respectively. This generally surpassed the previous methods in both sensitivity and specificity. Also employed in achieving a dropout rate of 0.2, this has been done to reduce the degree of overfitting and makes the model more reliable as a whole. The whole process relied on the ADNI fMRI dataset that consists of 138 subjects. "Preprocessed the images to JPG format with data augmentation and fine-tuned the ResNet18 model by unfreezing all layers along with the addition of a customized classifier using ReLU activation and dropout regularization" is just how this methodology works. It is believed that this approach lets one's model gain high diagnostic precision related to early-stage AD conditions but without creating false positives and maintaining false negatives to a minimum. Although the model sprints well on binary classification, the authors brought up a couple of possibilities for later work. Such avenues would involve visualization techniques in unveiling how the model arrives at its decisions, exploring hybrid models that incorporate into them other neural networks and extending the model beyond binary classification to serve as a more complete diagnostic tool for AD [18].

An automated computerized system to differentiate the three prevalent brain tumor types Glioma, Meningioma, and Pituitary tumors from MRI had been developed by Ghosal et al. With this system, an overall classification accuracy of 93.83% has been achieved and exceeds existing models. Conventional diagnostic tools always produce inaccuracy in brain tumor classifications. This is especially true when large datasets are analyzed. The study revealed that a deep convolutional neural network model, SE-ResNet-101, was built to enhance the performance of the ResNet-101 architecture by adding additional Squeeze-and-Excitation (SE) blocks. Modification or alteration of this network has made it operational in an efficient way to improve its accuracy for implementation in medical fields. The dataset contains 3064 T1-weighted images taken from contrast-enhanced MRI scans from two hospitals in China, representing data from 233 patients under the three tumor categories. A series of pre-processing steps, such as abnormal ROIs (regions of interest) related to tumor isolation followed by intensity normalization and data augmentation techniques, were applied to these images to improve model performances. The SE-ResNet-101 architecture was trained with the Adam optimizer, early stopping, and learning rate schedule to avoid overfitting, producing accuracies of 98.67% on Glioma, 91.81% on Meningioma, and 91.03% on Pituitary tumors. However, even though the model showed excellent performance, it exhibits certain limitations: it only works on 2-D MRI data and not classified all existing tumor types. Future research can aspire to improve this model by classifying it also under 3D MRI data and additional tumor types. Although this is an investigation into brain tumors, the authors believe that it can be extended to apply to other areas, such as liver lesions, for instance. and breast tumors. Furthermore, the study may have been affected by limitations in funding and collaborative feedback, which could lead to certain biases [19].

Jena et al. study the effect of U-Net depth changes on the performance of brain tumor segmentation. As it turns out, a reduction in U-Net depth can maintain performance levels similar to those of the original model while reducing computational needs. Not only are the typical U-Net architectures vast, but with their depth come great computational requirements that could be a hindrance in many instances, particularly in an operational setting. This research vigorously investigates the diminishing of convolutional pathways-in this case, specifically from the upsampling pathway, thus checking if the model could achieve comparable segmentation accuracy with a scaled-down track. Validating the depth-reduced U-Net schemes with BraTS-2017 and BraTS-2019 for brain tumor segmentation. These consist of varying numbers of convolutional layers (21, 19, 17, 15, and 13) in comparison with the original U-Net comprising 23 layers. Important elements in model composition include convolutional layers for feature extraction, max pooling for down-sampling, and up-sampling through concatenation on the expanding side. Most important results showed that depth-reduced U-Net models substantially reduce computation and hardly compromise segmentation accuracy. Reduction along the upsampling path gives better results as compared to similar reduction along the downsampling path with regard to protection and computational efficiency in segmentation maintenance. The authors claim that the conclusions may be relevant for other contexts of biomedical imaging. However, the authors admit some limitations, such as reduced performance on removing convolutions from the path of downsampling. This highlights the need for careful selection in layer reduction. The study also emphasizes that, while depth-reduced U-Net models show potential in biomedical imaging, the caveats must always be taken into consideration for specific applications"[20].

A hybrid framework was proposed by Ibrahim et al., in which a convolutional neural network is coupled with a particle swarm optimization technique to improve the efficiency of diagnostic analyses for Alzheimer's disease and brain tumors using MRI images. Fine-tuning hyperparameters in the traditional CNN model proves difficult, which can lead to a decline in classification accuracy. Thus, the framework incorporates PSO as part of the automated selection process of most appropriate hyperparameters for CNNs with the intent of improving detection and classification on both Alzheimer and brain tumor detection. PSO, in its turn around the CNN, fine-tunes important CNN parameters such as count of convolutional filters, size of filters, dimensions of pooling layers, striding length, which is the foundation of the approach. In training and evaluating the hybrid PSO-CNN model, have been benchmark datasets such as ADNI dataset for Alzheimer's disease and other dataset for brain tumors. The model uses Particle Swarm Optimization (PSO) over a period of time to refine the model hyperparameters and progressively minimize the loss function while increasing the prediction accuracy. High classification rates attained by the PSO-CNN model include 98.50% for the ADNI dataset, 98.83% for an Alzheimer's dataset, and 97.12% for a brain tumor dataset. The strategy outperformed the most popular transfer learning architectures, including ResNet50, Inception V3, and VGG16, for identifying possible Alzheimer disease and brain tumors and qualified as an option for clinical diagnostics. However, a significant limitation of the model is that it does not classify images accurately when it comes to low resolution and blurry images, which hampers good feature extraction as well. Future investigations will then focus attention on improving the methods that are suited for preprocessing or perhaps examining alternative approaches to solve the problem of degraded images [21].

