RESEARCH PAPER

Comprehensive Review of Ensemble Learning Techniques for Gliomas and Other Types of Brain Tumor Classification

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Abstract: Diagnosing and telling apart benign and malignant brain tumor poses a key challenge in medical diagnostics. It has a big effect on treatment plans and how patients fare. Ensemble learning, a cutting-edge machine learning method, has made brain tumor grouping better. This method combines several models to boost prediction accuracy. This systematic study aims to give a full breakdown of ensemble learning methods used to group brain tumor -related conditions. The survey covers a broad range of ensemble methods, like bagging, boosting, and stacking. It explains their basic ideas and real-world uses in brain tumor grouping. We stack these methods up against standard "machine learning and deep learning" methods. We assess each one using various criteria, including the area under the ROC curve, sensitivity, specificity, and overall accuracy. This survey also investigates the types of features and datasets used in ensemble learning for brain tumor grouping. We check how different feature picking methods pre-processing steps and adding various types of imaging data—like CT and MRI scans—change how well models work. Through this study, we find common issues such as feature size and uneven classes, and we talk about fixes.

The survey also examines fresh developments and possible areas to study for grouping brain tumor using ensemble learning. We investigate the chances to use data from multiple sources and advanced techniques like hybrid models and transfer learning to boost the accuracy of diagnosis. This survey aims to help researchers and doctors build more dependable and precise ensemble learning models for brain tumor classification. It does this by giving a thorough review of current methods and pointing out areas to explore further.

Keywords: Benign Brain Tumor, Malignant Brain Tumor, MRI, Bagging, Boosting, Stacking.

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Introduction:

Brain disease implies that there is a problem with the functioning of the brain. We can find several types of brain diseases like for example, tumors, which break down the brain over time: blood circulation problems in the brain, infections and epilepsy among others. These all mess up how the brain does its job (Jeri Freedman et al., 2011). Doctors look at many pictures of your head to find these illnesses. They might use MRI, CT scans, EEG, MEG, SPECT, PET scans or ultrasound (Islam, S.K.M.S., et al., 2023). Therefore, we should identify these troubles so that they are cured as soon as possible by doctors. An increasingly popular method among people is using computer programs that detect patterns to determine what is wrong. Ensemble Learning constitutes a powerful tool in this field where various computers are combined to perform better still than each other (Shahriar Hossain, et al., 2024).

One important aspect in clinical diagnosis is brain tumor classification which has a great influence on patient outcomes and treatment approaches. Detecting brain tumors correctly can be very helpful in treating patients hence increasing their survival rate and quality of life. More advanced tumor categorization techniques are now possible because to recent developments in medical imaging. Using ensemble learning, which mixes many models to improve classification accuracy and performance, is one noteworthy strategy..

Medical imaging is an area where learning, which combines predictions from multiple classifications into a complex composite model, has shown impressive results Such things as breaking down various examples into common traps that are caused by some loosely defined problems (Dasari, A.K., et al., 2024).

Background:

An abnormal cell development in the brain or central spinal canal is called a brain tumor. While secondary or metastatic brain tumors spread from other parts of the body, primary brain tumors originate in the brain. These tumors might vary greatly in terms of features, prognosis, and available treatments. An overview of the different kinds of brain tumors may be seen in Figure 1 (Pal, Adarsh, et al., 2024).

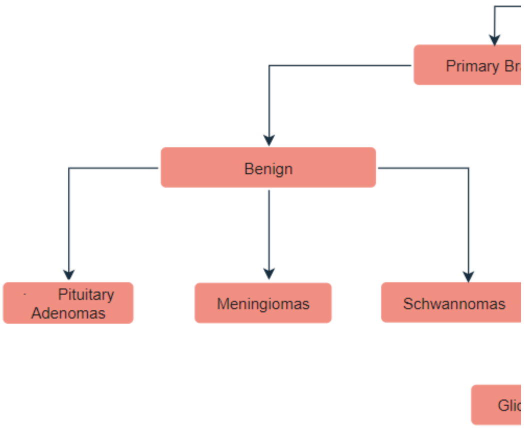

Figure 1: Brain Tumor Classification

a. Primary brain tumor

This type of brain tumor begins within the brain or in nearby areas. They can be classified as either cancerous (malignant) or non-cancerous (benign).

Benign:

Pituitary Adenomas

This type of tumors grows in the pituitary gland, commonly known as pituitary adenomas. They can alter the balance of hormones but are generally innocuous.

