

An Integrated Approach for Brain Tumor Detection using Deep Feature Extraction and Machine Learning Classifiers.

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ABSTRACT

Brain tumor classification using medical image processing is becoming easier with the fast pace of innovation in medical image analysis technology which has a large amount of MRI data sets related to brain tumors. The precise classification of brain tumors is vital for diagnosing and treating brain disorders. The current research project aims to design a hybrid computer-aided brain tumor classification system based on deep learning algorithms and conventional methods.

In contrast to the previous approach where only end-to-end deep neural networks have been used, this paper uses the DenseNet201 architecture as a pretrained architecture to learn high-level deep visual features from the MRI images. The learned deep features are further refined by applying the Extra Trees Classifier based feature selection process in order to retain only the most valuable features and reduce the redundancy. Finally, different supervised classifiers like Logistic Regression and other machine learning classifiers are used for evaluation purposes.

The experiments have been done using a publicly accessible Brain Tumor MRI Dataset provided by Kaggle, which consists of four types of The following classes were considered in this study: glioma, pituitary tumor, meningioma, and non-tumor. The criteria adopted to measure the efficiency of the proposed technique included accuracy, precision, recall, and F1 score. It was seen that both the models Linear SVM and Logistic Regression performed well during classification.

This demonstrates that there is a way of coming up with tumor classification systems that are both efficient and accurate, and yet do not require a lot of computing resources, unlike in the full training of deep neural networks. The system will be very instrumental in aiding medical professionals in diagnosing brain tumors. In addition, there is enough room for development, such as explainable artificial intelligence and attention maps for tumor localization.

Chapter 1

INTRODUCTION

The condition of brain tumors is among the most severe neurological diseases that can have a substantial impact on human well-being when not detected in its early stages. Brain tumors happen owing to the proliferation of cells in the brain and either it can be malignant or benign based on the degree of severity of the disorder. There are several kinds of brain tumors, such as glioma, pituitary tumors and meningioma each with varying methods of treatment. Thus, it is crucial to recognize the nature of brain tumors before proceeding with further diagnosis and treatment. One of the most prevalent diagnostic tools for brain tumors is MRI [1].

The conventional process of detecting brain tumors involves the work of radiologists who visually examine the brain MRIs. While manual inspection has been proven to be quite efficient, the approach is prone to errors due to the time-intensive nature of the task and the possibility of inconsistency among different observers, particularly when examining large volumes of data. This issue has led to advancements in computer-aided diagnostic systems that have the ability to help doctors detect and classify tumors [2]. Machine learning models and deep learning models have performed well in analyzing medical images [3].

Nowadays, Convolutional Neural Networks (CNNs) have gained immense popularity as feature extractors and classifiers. From this class, DenseNet201 is one of the best pretrained models, which facilitates the reusing of features using densely connected layers and ensures efficient propagation of gradients in training the model [4]. The features obtained through such CNN models are, however, high-dimensional and might include redundant information. In this regard, ETC acts as an effective method for selecting key features [5].

In this study, we propose a combination approach for brain tumor classification through feature extraction using the DenseNet201 architecture, and then selecting features using the ETC method. This feature subset is tested by applying different machine learning techniques like Logistic Regression, SVM, KNN, Decision Trees, Random Forests, and Gaussian Naive Bayes. The proposed model seeks to offer an effective, efficient, and dependable means of aiding medical practitioners in diagnosing brain tumors [6].

1.1 Motivation

Given the rising cases of neurological problems, brain tumor detection has been given paramount importance in today's era of healthcare[7][8]. Brain tumors will have a catastrophic effect on survival rates, physical capabilities, and cognitive functioning if they are not detected[9]. However, despite the fact that MRI has gained popularity as a means of diagnosing brain tumors, there is a great deal of pressure put on radiologists to interpret findings as fast as possible due to the high frequency of such examinations performed[10]. Due to varying workloads and skill levels, manually interpreting these information is a long and uneven procedure[11].

To deal with these problems, it is crucial to have intelligent automated tools that can help medical professionals diagnose and classify brain tumors in an effective manner[12][13]. With the recent development of advanced techniques in artificial intelligence such as deep learning and machine learning, it is now possible to mine meaningful information from medical images[14][15]. Unfortunately, deep learning-based tools demand high computational power and long training times[16].

This research is based on the requirement for creating a robust hybrid architecture which integrates feature extraction from deep learning models that are pre-trained with classifiers of machine learning algorithms[17][18]. This technique will ensure better accuracy while lowering costs associated with computation[19]. The suggested technique can help radiologists make informed decisions and help in improving healthcare services through effective analysis of brain tumors[20].

1.2 Objectives

The principal aims of this study are:

- Design and utilize a hybrid system that employs DenseNet201 and machine learning models to classify brain tumors based on MRI scans.
- Employ feature extraction techniques using pre-trained deep learning models instead of training a complete deep neural network.
- Test different models for their performance based on accuracy, precision, recall, F1-score.
- Conduct a comparative study to find out the best performing model for brain tumor prediction.

1.3 Challenges

There are several issues involved in utilizing deep learning techniques and machine learning techniques for brain tumor classification within the healthcare industry:

- **Image variability:** MRI images may have differences in resolution, contrast, orientation, and protocol used during acquisition.
- **Similarity between tumors:** The tumors from each class can look alike hence, distinguishing between glioma, meningioma, and pituitary tumors is complex.
- **High dimensional nature of the problem:** There are several features in the model, which makes it complicated to train.
- **Lack of labeled data:** It is hard to obtain annotated MRI images to train the deep learning model as publicly available data is relatively few.
- **Uninterpreted black-box model:** Most machine learning models act as black boxes, limiting their acceptability within healthcare.