A deep learning approach for brain tumor classification using ResNet-50 architecture with transfer learning was proposed by Sahaai et al. This model showed exceptional performance on the brain tumor dataset. This methodology proved to be different from usual computational intensive methods when manual feature extraction from MRI images were used, which turned out to be a useful alternative for efficiency to traditional classification methods. The advanced ResNet-50 model which incorporated transfer learning achieved a validation accuracy of 95.3% thus acting as assistance towards the exact multiclass classification of brain tumors.

This approach relied on an open-access brain tumor database that got severely pre-cooked images and various data augmentations such as rotation and flipping that enhanced the robustness of the model while reducing overfitting. Using residual connections of the ResNet-50 model effectively mitigated the vanishing gradient problem in deep neural networks for better performance. Application of transfer learning and hyperparameters optimization such as low learning rate and suitable optimizer significantly reduced training time and computing requirement compared to the conventional training from scratch. Interestingly, the classification accuracy delivered by the ResNet-50 model was 95.3%, which has the capability to differentiate between several classes of brain tumors. Efficiencies and effectiveness of the transfer learning technique include a 50% cut in training time and computations. Further authors developed a mobile app based on this model so that health professionals would assess patients quickly and give treatment recommendations in time. Limitations of this study include the fact that it was based on just one modality-imaging modality: MRI. It would be interesting to do research in the future incorporating other imaging modalities since there is a considerable opportunity to improve model accuracy and efficiency by increasing the amount of data set, tuning the hyperparameters, or exploring different possible architectures, such as U-Net. Future directions of research might further analyze multi-modal data for a more general framework of tumor detection [22].

Roy et al. introduced a new deep learning pipeline using the ResNet-152 architecture for the diagnosis of Alzheimer's disease. Conventional diagnostic methods have been inefficient and have an unreliable prognosis, especially at the early stages of the disease. The model reported an excellent performance achieving 99.30% accuracy on the binary classification test (Alzheimer's Disease vs. Cognitively Normal), while 98.79% accuracy was achieved multiclass classification across the four stages- Alzheimer's Disease (AD), Cognitively Normal (CN), Early Mild Cognitive Impairment (EMCI), and Late Mild Cognitive Impairment (LMCI). The technique also included transfer learning from the pre-trained ResNet-152 model, alongside robust preprocessing strategies, such as brain extraction with the Brain Extraction Tool and noise reduction using the SUSAN Noise Reduction. Translation of excellent classification capabilities of ResNet-152 model into clinical practices is expected to significantly benefit patients' affordable, early detection and management of Alzheimer's disease. The exclusivity of MRI data poses limitations on the study, as it could restrict accessibility and applicability in environments lacking advanced imaging facilities, and the model needs to be fortified further by a greater range of imaging techniques. Future endeavors could target multi-modal imaging data to enhance not just classification effectiveness, but also generalization [23].

In this research work, an effective framework for multiclass brain tumor classification is 'Developed' by Basthikodi et al. which used SVM as a primary classifier. Furthermore, this framework contains various feature extraction techniques, such as Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP), and this has a dimensionality reduction process using Principal Component Analysis (PCA) for improving model performance. Most of the conventional classification means focused on binary or ternary classifications and heavily depended on resource-hungry deep learning algorithms, which limited their applicability in practicality. The currently proposed framework was found to be successful and managed to achieve a phenomenal 96.03% accuracy in a four-class brain tumor classification problem-a clear improvement over existing approaches. The high accuracy, F1 measure, precision, and recall have all been measured at over 96% with the integrated use of SVM with PCA, HOG, and LBP, as verified by ROC curve evaluation. This model gives a quite economical computing tool for the overall multiclass classification of brain tumors and hence very feasible clinically. However, the authors also present the research limitations, such as difficulties with multiclass classification and the need for larger, more varied datasets to better the model's strength and applicability in the real world [24].

Dheepak et al. presented a novel framework for classifying brain tumors based on hybrid feature extraction using an ensemble of custom kernel functions in an SVM classifier. Traditional methods often failed in capturing fine structural and textural details or took plenty of computational resources for them to be considered effective in actual clinical applications. In an attempt to overcome all these challenges, the presented method incorporated GLCM and LBP in feature extraction to capture textural and spatial detail. Further, dimensions were reduced and selected by PCA for enhancing computational efficiency. The SVM classifier was basically equipped with four custom kernel functions which include Minkowski-Gaussian, exponential SVM, histogram intersection, and wavelet-meant to boost classification accuracy. The framework had a very thrilling overall accuracy of 93% in classifying glioma, meningioma, and pituitary tumors and was better than most advanced methods. Performance metrics included precision, recall, F1-score, Cohen's kappa coefficient, Matthews correlation coefficient which were used to evaluate the system and proved strong and reliable. The application of SMOTE for balancing classes also addressed the challenges associated with imbalanced data sets, ensuring that fair assessments were made of the model. The study, however, identified some limitations, including multiclass classification, and a need for the model to become more efficient in computation so as to improve its applicability in real life clinical setting environments [25].

Kemila and Al Maki et al. have put forward an innovative model that integrates Support Vector Machine (SVM) classifier with River Formation Dynamics (RFD) algorithm to enhance the brain tumor classification accuracy. The tumor is classified correctly to enable effective treatment; however, the traditional approaches are not truly optimizing the classifier's parameters for the best performance. This problem is remedied by SVM-RFD, which adjusts the SVM parameters, such as C and gamma, using an RFD nature-inspired algorithm to increase the efficiency of the classifier. The experiment produced a classification accuracy of 87.56% for the SVM-RFD model, which is 13.19% better than the traditional SVM model, which has 74.37% accuracy. The method applied Histogram of Oriented Gradients (HOG) for feature extraction and preprocessing consisted of rescaling MRI images and converting them into grayscale. The combination of RFD with SVM would therefore optimize parameters effectively so that SVM-RFD outperformed any previous work that incorporated SVM for brain tumor classification. However, it must be stressed that the study found a limitation in that the classification accuracy for the pituitary tumor class reduced when the SVM-RFD model was compared with the standard SVM model. This limitation was answered by the authors, who will explore further studies to consider different parameter values within the SVM-RFD framework in order to overcome this limitation and to provide better results from this model [26].