Meningioma

Tumors known as meningiomas arise from the meninges, the layers of tissue that surround the brain and spinal cord and provide protection. They often don't cause cancer and grow slowly. (Gour, G. B., et al., 2022).

Schwannomas

Schwann cells generate the myelin sheath that surrounds nerves, therefore, tumors derived from these cells are known as Schwannomas. An illustration would be an acoustic neuroma, which affects the nerves in charge of hearing and balance.

Malignant:

This types of tumor are cancerous and they have the several types such as:

Gliomas: (Gupta, Nidhi., et al., 2019) It occurs due to the glial cells that is used to protect the neurons. There different types of Glioma exits can be seen as below:

Glioblastoma (GBM): This type of tumor is very aggressive that easily penetrate and mal function the brain tissues. Their growth rate is very fast.

Anaplastic Astrocytoma: They are cancerous but mild. They consider as a grad III tumor.

Oligodendrogliomas: This type of tumor comes under the grade III and originated from oligodendrocytes.

Ependymomas: It is grade II tumor that develops from ependymal cell and spread to the central canal of the spinal cord.

Medulloblastomas: It is most dangerous malignant tumor that start from the cerebellum and travel through the cerebrospinal fluid and affect the spinal cord and different portion of the brain.

Primary Central Nervous System (CNS) Lymphomas: It develops from lymphocytes inside the brain or spinal cord (Bhatele, etal., 2023).

b. Secondary brain tumor

This kind of tumor develops when malignant cells go to the brain from another area of the body. These tumors are frequent in adults and are typically seen as metastases from diseases such as kidney and breast cancer.

Classifying brain tumors using machine learning

(Győrfi, Ágnes, et al., 2020) classification of brain tumor with the help of machine learning (ML) has grown to be an extremely useful tool. The goal of using ML approaches in this field is to diagnose brain cancers more consistently, accurately, and efficiently, which will benefit patients. These are some essential elements and methods for classifying brain tumors with the help of machine learning.

(Jehangir, Basra, and Soumya Ranjan Nayak , 2021) Three primary image types are used by machine learning to classify different kinds of brain tumors; histopathological images, CT (Computerized Tomography) scans, and MRI (Magnetic Resonance Imaging) scans. Brain tumors can now be accurately classified using several machine learning methods, as listed below:

Supervised learning

Neural network – his is a computer model that mimics the way that real neurons work in the brain. The Convolutional Neural Network (CNN), a kind of deep neural network used to train models for brain tumor classification, is a well-known example (Noreen, Neelum, et al., 2021.

Classification - Different algorithms including Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors (k-NN) are used to classify different types of tumors based on labelled training data.

Unsupervised learning

In unsupervised learning, the model is trained on data that does not have any predetermined labels or answers. Finding patterns, structures, and correlations in the data is the goal. Unsupervised learning algorithms have to find these hidden patterns on their own, in contrast to supervised learning, which relies on labeled data to guide the model. (Khan, Saif Ur Rehman, et al., 2021).

Clustering Algorithms: Methods such as hierarchical clustering and k-means clustering aid in identifying patterns in unlabeled data and classifying related tumor types collectively.

Dimensionality Reduction: By lowering the number of dimensions in the data, techniques like Principal Component Analysis (PCA) and t-Distributed Stochastic Neighbor Embedding (t-SNE) make the data less complex and easier to view and comprehend (Khan, Md Kamrul Hasan, et al., 2024).

Deep Learning method

(Alsubai, Shtwai, et al., 2022) Artificial Neural Networks (ANNs), a type of algorithm inspired by the structure of the brain, are used in deep learning, a branch of machine learning. These models work particularly well for handling big and complicated datasets since they are adept at automatically identifying nuanced patterns in data (Gopal S., Tandel et, al., 2023). They excel in natural language processing, picture and audio recognition, and other related activities. An introduction to the fundamental ideas of deep learning is given in this section.

Convolutional Neural Nets: They work really great for image classification tasks. To classify the brain tumor, models like VGGNet, ResNet, and InceptionNet have been fine-tuned.

Recurrent Neural Networks: These work very well for time-series imaging data. Thus, they are less commonly used for the purpose of image classification.