This research project seeks to resolve the above-mentioned challenges by implementing an intelligent framework based on feature extraction and classification using different classifiers.

1.4 Thesis Organization

- **Chapter 1: Introduction** — explains the problem, justification, objectives, and difficulties of the study and provides a high-level review of brain tumor categorization using MRI scans.
- **Chapter 2: Literature Review** — Covers the state-of-the-art research in brain tumor detection/classification techniques including machine learning algorithms, deep learning algorithms for medical images, and image processing.
- **Chapter 3: Purposed Work** — Includes details on the pre-processing, feature extraction using the DenseNet201 model, feature selection process using ETC method, classifier training procedure, and data used (Brain Tumor MRI Dataset by Kaggle).
- **Chapter 4: Results and Discussion** — Highlights the methodology used for experiments, performance comparison of various classifiers used, results obtained, and discussion of results achieved.
- **Chapter 5: Conclusion and Future Scope** — This chapter highlights some limitations in the current work, discusses conclusions drawn from this study, and highlights the scope for future improvement like explainable AI, tumor diagnosis with heatmaps, etc.

LITERATURE REVIEW

2.1 Literature Survey

Over the past ten years, researchers' interest in using MRI to categorize brain tumors has increased because to the growing need for precise and prompt identification. In the past, radiologists used image processing methods like segmentation, texture analysis, and hand-crafted features to manually analyze MRI images. While these techniques have contributed to the delivery of therapeutic assistance, their effectiveness has sometimes required advanced planning and prior understanding [7].

Classifying models such as SVM (Support Vector Machine), Decision Tree, KNN (K-Nearest Neighbor), and Random Forest have been developed in order to automate the process of cancer detection. Despite the success of these classifiers during training using manually constructed features from methods such as Histogram of Oriented Gradients, Gray Level Co-occurrence Matrix, and Local Binary Patterns, the results were restricted to the quality of manually generated features and the presence of redundant features [14].

Innovations in deep learning have significantly improved medical picture analysis. In order to understand the hierarchy of photographs in medicine, handcrafted features do not need to be created by deep learning models like CNNs. Brain tumor identification is successfully accomplished by algorithms like AlexNet, ResNet, VGGNet, and DenseNet. However, due to its dense connectedness, DenseNet201 is regarded as the best of all these algorithms [1].

There have been several studies conducted regarding the hybrid approach, where both the conventional machine learning techniques and deep features are combined. In this approach, the deep features can be extracted from the pre-trained CNN model by using external datasets and classified with SVM and Logistic Regression. The features required for classification have been selected and unnecessary features have been removed using MRMR and ETC.[2][14]

These experiments demonstrate that the combination of transfer learning, feature optimization, and machine learning approaches is a computationally feasible solution to brain tumor classification problems. This is the basis of the present investigation [8].

Table 2.1. Summarized review of literature papers

S. No	Ref.	Dataset	Mechanism	Benefits	Limitations
1	[1]	MRI Brain Tumor Dataset	Deep learning and machine learning model for MRI classification	Efficient Feature Extraction and Classification Process	Computation Complexity
2	[2]	MRI Brain Scans	Framework for Hybrid Deep Learning-Based Brain Tumor Classification	Automatic feature extraction	needs huge data acquisition.
3	[3]	Brain MRI Dataset	Hybrid transfer learning with self-attention mechanism	Better contextual feature representation	Complex architecture and higher training time
4	[4]	MRI Brain Tumor Dataset	Hybrid transfer learning-based tumor detection approach	Improved accuracy with transfer learning	Dependent on pretrained model quality
5	[5]	MRI Brain Images	Deep learning integrated MRI analysis framework	Robust feature extraction capability	Computationally expensive
6	[6]	MRI Tumor Dataset	Explainable AI integrated hybrid deep learning model	Improved model interpretability	Increased model complexity
7	[7]	ImageNet Dataset	DenseNet architecture with dense connectivity	Efficient feature reuse and gradient flow	Large memory requirements
8	[8]	General Classification Dataset	Extra Trees Classifier for feature selection	Reduces feature dimensionality efficiently	Randomization may affect stability
9	[9]	Classification Benchmark Dataset	Classification by means of Support Vector Machine (SVM)	High effectiveness in high dimensions	Sensitive to kernel selection
10	[10]	MRI Brain Tumor Dataset	Deep learning-based MRI tumor detection	High classification performance	Requires extensive training data
11	[11]	MRI Brain Images	Hybrid CNN-based tumor segmentation and classification	Better segmentation and classification accuracy	High computational overhead
12	[12]	General Classification Dataset	Random Forest ensemble learning	Reduces overfitting and improves robustness	Slower prediction for large forests
13	[13]	Classification Dataset	Decision Tree-based classification	Simple and interpretable model	Prone to overfitting
14	[14]	Pattern Recognition Dataset	Machine learning and pattern recognition techniques	Strong theoretical foundation	Limited deep learning integration
15	[15]	Brain MRI Dataset	Transfer learning with deep CNN features	Reduced training time and improved accuracy	Feature redundancy issue
16	[16]	MRI Brain Tumor Dataset	CNN-based brain tumor classification	Automatic hierarchical feature learning	Requires high computational resources
17	[17]	ImageNet Dataset	Deep CNN architecture for image classification	Significant improvement in deep	Large-scale computational

				learning performance	requirements
18	[18]	Kaggle Brain Tumor MRI Dataset	Public MRI dataset for tumor classification	Balanced and labeled dataset	Limited real-world diversity
19	[19]	TensorFlow Framework	Open-source deep learning platform	Efficient model development and deployment	Requires hardware acceleration
20	[20]	Google Colab Platform	Cloud-based GPU computing environment	Free GPU support for experimentation	Limited runtime resources
21	[21]	Machine Learning Dataset	Scikit-learn machine learning library	Easy implementation of ML models	Limited support for deep learning
22	[22]	ImageNet Dataset	Residual learning through ResNet architecture	Solves vanishing gradient problem	Complex architecture
23	[23]	Medical Image Dataset	Deep learning models for medical image analysis	High performance in medical imaging tasks	Requires large annotated datasets

2.2 Dataset

The data set used in research is a publicly available set of medical imaging data, the Brain Tumor MRI Data Set, sourced from Kaggle [11]. The data set contains a huge volume of images taken from MRI scans of the brain that have been categorized into four groups, including meningioma tumor, glioma tumor, pituitary tumor, and no tumor cases. Each of the images represents a specific case study based on the type of tumor.