Standard methods for segmentation and detection of brain tumors have been deferred from Bahadure et al. and are based on Berkeley Wavelet Transformation (BWT) for feature extraction. The Support Vector Machine (SVM) classifier classifies the tumor. The method gives high accuracy, sensitivity, and specificity in discriminating actually normal from abnormal tissues of the brain in MRI images, establishing a foothold for clinical application. Preprocessing consists mainly of signal-to-noise enhancement, artifact removal, and skull stripping to liberate brain tissue from non-brain tissues. BWT was used to segment brain tissue and extract two fundamentally different kinds of features: texture-based features and histogram-based features. All features were given to SVM classifier training to classify normal and abnormal tissues. Multiple steps have been taken into the segmentation, including thresholding, binarization, and morphological operations. The results reflect a classification accuracy of 94.2%, specificity was attained at 96.51%, and the sensitivity was 97.72%, which thereby generates a dice similarity index of 0.82. The results reveal an agreement between the automated and manual segmentation conducted by radiologists. Authors have suggested that the present methodology can be incorporated into clinical decision support systems toward screening and diagnosis of tumors by radiologists and clinicians. However, the technique will have serious drawbacks. The future scope will be to develop an advanced multi-classifier system integrated into the sophisticated feature selection techniques. This will further enhance the classification accuracies of existing systems. Increased sensitivity is expected to further generalize the methodology and make it robust enough to be tested on a larger and more diverse dataset for application in clinical setups. [27].

Gavkare et al. came up with a machine learning framework that classifies brain tumor types based on MRI images. The proposed framework used Histogram of Oriented Gradients (HOG) feature descriptor with different classifiers. Out of all classifiers applied, the best one was found as XGBoost classifier of 90.91% accuracy. This method captures all crucial features of the intensity gradient across brain tumor images that are helpful in defining and classifying tumors like gliomas, meningiomas, and pituitary tumors. The process involved preprocessing the MRI images by resizing them to an image size of 200x200 pixels, converting to gray scale, and applying the median and mean filter to reduce noise, after which the HOG feature descriptor was used to obtain a feature vector of length 3780 comprising attributes such as size, shape, texture, and intensity. Various classifiers, including XG Boost, Gradient Boost, and K Nearest, were applied in the framework [28].

Gavkare et al. demonstrated a new methodology for the classification of brain tumors using Histogram of Oriented Gradients (HOG) features and using multiple classifiers from Machine Learning. Tumor manual classification is also often tedious and error-prone, especially for large volumes of MRIs. Hence, the automated technique solves the problems, improving accuracy and efficiency in tumor identification. Their approach had excellent precision in brain tumor classification: the XGBoost model surpassed the other models such as Gradient Boosting, SVM, Logistic Regression, and KNN, considering an accuracy of 92.02%. It covers all phases, including preprocessing, feature extraction, enhancement of images, and spectral analysis, to identify the tumor's signature from MRI scans. The XGBoost model is best optimized for maximum depth at a learning rate of 0.01, and very astounding results were gathered by precision and accuracy. Although constrained by a small dataset, this technique promised a lot for brain tumor detection accuracy. Still, the study was limited in terms of the number and variety of the database, which needs further investigation with extensive and more diversified datasets. Furthermore, the study is still awaiting regulatory approval, and validation and testing are required to fulfill medical device standards [29].

III. RESEARCH METHODOLOGY

A. Research Approach: Quantitative, utilizing supervised deep learning and machine learning models**.**

B. Process for Literature Review and Selection

We used Title/Keyword “Brain Tumors detection using machine learning" and "Brain Tumors detection using deep learning" in the form of journal articles or conference pages for peer-reviewed ones by Google Scholar. It was determined that studies in the range of 2019 to 2024 would be accentuated. However, whenever appropriate, older literature was included. Inclusion criterions were set for studies specifically focused on the subject of the brain tumor detection through machine learning, especially those dealing with topics such as feature extraction methodologies, advanced architectures of neural networks, and comparative analyses of machine learning techniques. The process was initiated by reviewing abstracts, only including documents that appeared to fit the research subject under consideration. Articles from this review were excluded if they had no quantitative evaluations or were unrelated to brain tumor detect.