Ensemble Learning

Avery popular method named as ensemble learning a part of machine learning, where the solution to a problem is achieved by training and combining multiple models (Khan, Farhana, et al., 2023). This approach significantly accelerates the performance and accuracy of the machine learning process. Ensemble learning can be summed up as aiming at improving the performance, resiliency, and generalization of models by using varied learners' strengths (Győrfi, Ágnes, et al., 2023). Often, ensemble approaches are much better than any of the individual models that make them up in reducing variance or bias and improving predictions. Broadly, there are thee learning algorithm used for Ensemble learning such as “Bagging, Boosting, and Stacking”. Figure 2 shows the classification of ensemble learning (Dnyaneshwar Kirange , Patil, Suraj, 2023).

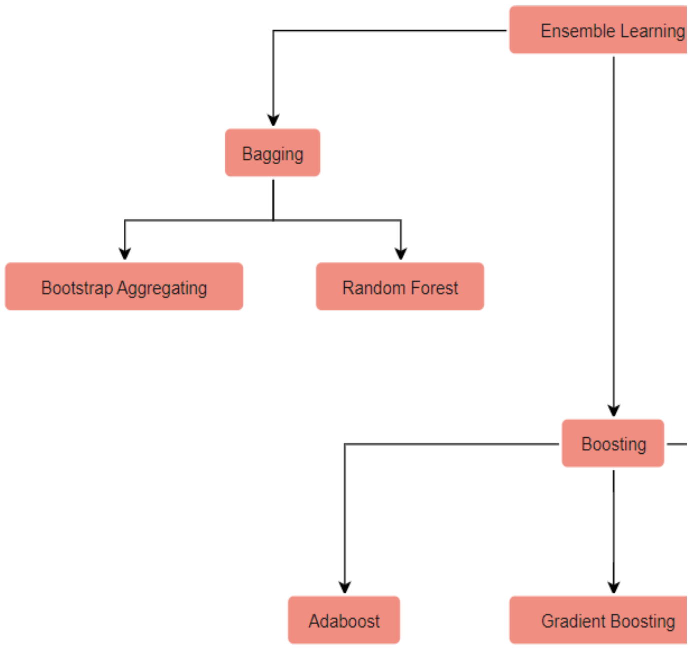

Figure 2: Ensemble Learning Types

Bagging

A meta-algorithm of machine learning ensemble that is referred to as bootstrap aggregating or bagging, describes how this method aims at improving precision and stability for machine learning algorithms used in statistical regression and classification. A variety of models in bagging are generated from an original dataset by creating multiple subsets using random sampling with replacement. These individual models can be pooled after training on different subsets by regression averaging . This helps in mitigating overfitting and reducing variance. In almost all the cases, decision tree methods were used with it. A special use of the model averaging method is that of bagging. When performing bagging, a model is realized various times from different disjoint training set samples, after which the predictions are finally averaged (Fülöp, Tímea, et al., 2020).

Random Forest: A popular decision tree-based bagging method, used in brain tumor classification.

Boosting

Boosting is an ensemble learning method that combines a number of ineffective classifiers to produce a powerful, useful model. Enhancing the learning algorithm's accuracy is the goal. The main idea is to train models sequentially, with each new model especially aimed at correcting the flaws of its predecessors. Boosting can be implemented by many ways each having unique way of generating learners.

AdaBoost (Adaptive Boosting) tries to make successive learners focus more on difficult cases by changing the weights associated with misclassified training examples, whilst Gradient Boosting continually adds models in a greedy fashion to minimize the loss function.

With sophisticated regularization to prevent overfitting, XGBoost (Extreme Gradient Boosting), the next gen-eration of Gradient Boosting, has been widely adopted for good performance and scalability. Another widely adopted variant is LightGBM (“Light Gradient Boosting Machine”). Histogram-based strategy can be used for decision splitting rather than post-order traversal of all training examples that enhances the training speed and overcome the memory usages issues. In combination, boosting methods provide a powerful set of tools for improving performance of prediction that uses the machine learning. Each boosting method has different strengths that make it suitable to different types of data or problems.