The data set has been split into various sets of training and testing data, which means that there is a definite line between the two types of data sets. The data set consists of thousands of MRI images with a balanced class distribution, thus minimizing any form of bias during the training process. All the images have been resized to a single size.

In the current research, the MRI images will be fed into the pretrained model called DenseNet201 where high-level deep features will be extracted. After that, the features will be optimized via feature selection. The selected database is suitable for the research because it is large enough and highly diversified. It also has practical application in the sphere of medicine.

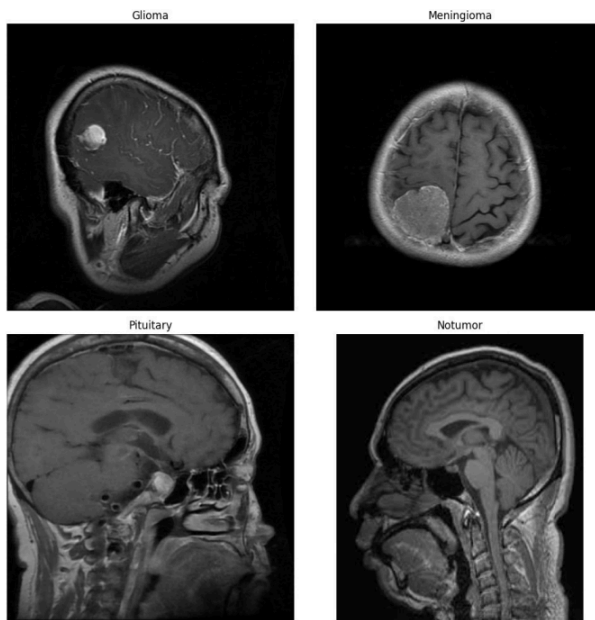


Figure 2.1: Sample MRI images representing different classes in the Brain Tumor dataset.

2.3 Problem Statement

While MRI scanning of the brain can be very helpful in determining whether there are any abnormalities including brain tumors, identifying brain tumors is not an easy task. Brain tumors such as glioma, pituitary tumors and meningioma at end to look similar to one another in terms of appearance through MRI scanning. Therefore, identifying them can be considered to be a difficult task even among the most skilled radiologists. The process usually involves manually extracting the features from the image and then segmenting them accordingly. However, although these procedures can be used in making the diagnosis, they have certain drawbacks.

Due to the rapid development of the application of the deep learning algorithm, the performance of the deep learning algorithm in feature extraction in medicine has proven to be highly effective. The issue that emerges from this situation is the high-dimensional nature of the feature vectors extracted using the deep learning algorithm. Not only does this complicate the computational process, but it also reduces the efficiency of the process.

The main issue tackled in the current thesis revolves around the creation of a brain tumor classification model through the use of MRI imaging. Instead of employing end-to-end deep learning classification, the suggested methodology incorporates deep feature extraction through DenseNet201 and feature selection based on the Extra Trees Classifier as well as different machine learning techniques. This approach was designed to minimize the processing time needed for accurate classification results.

Another significant problem with brain tumor classification lies in the absence of generalized and computationally efficient models. Even though deep learning-based approaches have proven highly effective in solving tasks related to medical image processing, they still require plenty of labeled data, powerful computational hardware, and sufficient training time. In most hospitals, particularly in the developing countries that lack appropriate resources, constructing sophisticated deep learning architectures might prove to be impossible.

Indeed, the presence of irrelevant attributes in deep features may lead to an increase in processing difficulty. It becomes important to consider a combination approach, which will be able to merge the speed and ease of application in the process of machine learning with the attribute extraction capability in the deep neural network model. Other than simplifying computations, the approach will be able to classify brain tumors appropriately.

2.4 Research Gap

There are many scientific studies on the classification of brain tumors where ¹⁰ machine learning models and deep learning approaches have been used. However, the current scientific research shows that end-to-end learning systems, transfer learning algorithms, and hybrid methods are more appropriate when it comes to classifying MRI images. Even though most of these algorithms classify brain tumors very accurately, the problem is that they have high computational requirements and need big datasets for training.

One of the key problems that has been identified by various researchers with respect to deep features generated by pre-trained CNN models in high-dimensional spaces is being discussed in the literature at present. While deep features are shown to have adequate texture and structure, there is no account made for the inclusion of redundant and unnecessary features, thus leading to higher computational costs.

In addition, the different techniques used till date are only concerned with using deep learning classifiers, and never do they look investigating ⁴¹ the performance efficiency of the classical machine learning classifiers together with the use of deep features. A comparative analysis must be made between the various machine learning classifiers taking into account the deep features.

A highly effective approach must be developed in order for the machine learning technique to become highly efficient in feature selection and classifying brain tumors. At this stage, the emphasis must be made on using the hybrid technique for ² the classification of brain tumors based on MRI images.