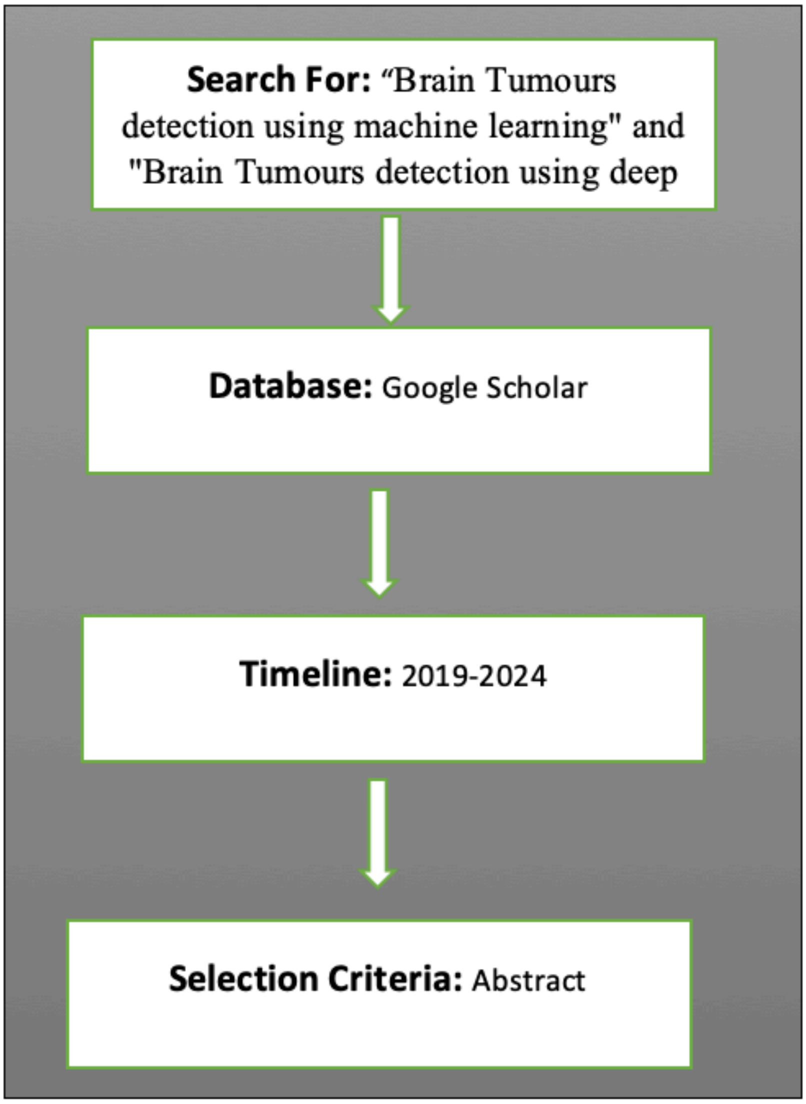

Fig. 3: Diagram of Selection of Paper For Literature Review

IV. DATA COLLECTION

A. BraTS Dataset

The Brain Tumor Segmentation (BraTS) dataset is one among the very important datasets available in the field of brain tumor research. For example, it includes various kinds of MRI images, such as T1, T2, T1-contrast, and FLAIR. The annotations for sub-regions of a tumor include enhancing tumors, peritumoral edema, and areas of necrosis. The dataset renders 3-dimensional volumetric data and helps researchers investigate segmentation and classification tasks in a practically clinical environment. BraTS is known for its comprehensive annotations done by professional radiologists and considered a standard for the evaluation of developed ML and DL algorithms. However, with respect to the population of subjects in comparison with common imaging datasets, this dataset is comparatively very less populated, which makes generalization difficult; therefore, there is a need for augmentation methods or synthetic data to enhance model robustness.

B. Kaggle Brain MRI Dataset

Kaggle has numerous datasets such as brain MRI datasets for the purposes including, and not limited to, the differences between detections with classification for either the presence or absence of tumors and multiclass classification of tumor varieties like gliomas, meningiomas, and pituitary tumors. These data are essentially 2D slices gained from an MRI volume. They are pretty handy for easy sample representation. While Kaggle datasets will probably not have the same 3D context or finer nuances in annotation detail as would be the case in BraTS, they are indeed useful grounds on which researchers can use less complicated classification tasks. The real-world variability (noise, resolution changes) makes these datasets an ideal source to evaluate the robustness of machine learning models.

C. Figshare Brain Tumor Dataset:

Figshare brain tumor data contains different types of T1-weighted MRI images, which are categorized into the following three types of brain tumors: gliomas, meningiomas, and pituitary tumors. This dataset is often used for tumor classification because of its balance in the number of tumors and its accurate labels; since it is available in 2D, preprocessing can therefore be easy and fast, thereby quickly facilitating the training process. However limited in number of images with no multimodel sequences, such shortcomings show its ineffectiveness in superior segmentation or classification task operations requiring 3D data.

V. DISCUSSION

A. Comparative Analysis of Medical Imaging Techniques for Detecting Brain Tumors

a) Magnetic Resonance Imaging (MRI)

Magnetic Resonance Imaging (MRI) is largely accepted as the optimal technique for the detection of brain tumors, given that it shows unmatched ability to demonstrate structures in soft tissue. Using magnetic fields with radiofrequency pulses, high-generating-three-dimensional-images of the brain are produced to facilitate accurate localization and characterization of tumors. It is also superior in defining tumor borders, peritumoral edema, and infiltrative patterns. Functional MRI (fMRI) and Magnetic Resonance Spectroscopy (MRS) are explanatory approaches that complement classic imaging with functional and metabolic information about the tumor. Unfortunately, despite this high sensitivity of MRI, it still has limitations, including prolonged scanning times, artifacts, especially among patients with metallic implants, cost, and complexity, all of which could inhibit the availability of this procedure in certain healthcare settings.

b) Diffusion Tensor Imaging Technique (DTI)

Diffusion Tensor Imaging technique is among the more sophisticated techniques available for magnetic resonance imaging (MRI). This assists in charting white matter pathways in the brain by tracking how water molecules diffuse throughout their internal structure. It is invaluable in the identification of tumors that invade or disrupt white matter pathways, mostly gliomas. The information produced by DTI includes quantitative measurements such as Fractional Anisotropy (FA) or Mean Diffusivity (MD) that help in assessing the condition of white matter and differentiating tumors at vary extent or types. Its advantages include proper mapping of important brain structure involved in surgical planning; However, DTI does suffer from motion artifacts or may show resolution problems in the identification of crossing fiber tracts, which might reduce the accuracy in tractography.

c) Computed Tomography (CT) Scan

Computed tomographs basically use X-rays in producing cross-sectional sections or slices of the brain. It is a very quick and easy way of diagnosing a brain tumor. It is very good at picking out that which is typically associated with a tumor that has calcifications, that has bleeding, or that is affecting any adjacent bony structures. With contrast agents, that brings in CT the opportunity to visualize tumor outlines and blood supply very well. These advantages, however, come with certain limitations since soft tissue contrast is not as good as that of MRI and there are health risks involved in the ionizing radiation exposure. However, with all these limitations, CTs still serve as an invaluable adjunct to emergency and initial assessment.