Stacking

Stacking, also called stacked generalization, is an ensemble learning technique that improves overall predictive performance by efficiently combining predictions from several base models using a meta-learner. Using the training data, several base models, also known as level 0 models, are first trained. Next, based on the test data, these models produce predictions. A meta-model, also known as a level 1 model, is trained using the outputs from the base models as new input features to determine how to weight the base models' predictions. Theoretically, stacking achieves greater results than any one model could by utilizing the capabilities of all models. There are many different forms of stacking with various applications and complexities. If you simply use the predictions from the level 0 models as new features for training the meta-level model, it’s called simple stacking. While if you set aside a subset of training data pooling for training in order not exposed information leak out from meta-model fitting process. It named blending, Some more advanced forms such as cross-validated stacking generalize better by using out-of-fold predictions that help prevent overfitting by learning from single modelling while others were testing error rate dependent upon multiple modelling situations. Both homogeneous and heterogeneous ensembles as well as any type of regression or classification algorithm can be used with stacking as base-models or meta-level learners. Therefore, it makes stacking approaches being easy-to-program. Notations required here are similar enough with Stacking.

Below question can be answered as below:

- Which learning method is best to classify the brain tumor.
- What is the latest research has been performed till date that has maximum accuracy and efficiency.

The whole purpose of this systematic is to put lights on an the way ensemble techniques was used to classifying brain tumors. We aim at dissecting the current “state-of-the-art” methods, emphasizing the strengths and weaknesses of different ensemble techniques and then scrutinizing these works meticulously to identify their dominant modes and future research directions. An overview of several ensemble methods, such as stacking, boosting, bagging, and hybrid ensembles, is given in this survey. It also looks at how these techniques are used to categorize brain tumors (Matheus Henrique Dal Molin, et al., 2020).

This survey aims to provide useful insights and guidance to researchers and practitioners in the field of brain tumor identification and its classification. By amalgamating existing knowledge and identifying gaps, this work seeks to contribute towards the current attempts to exploit ensemble learning for improved medical diagnosis and treatment planning in neuro-oncology.

This survey paper also answer why we should move ahead with ensembled learning because it trained the model more efficiently and more promising results were seen. Further combination can show more accuracy. There are several methods have been used so far to classify the different types of tomor.

Literature Review:

This survey follows a systematic approach to gather, analyse, and present information on ensemble learning in terms of classification of brain tumor.

(Kang, J et al., 2021) have used pre-trained CNN models with transfer learning to extract features from the scans. The authors worked with three datasets: BT-small-2c and BT-large-2c for classifying data as normal or tumor, and BT-large-4c for distinguishing between pituitary, meningioma, glioma, and normal. The study showed that using a radial basis function in support vector machines improved performance, especially with larger datasets. They addressed challenges of manual feature extraction by employing deep learning and various CNN models, which require substantial annotated data to automatically identify features.

(F. Khan et al., 2023) have used ensemble model, "XG-Ada-RF", combines "Extreme Gradient Boosting, Ada-Boost, and Random Forest" to improve the accuracy. This model achieved more than ninety-five percents (95.9%) accuracy for tumor classification and "94.9%" for normal brain classification, outperforming each method. The study evaluated performance using metrics such as F1-score, AUC, accuracy, recall and precision. The dataset, available on fig share, includes 3,762 cases of tumor and healthy brains. Future work will explore how improving the model's interpretability can aid medical decision-making.

(S. Saeedi et al., 2024) they have highlighted the importance of tumor detection at the beginning stage that elevates the survival rates and shows the limitations of invasive biopsies, advocating for non-invasive MRI techniques. Advances in convolutional deep learning have shown promise in identifying tumor features. CNNs, with their layered structure, achieve high accuracy in diagnosis. The proposed "2D CNN" and "auto-encoder" networks that have shone the promising results neat about 96.47% for first method and 95.63% for second method, with recall rates around 95%. ROC curves indicate an AUC of 0.99 for both. Compared to methods like Multilayer Perceptron (28%) and K-Nearest Neighbours (86%), the study's approaches showed significant performance differences (p-value <0.05).

(S. S. Kuntan, et al., 2024) have used a "Convolutional Neural Network (CNN)" within an Android app, the method improves on manual MRI analysis by providing faster and more accurate tumor detection. The study highlights that manual methods are error-prone and time-consuming. Future improvements suggested including integrating the app with hospital systems for seamless data sharing and adding features for treatment recommendations.

(K, S. & N,A., 2023). introduces an enhanced U-Net architecture with an attention mechanism, eliminating the need for a pre-trained network when working with sparsely labelled data. With 0.89 for the core, 0.95 for the augmenting regions, and 0.95 for the entire tumor, the model demonstrated impressive Dice similarity coefficients. Its ability to precisely separate brain tumors from 3D MRI scans is demonstrated by these studies.