Chapter 3

PROPOSED WORK

3.1 Research Design

In the present study, an empirical framework is adopted to propose and validate the proposed hybrid framework for the classification of brain tumors from MRI images. In particular, machine learning classification comes after deep feature extraction using the DenseNet201 framework. In order to extract the pertinent elements from the photos, the proposed method makes use of current knowledge.

The following five steps are part of the entire research process:

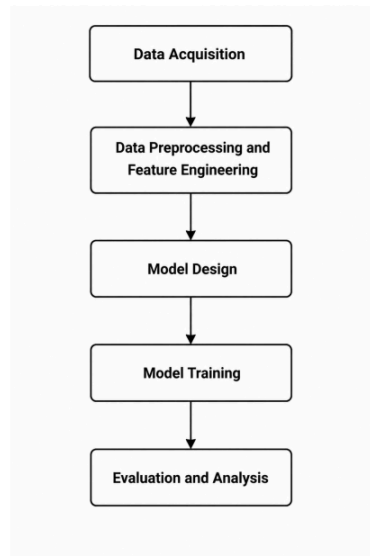


Figure 3.1: Flowchart illustrating the end-to-end research design process.

1. **Data Acquisition** — Gathering and classifying images regarding MRI from the Kaggle Brain Tumor dataset for train/test split.

2. **Data Preprocessing and Feature Engineering** — Deep features extraction through the DenseNet201 algorithm following resizing of images and standardization of pixel intensities.
3. **Model Design** — Application of dimensionality reduction and feature selection techniques through the use of Extra Trees classifier.
4. **Model Training** — Training various Machine Learning algorithms like KNN, Naive Bayes, Decision Tree, Random Forest, Support Vector Machine, and Logistic Regression etcetera.
5. **Analysis and Evaluation** — Evaluating the accuracy of trained model using classification performance metrics.

This structured methodology ensures reproducibility, enables systematic experimentation, and supports accurate evaluation of the proposed brain tumor classification system.

3.2 Dataset Description

The data set that will be employed in this study is the open source medical image data set called Brain Tumor MRI Data Set available on Kaggle [11]. This dataset consists of a lot of brain MRI images and are categorized under one of the four categories – meningioma, glioma, pituitary and no tumor. The significant thing about this dataset to highlight here is that it has been categorized already into these four categories and therefore needs no further classification.

- **Glioma tumor** images represent abnormal growth in brain tissue.
- **Meningioma tumor** images correspond to tumors arising from brain membranes.
- **Pituitary tumor** images indicate abnormalities in the pituitary gland.
- **No tumor images** represent healthy brain scans.

The data set is very suitable for classification since it has an equal number of classes, and it captures a real-world application. The varying MRIs enable the model to learn the pattern that enables it to classify brain tumors. The inclusion of a variety of tumor morphology, texture, and intensity data in the data set under examination further enhances its efficacy. Since these MRI scans are taken in real-world scenarios, the software will be able to identify significant trends for the precise classification of cancers. As a result, the data set will provide a trustworthy standard for assessing machine/deep learning methods for brain tumor detection.

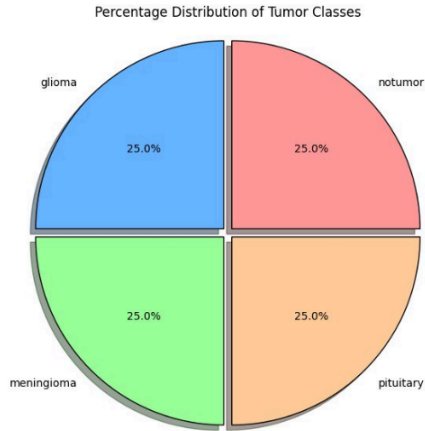


Figure 3.2: Pie chart showing class distribution of MRI images in brain tumor dataset.

3.3 Data Preprocessing

Pre-processing is an extremely important process where raw MRI data is converted to an appropriate form for use by the deep learning algorithm. The pre-processing steps performed on the input brain MRI data include:

- **Images Size Modification:** All the MRI images are resized to maintain the same size (224×224 pixels) as it should be compatible with the DenseNet201 model.
- **Normalization:** Normalization is conducted for scaling the pixel intensities between 0 and 1 to aid model processing.
- **Consistency in the Data:** For extracting features from images, they are passed to the DenseNet201 model in the form of arrays.
- **Data Augmentation:** In order to extract features, images are provided as input to the DenseNet201 model in a format of arrays.
- **Feature Extraction Preparation:** In order to prepare for feature extraction, extracted features are converted into feature vectors.
- **Formation of Feature Vectors:** Feature extraction is achieved through the conversion of features into feature vectors.

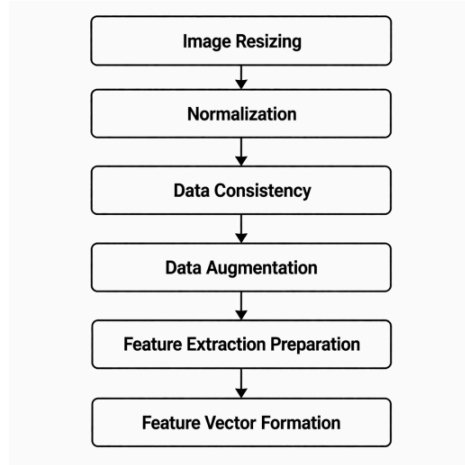


Figure 3.3: Preprocessing pipeline applied to the Brain MRI dataset.

After preprocessing, the extracted deep features are stored as numerical arrays representing each MRI image. These feature vectors are then used as input for feature selection and classification stages, enabling efficient learning and accurate prediction of brain tumor classes.