d. Positron Emission Tomography Scan (PET)

PET scans, which analyze metabolic activity in brain soft tissues, serve to create functional imaging. The patency of this form of imaging has been based upon the use of radiotracers, especially fluorodeoxyglucose (FDG), which tend to be deposited in sites of heightened glucose metabolism, commonly indicating malignancy. PET provides opportunities in differentiating malignant and benign tumors and examines tumor recurrence versus changes induced by treatment, which may include radiation necroses. PET is associated with challenges, such as a less spatially resolved comparability with MRI or CT and the use of radioactive tracers, which limit its repeated application. On such constraints, PET is a necessary adjunct to structure imaging techniques and illuminates otherwise unique aspects of tumor biology.

B. Comparative Analysis of Machine Learning Model Technique:

a) Support Vector Machine Classification Technique (SVM):

The popular machine learning method, Support Vector Machine (SVM), is used mostly for classification tasks. It uses a hyperplane that separates the two classes of data and maximizes the margin between them. SVM works marvelously in high-dimensional spaces and comes with the advantage of reduced overfitting if proper kernel functions have been applied. SVM-based brain tumor detection ends with combining SVM with feature extraction methods like Histogram of Oriented Gradients (HOG) and Principal Component Analysis (PCA) to extract important features from MRI scans and ultimately boost their classification accuracy. Part of the best thing about SVM is that it allows for the creation of non-linear boundaries by using kernels like the Radial Basis Function. SVM requires a lot of resources computationally, especially when working with large amounts of data, and sometimes requires perfect tuning of hyperparameters for best results. SVM also does not perform well with noisy data and is sensitive to kernel-and-margin selection.

b) CNN Technique:

CNNs are sophisticated deep architectures designed to serve specific purposes in the image processing domain such as classification and segmentation. The convolution layers allow CNNs to autonomously capture spatial hierarchies of features from input images, therefore exhibiting high efficiency in pattern detection such as tumor identification in medical imaging. Frameworks like VGG, Resnet, and AlexNet have been successfully utilized in the classification and segmentation of brain tumors. What makes CNNs important is their ability to gather sophisticated features directly from the raw image data, eliminating the need for any kind of feature extraction. They also work well on huge image datasets and, even more so, in transfer learning models where pretrained models are fine-tuned for particular applications. They, however, would require huge computational resources as well as large labelled data to be effective. Furthermore, without proper regularization, they are prone to overfitting and may not allow much scope in terms of interpretation of the learned features.

c) U-Net Architecture:

The U-Net architecture is a typical example of convolutional neural networks designed specifically for semantic segmentation in medical image applications. It is an architecture in encoder-decoder format incorporating skip connections that provide the segmentation of images while preserving much of the fine detail. The most considerable strength of U-Net lies in its capacity to yield pixel-wise predictions, making it a turn-on for tumor segmentation in MRI or CT image. The symmetrical layout of U-Net would hold the very spatial information relevant to tasks in the medical imaging domain. U-Net is most likely advantageous in the situation of a very small amount of labelled data, where it usually requires much lesser number of training samples compared to other deep learning techniques. The cost it carries is that of more computation and not working very well under substantial noise or artifacts in images. Furthermore, it would be best to use U-Net in combination with other models to achieve the classification purpose even though it is excellent in segmentation.

d) ResNet Models (ResNet-18, ResNet-50, ResNet-152):

The ResNet (Residual Networks) model consists of deep learning frameworks that are used to address the very commonly arising vanishing gradient problems while using deeper networks. ResNet gave a solid ground for training much deeper networks which can be used to describe more such complex patterns by using residual connections. In the realm of brain tumor identification, models such as ResNet-50 and ResNet-152 are used as classifiers and feature extractors for the recognition of tumor cells. The important feature attributed to ResNet was in enabling the training of the extremely deep networks without loss of performance, something very important for processing complex high-dimensional medical images. Residual connections also work to improve gradient flow during training and thus help stabilize a model. On the downside, ResNet models can be memory hungry and computationally expensive, especially during deeper iterations. Although effective, they are often trained on very large datasets and their performance relies heavily on network depth and hyperparameter settings.

e) VGG (Visual Geometry Group) Models (VGG-16, VGG-19):

The VGG models are indeed deep convolution networks that aim to have simple yet consistent architecture with successive layers of smaller 3x3 convolutional filters upon ReLU activation, mainly focused on extracting features by depth via “stacking” convolutional layers then connected fully into a single classifier. The VGG models extend into VGG16 and VGG19, which had been used in medical image analysis and brain tumor detection due to the hierarchical representation learned using such models. They are mainly because of simple architecture and great implementation efficacy of these models with large datasets, thus making the benchmark of image classifications. However, very deep models such as these usually require huge computational resources and memory and have propensities toward overfitting when trained on smaller datasets. Unlike the shallow older models or hybrid CNN-SVM structures, VGG models have embedded learning deeper into the data representation, thus accustomed to more intricate patterns of data. On the contrary, they are concerned only with depth feature extraction and fail to consider the union of shallow and deep features present in hybrid models. Also, unlike others, they are poorly equipped to handle three-dimensional data corresponding to the case, well understood in models like U-Net that are used in better volumetric medical data. For thus, VGG models are an excellent asset in medical imaging while being computationally expensive.

f) Inception Models (InceptionV3, InceptionResNetV2):