(Garg, A. et al., 2023) Deep learning architecture was used to detect brain tumor from MRI data, achieving an accuracy of 98.66%. The paper doesn't explore how different CNN architectures or datasets affect MRI image classification for brain diseases. However, it does present results from a pre-trained model applied to raw fMRI data, which achieved an accuracy of 80.2% and successfully classified 11 out of 13 cases. The study also introduces a new end-to-end temporal contrastive self-supervised learning technique, which uses pairs of fMRI signals for training. A noted limitation is that the paper doesn't address transfer learning for MRI image classification models focused on brain illnesses.

(Veni, N., et al., 2023) authors evaluated the VGG-16 technique by examining performance metrics such as accuracy, recall , F1- score, and precision, while considering the constraints of limited processing resources and lower complexity. They demonstrated how transfer learning with the VGG-16 model architecture, which includes convolutional and max-pooling layers, can effectively classify brain tumors. Their findings conclude that the VGG-16 CNN architecture offers strong performance for this task. However, the study does not address how different datasets and CNN architectures might affect MRI image classification performance.

(Angurala, M., 2023) has explored the use of transfer learning techniques, including DenseNet, ResNetV2, and InceptionResNetv2, to identify the best algorithm based on various metrics like accuracy, precision, and recall. The validation accuracy for Inception and ResNetV2 were reported as 77% and 80%, respectively. A noted limitation is that the paper does not specifically address how transfer learning can be applied to MRI image classification models for brain diseases.

(Xavier, S. B. et al., 2024) authors have used MobileNet and ResNet deep convolutional neural networks to estimate patients' ages and predict the types of brain diseases they have. By applying transfer learning with pre-trained models from MobileNet and ResNet, they improved the accuracy of MRI image classification for brain conditions. While the results are promising, a noted limitation is that they did not compare their methods with the latest architectural advancements to evaluate their relative effectiveness.

(Ramesh, L., et al., 2023) explores a deep convolutional network model designed for the detection of Alzheimer's disease at the early stage using brain MRI data. This model excels at detecting different stages of the disease, making it particularly effective for early diagnosis. By leveraging deep learning techniques on brain MRI data, the proposed approach significantly improves the accuracy of identifying Alzheimer's at an early stage.

(Ayshwarya, B., et al., 2023) introduces a new "Deep Convolutional Neural Network (DCNN) "architecture combined with a 3-step preprocessing strategy to improve MRI image quality. This approach enhances accuracy for the identification of brain diseases with MRI datasets, achieving impressive results. By integrating batch normalization within the DCNN architecture, the proposed method boosts accuracy and provides better detection of brain tumors, which are a particularly aggressive form of cancer.

(Hendrickson, T. J., et al., 2023) The study presents BIBSNet, a deep neural network designed for segmenting newborn brains from MRI data. Although it doesn't specifically cover the use of deep neural networks for brain disorders, the paper introduces BIBSNet (Baby and Infant Brain Segmentation Neural Network) as a tool for accurately segmenting infant brains. This method outperforms the JLF segmentation technique in cortical measurements and is 600 times faster. Additionally, BIBSNet can be easily integrated into other processing pipelines. The researchers used extensive manual annotations and data augmentation to train the model effectively.

(Mehta, D., et al., 2022) The study suggests a U-Net architecture for denoising MRI scans in conjunction with image processing methods, which can improve the precision of brain tumor prediction. The authors of this study developed a U-Net architecture for denoising MRI scans that included two pairs of encoders and decoders. The design was fine-tuned using a dataset created by injecting synthetic Gaussian noise. Denoising MRI scans using a U-Net design with two pairs of encoders and decoders. A higher peak signal to noise ratio (PSNR) of 30.96 compared to 11.90. The paper focuses on image processing methods such as U-Net for MRI image denoising. Image processing and deep learning algorithms work together to improve the quality of MRI images.

(Ren, Y., et al., 2022) introduces a novel approach for MRI reconstruction using a complex-valued dual-domain dilated convolutional neural network (C3DNet), which speeds up image acquisition and improves image quality. While it doesn't specifically address brain disorders, the research by Wang et al. presents C3DNet as an innovative method for fast and accurate MRI reconstruction. This network achieves dual-domain feature fusion by independently extracting complex-valued features from both k-space and image-domain data. The proposed technique outperforms several state-of-the-art algorithms, offering superior performance not only in image quality but also in computational efficiency.