3.4 Model Architectures and Working Principles

3.4.1 Convolutional Neural Networks (CNN)

CNNs work excellently in detecting spatial information from the input data [17]. As per sentiment analysis using CNNs, filters are passed across the embedding of text to find out local n-gram patterns related to sentiment. Thus, CNNs are suitable for capturing key phrases/expressions.

This architecture begins with the input embedding layer where token embedding is done. After that, comes the one-dimensional convolutional layer, which passes over the embeddings with ReLU activation function. Then max-pooling is done to reduce dimensionality but retain important features. Finally, classification is performed by means of a dense layer along with softmax activation function. The loss function chosen here for training CNN is categorical cross-entropy [14]. CNNs can recognize visual features from an image and therefore are very useful in medical imaging tasks [23]. Pooling operations minimize computation, while convolutions detect features including edges and tumors [22].



Figure 3.4: CNN Architecture

3.4.2 DenseNet201 Architecture

DenseNet201 is an advanced version of the convolutional neural network which increases information transfer through dense connectivity[7]. In contrast to the usual CNN architecture where a single layer only gets input from the previous layer, DenseNet connects all the layers forward. This increases efficiency and can help prevent problems such as vanishing gradients[22].

Using DenseNet201, feature maps produced by the preceding layers will be used as input, allowing the model to better capture low and high level features. Pre-trained DenseNet201 will be used for this project. Classification layers will be removed, and output will be considered as deep features of the MRI images[15].

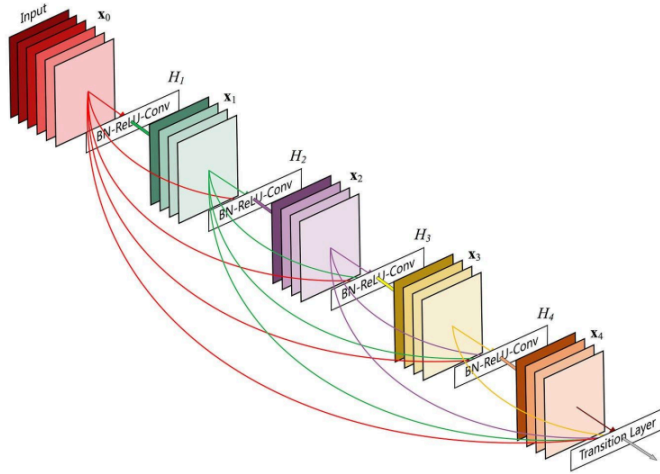


Figure 3.5: DenseNet201 Architecture

3.4.3 Feature Extraction Using DenseNet

Pre-trained DenseNet201 model is utilized for extracting the deep features from the MRI images [7]. All images undergo processing by the model, and the features are extracted based on the output at the last pooling layer in the network. The extracted features consist of high-level patterns that include important structural and textural characteristics of the images[15].

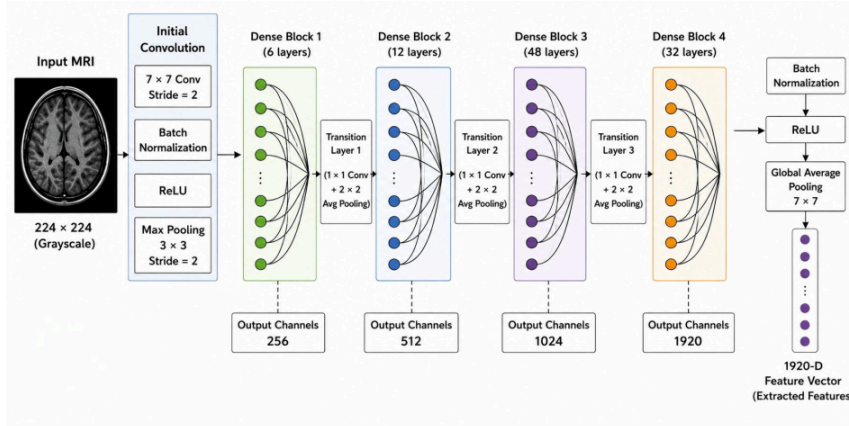


Figure 3.6: DenseNet-201 architecture used for deep feature extraction from MRI images.

Although the above-described feature representation consists of valuable data, the extracted features might contain unnecessary dimensions which will increase the complexity of computations, as well as decrease classification performance. For addressing this problem, feature selection is performed in order to reduce the number of dimensions while keeping valuable characteristics of the features intact[8]. The deep features recovered from the MRI images are represented as feature vectors in numerical form that capture the essential characteristics of the pictures. These enhanced feature vectors are then fed into different machine learning classifiers to detect the cancer. Because dense net 201-based feature extraction and feature selection are combined, the proposed technique improves processing efficiency without sacrificing classification job accuracy[1] [10].

3.4.4 Extra Trees Classifier (ETC)

Extra Trees Classifier (ETC) is used as a feature selection method for selecting the important features out of the deep feature set generated from the network[8]. The ETC method works as an ensemble learning model that uses random subspace selection strategy in order to build several decision trees. The main difference between ETC and other tree-based methods is that while other decision trees use randomness while building trees, ETC uses more randomness during splitting process that helps to minimize the variance[8].

Even though the deep features are highly informative, a large number of features could be redundant or irrelevant as well. This is where feature selection using ETC can be helpful since this approach will enable us to perform dimensionality reduction[14].