The above-mentioned architectures of deep learning, for instance, the InceptionV3 and InceptionResNetV2, are multi-branch architectures where sets of convolutions varying in kernel size are performed to capture different feature patterns resulting from multi-scaled analysis. They are, thus, one of the most efficient models tested on various tasks, including brain tumor detection via image classification. Perhaps, this is the greatest boon of Inception models-their aptitude for handling multi-scaled and multi-dimensional features essential for the variety of possible tumor attributes in medical imaging. This is further supported by the fact that they are factorized convolutions and consequently lower in computational complexity level; this lends speed and memory efficiency compared with other deep learning architectures. While this kind of design is generally overly complicated in terms of interpretation, compared to very simple models, it requires a great deal of labeled data and computational power to be effectively trained. The models can, however, be influenced by the fine-tuning of their configuration of Inception blocks.

g) EfficientNet Models:

A family of such convolutional neural networks is EfficientNet. These are built to optimally use their accuracies, execution speed, and model sizes. EfficientNet is a compound scaling methodology using which scales a network along its depth, width, and resolution while providing very high accuracies with lesser parameters and less computation when compared with other architectures like Renat and Inception. EfficientNet showed some impressive performance in image classification tasks, like brain tumor detection, in comparison to those from popular architectures of CNN-types - while needing lesser computing power.

Paramount advantages of EfficientNet include achieving state-of-the-art results with fewer parameters, making it memory and computation efficient. While on the other hand, - EfficientNet is not as popular or studied widely in comparison to other models regarding application in medical imaging, i.e., community support may be limited. Also, the whole scaling process needs a lot of careful tuning - so trade-offs would not be properly managed.

h) Random Forest Method (RF):

We have the random forests, which is from ensemble learning, which makes a lot of decision trees and classifies data according to the majority vote of those trees during the learning of the data. Random Forest can classify some tumors through their textural, shape as well as intensity descriptors when it comes to brain tumor classification. The main forte of RF is that it is quite resistant to overfitting while also dealing with the high dimensional dataset, as it reduces the variance through the average prediction across many trees. Besides, this approach is simpler to implement and interpret compared to deep learning alternatives, however, Random Forest models are not always scalable with the growing datasets which would mean more computational inefficiencies as tree count increases. Moreover, unlike deep learning models that learn spatial or hierarchical features with less input from users, RF completely lacks this internal capacity and therefore works exceptionally less in tasks like tumor segmentation.

Every algorithm has its bright sides and flip sides. SVM works fine on small data sets and also a binary classification problem, while more complicated image processing and segmentation problems can be taken care of easily by ResNet and U-Net models based on CNN. Inception and EfficientNet are models that extract features efficiently at less computational cost; Random Forest is helpful for huge data with low computational cost. Algorithm selection is dependent on the specific requirement of the task, the amount of data and computation that can be allocated for the process.

TABLE 1: Model(s) for Detecting Brain tumor and their accuracy

SR.No.	Author	Model	Technique	Dataset	Accuracy
1	Sanui et al.	U-Net	Deep Learning (DL)	BraTS-2020	99.40%
2	Sahaai et al.	DNN-ResNet50	Deep Learning (DL)	Fig Share	95.30%
3	Patil and Kirange	Ensemble Deep Learning Model (EDCNN)[SCNN+VGG16]	Deep Learning (DL)	Fig Share	96.49%
		VGG16 Model	Deep Learning (DL)		95.00%
		Shallow CNN Model (SCNN)	Deep Learning (DL)		77.96%
4	Adinegoro et al.	EfficientNet-B7 and U-Net	Deep Learning (DL)	Brain tumor MRI dataset. Kaggle(2018)	95.00%
5	Bahadure et al.	SVM with GLCM	Machine Learning (ML)		96.51%
6	Basthikodi et al.	SVM with HOG, LBPAnd PCA	Machine Learning (ML)	Kaggle	96.02%
7	Dheepak	Distinct Customised Kernel	Machine	Fig Share	93.00%

	et al.	(Ensemble) with SVM Classifier	Learning (ML)		
8	Gavkare et al.	XG Boost	Machine Learning (ML)	SARTAJ,Br25H and Fig Share	92.02%
		SVM	Machine Learning (ML)		74.20%
9	Kemila et al.	SVM-RFD	Machine Learning (ML)	SARTAJ	87.56%
10	Vani et al.	SVM	Machine Learning (ML)	Not Mentioned Properly	85.00%
11	Mahmoud et al.	VGG-19 with AQO	Transfer Learning (TL)	Br35H: Brain Tumor Detection 2020	98.95%
		VGG-16 with modified AQO	Transfer Learning (TL)		98.66%
		Inception-V3 with AQO	Transfer Learning (TL)		97.38%
12	Khaliki Başarslan	VGG-16	Transfer Learning (TL)	Brain tumor classification (MRI). Kaggle (2020).	98.00%
		EfficientNETB4	Transfer Learning (TL)		97.00%
		InceptionV3	Transfer Learning (TL)		96.00%
13	Ghosal et al.	ResNet-101	Transfer Learning (TL)	Collected From Hospital	93.83%
14	Jena et al.	U-Net	Transfer Learning (TL)	BraTS- 2017 and BraTS-2019	89.00%

C. Comparative Analysis of Feature Extraction Technique:

a) Histogram of Gradient Orientations (HOG):

Histogram of Oriented Gradients (HOG) is one technique for feature extraction, wherein small regions are examined to find the fundamental orientation of gradients rain. This means the larger image is partitioned into smaller blocks or what is known as a cell with a histogram plot for that cell measuring how these cells are oriented in terms of the direction of gradients. Normalizing these histograms renders unavoidable the change in the lighting and contrast conditions, thus making it more robust for classification. HOG is very widely used overall in object detection, especially when texture and shape become vital, like in medical image analysis of brain tumor detection. It is very capable in capturing structural and edge features that will eventually help differentiate tissues in various medical image cases. Moreover, HOG is very stacked for real-time applications. Furthermore, it is also invariant to small translations and rotations of objects in image which further reinforces the strength of the feature extraction process. On the contrary, it is highly sensitive to large scaling of objects, rotations, and so on and therefore may affect the accuracy of the classification in some scenarios. It doesn't pick up fine details in an image such as texture changes which might be very important for some tasks, such as tumor detection.