(Ke, H., et al., 2023) The primary goal of this research is to develop a Deep Factor Learning model (HB-DFL) for the analysis of neuroimaging data with the specific goal of distinguishing between ADHD and Parkinson's disease (PD). The article presents the HB-DFL model, which is based on a Hilbert basis tensor, even if it doesn't specifically address the use of deep neural networks for processing MRI data associated with brain illnesses. The model effectively extracts low-dimensional, concise factors from tensors and outperforms existing techniques in both factor learning and stability. Additionally, HB-DFL delivers more accurate results in discriminating between PD and ADHD.

(Jaisingh, W., et al., 2022) The authors have introduced a deep transfer learning approach incorporates the K-Means model along with “Convolutional Neural Network (CNN)” to automatically classify brain MRI images into normal and abnormal categories. This paper presents a method that leverages deep transfer learning alongside a CNN for this classification task. The approach was evaluated using imaging data from the Kaggle dataset, demonstrating its effectiveness in distinguishing between brain MR pictures, both normal and pathological.

(Yahya R bat, J., et al., 2022) This study explores the use of MRI scans that classify brain tumors through Convolutional Neural Network (CNN) approach. While it doesn't delve into image processing or deep neural networks for brain disorders, using MRI technologies, the authors used a condensed CNN structure to predict brain cancers. When it came to classifying brain tumors, the recently created CNN approach obtained an astounding maximum accuracy of 98%. The 154 picture samples in the dataset were used to train and assess the model.

(Du, Y. et al., 2022) Researchers have focused on correcting bias fields in brain MRI images with the help of deep learning techniques, an essential preprocessing step for tasks like segmentation and registration. Although the paper doesn't specifically discuss the application of DNN (deep neural networks) to perform MRI image processing that shows brain disorders, it proposes Convolutional Neural Network (CNN) with batch normalization and residual learning to enhance bias correction performance and speed up training. The suggested deep learning model outperformed traditional methods in removing bias fields, particularly excelling in correcting images with high levels of intensity non-uniformity.

(Nidaan Khofiya, Sy., et al., 2022) Research paper [24] have shown the new system that classifies the brain

Authors and reference	Methodology/Algorithm	Result
(André et at., 2023)	• CNNs and Transformer models enhanced through transfer learning. • Unsupervised manifold learning techniques for better measuring similarities.	• Effective results in retrieval and classification tasks on MRI images. • Competitive or superior outcomes compared to deep learning in limited data.
(Sreedhar et al., 2024)	• For training they have used MRI scans. • For deep learning they have used convolutional neural network.	• Superior results compared to conventional deep learning techniques. • EfficientNet-based DL model for brain tumor classification.
(Eid, Albalawi. et al., 2024)	• A customized CNN architecture created especially to categorize MRI images of brain tumors. • Multi-task model that not only detects tumors but also pinpoints their exact location.	• Tumor classification accuracy: 99% • all the techniques used at the moment to identify brain tumors.
(Ch., Rajendra et al., 2024)	• a comprehensive CNN method for identifying and categorizing brain cancers. • The experiments were conducted using the SARTAJ, Br35H, and Figshare datasets.	• Delivers better results in accuracy, recall, F1 score, and precision. • Improves medical imaging in order to analyze brain tumors.
(Archana, Reddy. et al., 2023)	• CNN-VGG-19 has been utilized for the identification and categorization of brain tumors. • Simulated Annealing technique for feature selection	• Better sensitivity, accuracy, and precision compared to current methods. • Effective brain tumor segmentation using CNN-VGG-19 technique.

tumors as no tumor, meningioma , glioma, and pituitary. AlexNet architecture was utilised that incorporates the feature extraction techniques. Their findings showed that the Adamax optimizer, 0.001 learning rate, achieved the highest accuracy of 93% for classifying brain tumors in MRI images. This paper highlights that MRI image processing combined with CNN can efficiently classify different types of brain tumors, achieving a notable accuracy of 93%.

(Pranay, A., et al., 2024) In order to increase classification accuracy, the authors talk about using a pre-processed medical imaging dataset. Convolutional Neural Networks (CNNs), which are ideal for image processing applications, are the main focus of their attention when it comes to neural network architectures. These networks are used in this work to perform crucial tasks like feature extraction, dimensionality reduction, and classification on MRI brain images. They use Principal Component Analysis (PCA) for dimensionality reduction and Discrete Wavelet Transformation (DWT) for feature extraction. The complete development process is described in the paper, from gathering and improving data to training and evaluating the model. Additionally, it evaluates the effectiveness of the categorization models by utilizing measures such as specificity, sensitivity, and accuracy.