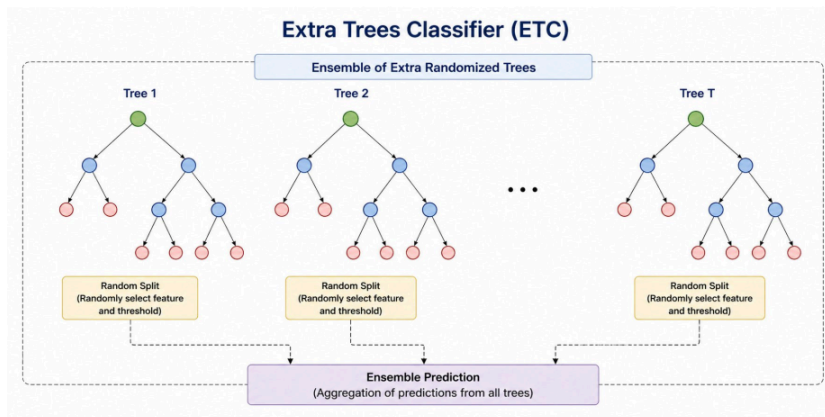


Figure 3.7: Extra Trees Classifier

3.4.5 Machine Learning Classifiers

The attributes that will be extracted through the DenseNet201 and will then be refined using the Extra Trees Classifier will be used as input for various classifiers based on different learning approaches including linear, non-linear, probabilistic, and ensemble approaches. This will be done to assess their effectiveness in identifying brain tumors through MRI attributes.

• Logistic Regression (LR)

Logistic regression is an elementary type of linear classifier used to predict the chances that any particular point will fall into one or more classes or categories. Logistic regression works best when the various categories being predicted can be categorized clearly in a straight line as opposed to being mixed together. The results of logistic regression can be determined by taking the raw data that is being analyzed and applying a sigmoid function as follows:

$$P(y = 1 | x) = \frac{1}{1 + e^{-(w^T x + b)}} \quad (3.1)$$

where

- $P(y = 1 | x)$ Equals to probability sample belonging to class 1,
- x : feature vector,
- w : weight vector,
- b : bias term,
- $w^T x + b$: linear combination of input feature

For multi-class classification, the softmax function is used:

$$P(y = i | x) = \frac{e^{w_i^T x}}{\sum_{j=1}^k e^{w_j^T x}} \quad (3.2)$$

where:

- $P(y = i | x)$ Equals to probability of the sample belonging to class i ,
- k : total number of classes,
- w_i : weight vector corresponding to class i

The model parameters are optimized using cross-entropy loss function:

$$L = -\sum_{i=1}^N y_i \log(\hat{y}_i) \quad (3.3)$$

- L denotes the loss function,
- N represents the total number of training samples.

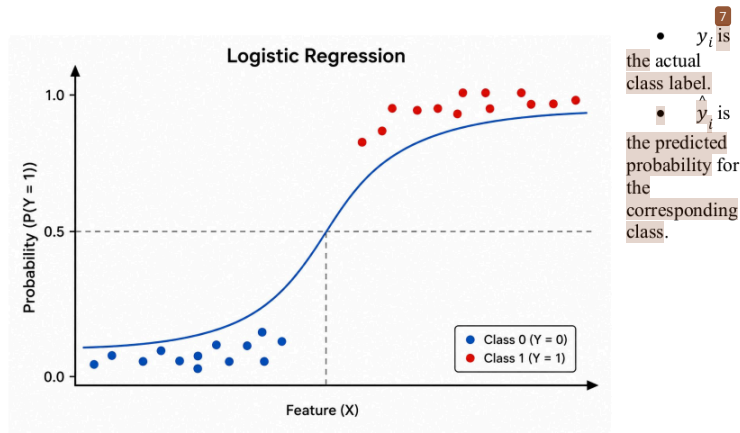


Figure 3.8: Logistic Regression

• Support Vector Machine (SVM)

A Support Vector Machine is a classifier. It finds the line to separate classes. This line maximizes the space between them.

Support Vector Machines work well in spaces. These big spaces have details.

They are good for data, with features.

$$W^T x + b = 0 \quad (3.4)$$

where:

- w : weight vector,
- x : input feature vector,
- b : bias term,
- $w^T x + b$: separating hyperplane.

The optimization problem is defined as:

$$\min_{w,b} \frac{1}{2} ||w||^2 \quad (3.5)$$

subject to:

$$y_i(W^T x_i + b) \geq 1 \quad (3.6)$$

where:

- y_i represents the class label of the i^{th} sample,
- x_i denotes the input feature vector,
- $\|w\|^2$ represents the squared magnitude of the weight vector.

For nonlinear classification, kernel functions are applied, such as the **Radial Basis Function**:

$$K(x_i, x_j) = e^{-\gamma \|x_i - x_j\|^2} \quad (3.7)$$

where:

- $K(x_i, x_j)$ represents the similarity between two feature vectors,
- γ controls the influence of training samples,
- $\|x_i - x_j\|^2$ denotes the Euclidean distance between feature vectors.

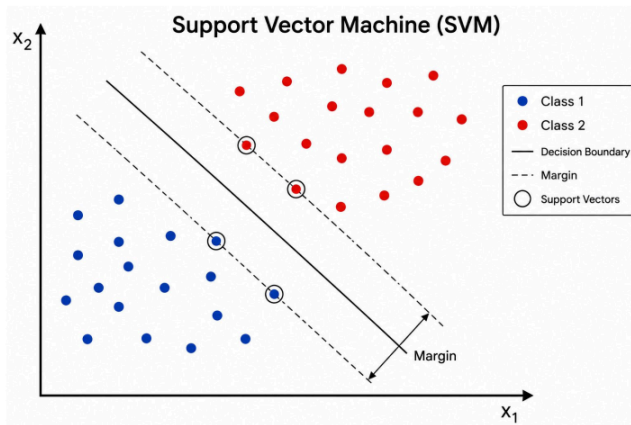


Figure 3.9: Support Vector Machine

6 • K-Nearest Neighbors (KNN)

K Nearest Neighbors (KNN) is an instance-based method where class membership is based on the class of the majority of the K-nearest neighbors determined by how far they are from the unknown example by some measure of distance, such as Euclidean distance.