b) Principal Component Analysis Algorithm (PCA):

Principal Component Analysis (PCA) is a widely used statistical method for reducing the dimensionality of data. which is meant for transforming the collection of correlated features into uncorrelated components. It reduces the dimensions of the original data by projecting them onto a smaller set of principal components reflective of maximum variance. Much valued in feature extraction, PCA indeed minimizes the dimensional values while simplifying high- dimensional data complexity without loss of original information. Accordingly, PCA with respect to medical imaging helps diminish the number of features needed in brain tumor classification, hence reducing the processing effort in handling subsequent analyses. This method is considered a viable one for reducing the computation's complexity by keeping the important features while throwing noise or less important details resulting in faster processing and classification. Moreover, It Possesses Strong Potential in the Visualization of High-Dimensional Data in Dimensionally Reduced Spaces For Better Pattern Analysis. One major limitation of PCA is its assumption of linear relationships among features, which may be less valid in complicated medical datasets. Further, it requires too large a dataset for optimal results, and its derived components may not be readily interpretable, making it difficult to extract meaningful insights concerning the reduced features in a medical context.

c) Local Binary Pattern Method (LBP):

The Local Binary Pattern is a texture-based feature extraction technique that compares each pixel with its n neighboring pixels to derive local texture information. It gives binary values based on the thresholding of the neighborhoods around each pixel in reference to the value at the center pixel. The features extracted from the LBP are useful in image classification applications, even in texture analysis for a medical image in which the tumor and non-tumor tissues are separately classified. LBP is mostly employed in MRI and CT images for detecting tumors simply and efficiently. The method involves both computational efficiency and simplicity of implementation, making it hold good in large-scale image classification tasks. It's impressive for extracting the crucial texture patterns that help distinguish different types of tissues in medical imaging and is invariant to monotonic gray-scale changes; hence, it is robust against variations in illumination changes. LBP noise, however, and it is particularly bad in images characterized by a low resolution; it tends to be incapable in terms of fine-texture discrimination. Global feature spotting or representation of complex image shapes is another area where it lacks excellence. Additionally, it has lesser robustness to those transformations which involve scale and rotation, which impacts its performance in some instances.

d) Gray-Level Co-occurrence Matrix Technique:

The Gray-Level Co-occurrence Matrix is a statistical method when data has to be processed in descriptive terms for spatial distances caused by the intensity of each pixel through an image. In this way, the method treats a pair of pixels through one or more angles and at given distances before finally checking the frequency of pairs. Therefore, it creates a matrix, which usually is known as GLCM. Most GLCM texture features like that of contrast, correlation, homogeneity, and energy are indeed important for distinguishing different tissue types in medical images. This method is extensively used for tumor identification, where textures of normal and abnormal tissues become very important for diagnosis purposes. The defining texture features which differentiate tissues are best captured using GLCM. According to its general definition, it gives essential information concerning spatial-wise arrangements of pixel intensities and is frequently very critical to the classification of medical images.

Consequently, GLCM could be useful when it comes to gray variation in brightness in medical images since it had very high effectiveness, especially with respect to tumor identification or any anomalies. Another major factor is computational requirements or extra effort that is required for any high-resolution image and large datasets. The features of GLCM are significantly affected by noise because they are enriched by it; thus, GLCM will show a poor performance when considered for a noisy environment. This method also highly relies on an exact choice of parameters like distance and angle of pixel pairs, which drastically influence the feature extraction process.

VI. RESEARCH GAPS

Noteworthy advancements have been witnessed over the years in the branch of machine learning (ML) intended for automated detection of brain tumors, though there still remain quite a lot of research areas to be explored. Largely, the research has been limited to the 2D MRI scans, which, due to their lack of representation of the complex 3D nature of the tumor, do not allow for high-precision diagnosis nor make models widely applicable. Furthermore, there is the absence of a lot of extensive annotated datasets, which will generally offer good performance for generalized ML systems as they are usually biased by small or unbalanced datasets. Strong architectures like CNNs and U-Net have produced very promising results but have yet to gain acceptance in the clinical environment because the very reason they possess interpretability limitations. Several of the investigations also disregard multimodal imaging approaches which could complement the MRI with CT or PET parts and provide possibly additional information about the characteristics of the tumors. These gaps have led to the need for scalable, interpretable, and multimodal ML-based solutions towards the augmentation of the accuracy and clinical relevance of brain tumor detection-needs that this research proposes to address.

VII. CHALLENGES

A. Limited Dataset Size and Class Imbalance:

A notable limitation with regard to medical image categorization is the restricted size of some of the datasets. This is detrimental to the model's capability to generalize. Furthermore, the issue has a class imbalance, rendering quite hard the detection of certain uncommon types of conditions/tumors. The views regarding the necessity of bigger and more diverse datasets that can more effectively represent the wide spectrum of medical conditions and patient populations were converging. Bigger datasets would mean superior reproducibility and accuracy in constructing the models for translating texts into real-world clinical use.

B. Issues with Data Quality and Preprocessing:

The primary hindrances from low-resolution, noisy, and vague features in medical data have great limitations within mitigating the model performance, especially in the area of brain tumor detection. Moreover, unelaborate preprocessing techniques like ignoring rotation, cropping, and things like that as failing to adopt those techniques affect the generalization capability of the model.