(Nabil, M., et al., 2024) The authors have introduced a new method called the MGMT-PMP approach for predicting genetic subtypes and extracting features using deep learning combined with radio genomic characteristics. This method, which focuses on predicting MGMT promoter methylation, achieves a high classification accuracy of 99.13% for identifying MGMT methylation status for glioblastoma patients. The MGMT-PMP approach helps determine the genetic subtype of glioblastoma and enhances diagnosis by integrating genetic data with radionics features, leading to more informed treatment planning.

Table 1: Comparative analysis of different learning algorithms used for tumor classification between 2023 - 2024

(Miri, et al., 2023) author have shown the promising result for the classification where they have done categorization of malignant brain tumors with CNN and MRI data. Hyper parameters optimization was done to get accurate tumor classification, focusing on Glioblastomas. Two-level approach was used such as MRI modalities evaluation, CNN architectures comparison. However, Hyper parameter optimization was done using hyper parameter pruning or tuning such as epochs, batch sizes, learning rates, dropout rates.

Method Comparison:

A detailed summary of the different learning strategies applied in 2023 and 2024 for the classification of brain cancers from MRI images can be found in Table 1. The table compares deep learning models, hybrid techniques, and conventional machine learning algorithms, assessing each technique according to important parameters like computing efficiency, sensitivity, accuracy, and specificity. It demonstrates how deep architectures like recurrent and convolutional neural networks improve more conventional approaches, such as random forests and deep neural networks like VGG19. It also highlights hybrid approaches that efficiently integrate these two families of techniques to enhance classification performance even further. This comparative analysis will help researchers and practitioners choose the best technique for their needs by illuminating how well various learning strategies perform when it comes to correctly diagnosing brain cancers from MRI images.

Methodology:

Main objective of this survey paper is exploring the various techniques that has been used to classify the brain tumor with the help of ensembled learning. However, different other approach such as convolution neural network have also been explored in this area. Qualitative methods have been used to explore the several techniques. To find the information; Google Scholar, IEEE explore, and SpringerLink was used. While searching some of the keywords were used such as “brain tumor classification”, Different ensemble learning method used to classify brain tumors”, “Types of brain tumor” and many more.

There are certain benchmarks have been set to select the paper are as below:

- Types of brain tumor studied such as Benign and Malignant.
- Research papers that shows survey on ensembled learning methods.
- Use of ensembled learning used for medical image classification such as MRI CT etc.

Exclusion was done based on the below points:

- Paper that doesn’t include medical image processing such as MRI or CT
- Paper that doesn't include ensembled learning or other CNN and NN models.
- Paper that does not shows the effective data or have not included the reputed articles or journals.

Discussion:

This survey aims to identifies the latest work that is going on to improve the performance and the accuracy of the brain tumor classification using ensembled learning. Only MRI and CT images were searched for the classification. Survey can also be done on the different images such as MRI, fMRI, PET etc.

In future, the area of ensemble learning applications need to be explored for brain tumor classification for multimodal data (e.g., MRI, fMRI, PET etc.), hybrid models, and the integration of cutting-edge approaches such as transfer learning to enhance classification accuracy and clinical applicability (Xenya, et al., 2021).

Conclusion:

To sum up, ensemble learning techniques have made great strides towards the classification of brain disorders, especially tumors. These strategies provide accurate and dependable diagnostic tools, which are essential for early identification and well-thought-out treatment planning, by combining the benefits of multiple models. The progress made in this field is heartening, and there is great room for improvement in patient outcomes through ongoing research and innovation. Ensemble learning holds a lot of promise for improving medical diagnostics and could truly change the way we diagnose and treat brain diseases.

Conflict of Interest:

This survey paper provides an impartial overview of "Systematic Survey on Ensemble Learning Approaches to Classify Brain Tumor Diseases." It is free from any external influence or financial backing that could promote specific work. The paper presents a personal perspective and offers suggestions for improving methods related to brain tumor classification.

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Data Availability Statement: Not Applicable
Research Involving Human and /or Animals: Not Applicable
Informed Consent: Not Applicable

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