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^n (x_{ik} - x_{jk})^2} \quad (3.8)$$

where:

- $d(x_i, x_j)$ represents the Euclidean distance between two samples,
- x_{ik} and x_{jk} denote the k^{th} feature values of samples x_i and x_j ,
- n is total no. of features.

The predicted class is determined as:

$$y = \arg \max_c \sum_{i \in N_k} 1(y_i = c) \quad (3.9)$$

- N_k represents the set of kk -nearest neighbors,
- $1(y_i = c)$ is an indicator function,
- c denotes the class label.

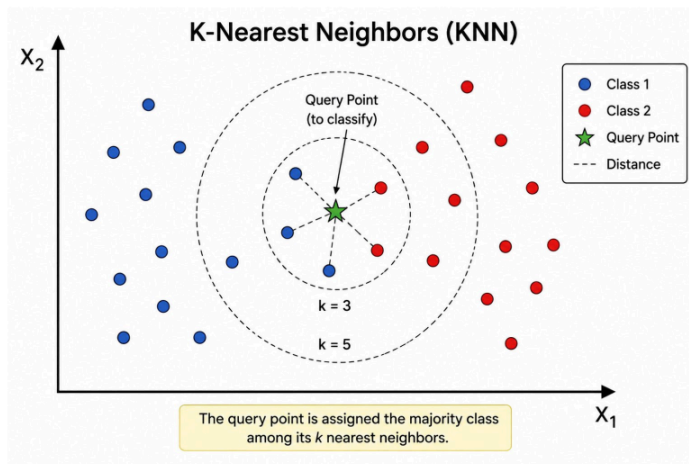


Figure 3.10: K-Nearest Neighbors

• Decision Tree (DT)

Data classification through Decision Trees occurs using a recursive approach, wherein data is split in relation to their feature values. The impurity values used for determining the splits are provided by Gini Index, Entropy, or an alternative measurement method.

$$Gini = 1 - \sum_{i=1}^c p_i^2 \quad (3.10)$$

where:

- p_i : probability of class i .
- c : total number of classes.

$$Entropy = -\sum_{i=1}^c p_i \log_2 p_i \quad (3.11)$$

where:

- p_i : probability of class i .

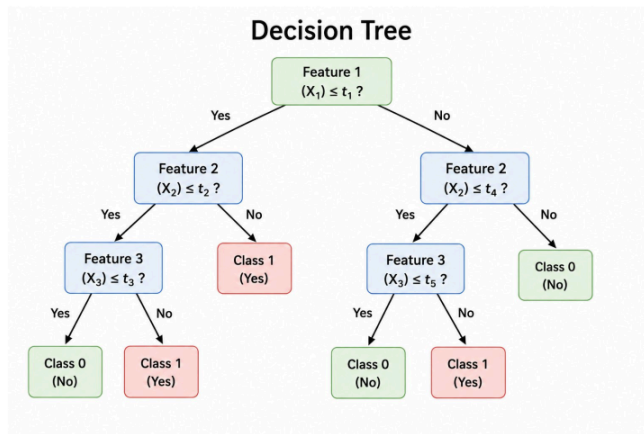


Figure 3.11: Decision Tree

• Random Forest (RF)

Random Forest is an ensemble ML approach used to build many decision trees (DTs) that generate predictions. The goal of this strategy is to provide better performance while reducing overfitting by utilizing random feature and sample selection for training each DT (decision tree) in the ensemble. Finally, the predictions made by all of the DT's will be combined together.

$$\hat{y} = \frac{1}{T} \sum_{t=1}^T h_t(x) \quad (3.12)$$

where:

- $\hat{y}$: final predicted output,
- T : total number of decision trees,
- $h_t(x)$: prediction of the t^{th} decision tree.

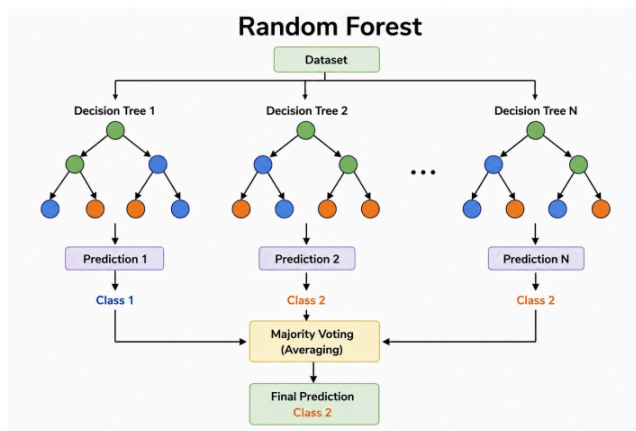


Figure 3.12: Random Forest

• Gaussian Naive Bayes (GNB)

Gaussian Naive Bayes is a probabilistic classifier based on Bayes' theorem that assumes that all features are independent from one another. The below is how to compute the posterior probability:

$$P(y|x) = \frac{P(x|y)P(y)}{P(x)} \quad (3.13)$$

where:

- $P(y|x)$: posterior probability
- $P(x|y)$: likelihood
- $P(y)$: prior probability
- $P(x)$: evidence probability

Assuming a Gaussian distribution for features:

$$P(x_i|y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} e^{-\frac{(x_i-\mu_y)^2}{2\sigma_y^2}} \quad (3.14)$$

where:

- μ_y : mean of feature values for class y ,
- σ_y^2 : variance,
- x_i : input feature value.