C. Constraints in Computation and Storage:

The main bottleneck is the requirement for extensive computational power and storage capacity, especially in 3D medical images such as MRI and CT scans. Long training periods and substantial resource requirements pose significant challenges to implementing deep learning models in a real-life clinical scenario.

D. Complexity of Models and Interpretability Issues:

One of the most critical restrictions is that CNNs are mostly uninterpretable models, which is especially serious when making medical decisions involving issues like trust and transparency. adoption of the Explainable Artificial Intelligence (XAI) tools will solve such problems. Moreover, the inefficiency of models regarding their task such as differentiation of several stroke types or tumor classifications limits their application in broad diagnostic services.

E. Narrow Focus and Use of Single Imaging Modality:

Many models suffer from being modality specific (e.g. MRI) and lack the generalization to the other modalities such as CT or PET scans. This limitation prevents the model from being sufficiently flexible or effective in detecting tumors under various conditions. In addition to that, preference to 2D images over 3D volumes actually diminishes the amount of information that can be gained from the medical images.

VII. FUTURE OPPORTUNITIES

A. Advancements in Feature Extraction and Model Architectures

The dedicated efforts are being carried out for improving feature extraction methodologies and enhancement of model architectures for increasing classification accuracies and robustness. The next goal for researchers is to cure all the pre-existing flaws in the latest models like Vision Transformers (ViT), U-Net, and deep convolutional networks while being applied to 3D medical imaging data. There will be hybrid approaches where shallow and deep features are combined and ensemble methods to reduce loss of information and enhance overall performance. These together with hyperparameter optimization techniques such as Particle Swarm Optimization (PSO) aim to increase the potency of prediction in models to make them most capable in interpretation of medical images.

B. Expansion and Quality Improvement of Datasets

It is necessary to increase the size, diversity, and quality of datasets to ensure the improvement of reliability and generalization of medical image analysis models. Future research will address the dearth of data by exploring approaches such as crowdsourcing the long-term availability of annotated data, establishing collaborations with radiologists, and deploying advanced data augmentation techniques, including rotation and cropping. Building datasets formed from classes with balanced representation and consistent annotation is, therefore, a supplementary requirement in addressing challenges such as class imbalance and noise in data. Integrating multi-modal datasets featuring MRI, CT, and PET scans, as well as other types of data, would further benefit model building towards more complex and varied challenges relative to medical imaging.

C. Application in Clinical Settings

That is an AI model trained on data till October 2023, and those are the aspects that are critical in validating AI models for assessing their effectiveness in assisting healthcare providers in creating direct applications It will be possible to evaluate validity and reliability, as well as applicability for diagnostics and treatment planning, with these models being tested in clinical trials and field tests from which such data can be derived. In addition, Incorporating Explainable AI (XAI) strategies would significantly enhance the trust in these technologies by making their entailments as transparent as possible. The anticipated trend is that these artificial intelligence algorithms will handle more sophisticated tasks in the future and become an integral part of everyday medicine. including multiclass classification, predicting patient outcomes, and supporting early disease detection. All of them ensure greater relevance to healthcare applications for AI-based tools.

D. Integrating Advanced Modalities and Hybrid Strategies

The inference recognizes the increasing integration of advanced imaging modalities and hybrid strategies into research solutions that can effectively improve diagnostic performance. Future studies will integrate MRI with PET scans and other acquisition modalities like FLAIR for more comprehensive investigations on medical conditions. 3D volumetric imaging instead of the 2D slice-bases evaluation should be used in capturing the extreme spatial relations the medical data has, which is expected to improve the accuracy of diagnosis. Moreover, tensor-based models have been suggested for analyzing multimodal, high-dimensional data to provide a better way to achieve efficacious solutions for intricate medical imaging problems.

E. Enhancing Efficiency and Computational Optimization

It's important to increase the computational efficiency of AI models so they can be really used in applications in medicine. Further research would concern reducing the cost of training, memory requirements, and inference times of heavy architectures such as TransUNet and CNN-like models. It includes scalable algorithms, light architectures, and optimization techniques that make these models computationally efficient and deal with huge datasets. Eventually, such advancements would open possibilities for real-time deployments of AI systems, especially in poorly resourced clinical settings.

Engaging in the enhancement of the computational efficiency of AI models in real life is a concern when it comes to using that in medical applications. Future studies will focus on cutting down the costs of training, memory requirements, and inference times for heavy architectures, such as TransUNet models, based on CNN. Proposals will stretch through scalable algorithms and lightweight architectures, as well as optimization techniques, to ensure these models remain computationally efficient and applicable to vast datasets. These would ensure, in the end, real-time deployment of artificial intelligence systems, particularly in under-resourced clinical conditions.

IX. CONCLUSION

Machine learning (ML) has emerged recently as a disruptive technology in the analysis and classification of tumors, specifically in the brain-used analysis and ultrasound. It has enabled deeper analysis, including complex structures, which are not easily visible in medical imaging. CNNs, SVMs, and hybrid models have shown potential in improving diagnostic accuracy and aiding early diagnosis of tumors by clinicians. A few drawbacks remain, namely, unavailability of large high-quality annotation datasets, difficulties in interpretability of the model, and high computational costs. Moreover, previous models are dependent on 2D imaging, which cannot capture the true three-dimensional structure of the tumor in its entirety, and they suffer class-imbalance and variation in expert annotation. More concentration in the future should be focused on solving these limitations through the incorporation of Explainable AI (XAI) approaches, the application of multimodal imaging techniques, and the enlargement of datasets through collaboration and data augmentation. Advanced neural network architectures, transfer learning techniques, and ensemble methods can improve the classification performance further. Validation of the models in real clinical settings and ethical issues related to data privacy are very crucial for the successful implementation of these ML-based solutions. By overcoming these barriers, it can revolutionize brain tumor detection by enabling a quicker, sharper diagnosis eventually benefiting the patient.

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