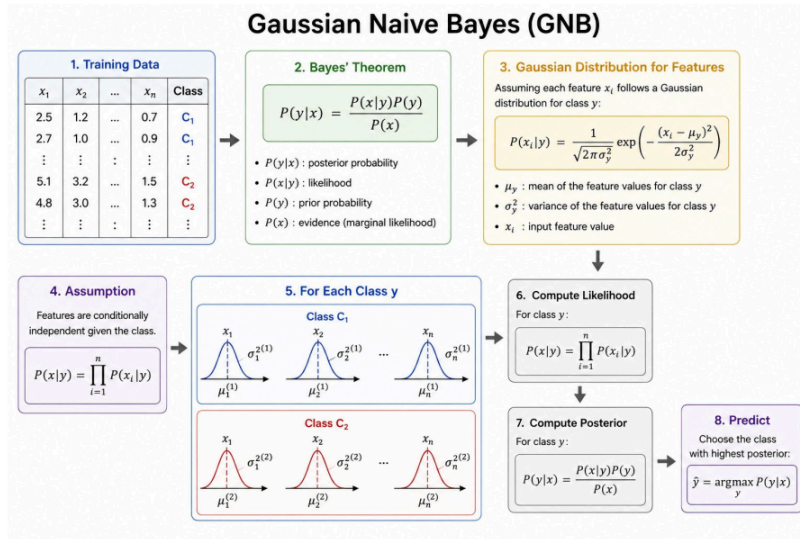


Figure 3.13: Gaussian Naive Bayes

3.4.6 Hybrid Framework

This hybrid method employs **deep learning** methods **for feature extraction and machine learning** methods **for classification**. Due to deep learning's ability to perform excellent feature extraction and the power of combining them together with the simpler yet effective traditional Machine Learning classifiers we aim to achieve a strong balance between accuracy and interpretability.

The use of DenseNet201 and ETC in conjunction with various classifiers creates an incredible combination that produces superior results while maintaining model interpretability. This method is well suited for medical applications in particular.

3.5 Training and Evaluation Strategy

Separate groups of training and testing data gives a more exact evaluation of the quality of a model. The training dataset will be used to train the classifiers of machine learning and generate deep features, while the testing dataset will prove how well a model will generalise. Deep features will be generated using a DenseNet201 pre-trained network, rather than learning a completely new network from scratch.

The deep-represented features will next be distilled down to their most significant components by utilising an Extra Trees Classifier (ETC). Using the final deep features, all six types of classifiers (Logistic Regression, Decision Trees, SVMs, KNNs, Random Forests, and Gaussian Naive Bayes) will be trained.

Several evaluation metrics are used to gauge the models' efficacy:

1. **Accuracy:** the proportion of correct predictions made compared to the overall number of predictions made.
2. **Precision:** This represents to the ratio of correct predictions to all positive predictions.
3. **Recall:** how well the model is able to identify all of the relevant positives.
4. **F1-Score:** This is the metric used for evaluating performance, which is the harmonic mean of the recall and precision.
5. **Confusion Matrix:** This is the graphic representation of all predictions made.

The test dataset is used to calculate the metrics in order to rate the performance of the model and verify the accuracy of a classification result.

Graphically, analytical methods are used to show how classifiers perform in different ways than does the classifier performance metric. These graphical representations of the characteristics of how each classifier behaves in terms of classifying data and making decisions include confusion matrices, accuracy comparison charts, and graphical representations of the importance of the features used to train each classifier. This type of representation makes it easier to identify the strengths and weaknesses of each classifier when separating two types of brain tumors from one another.

The methodology suggested here ensures that both processing effectiveness and classification performance are considered with equal importance. Transfer learning using DenseNet201 greatly simplifies the training process while still maintaining strong feature representation compared to training a deep learning architecture from scratch. Feature reduction using ETC removes redundant features.

In addition, the best deep features-based method for brain tumor classification can be determined using the comparison of different machine learning techniques. This will help in accurate performance evaluation and lead to the construction of a useful computer-aided diagnosis system for classifying medical images.

RESULTS AND DISCUSSION

4.1 Experimental Setup

Google Colab was used for all tests, and GPU acceleration techniques were applied effectively extract features and to analyze models. The TensorFlow & Scikit-learn programming libraries will serve as the foundation for the implementation framework. Seventy-five percent of the overall dataset will be used for training the model, with a quarter left aside for testing. Datasets will be divided in this manner.

The deep features of MRIs will be extracted using the DenseNet201 pretrained model, and then extra trees classifier would be used for the optimization of these features in order to select the feature vector for each MRI image. These vectors will serve as input data for various machine learning Classifiers; all models will be trained on the standardized feature datasets, & hyperparameters will be empirically chosen.

All of the data was preprocessed prior to the feature extraction process from the images that would be used in the learning and testing procedures in order to guarantee consistency in the data supplied to the model during training. Scaling, standardization, and creating hierarchies for training and testing folders in compliance with the database structure were among the preprocessing techniques. Prior to being used in the classifier's training, the collected attributes were normalized.

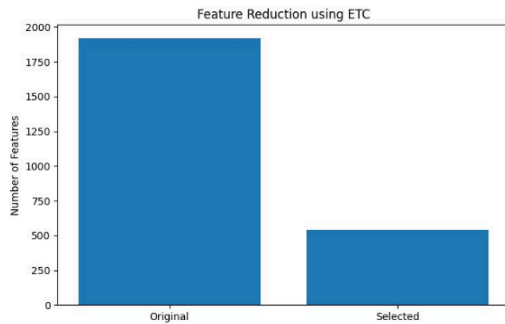


Figure 4.1: Feature Reduction using Extra Trees Classification

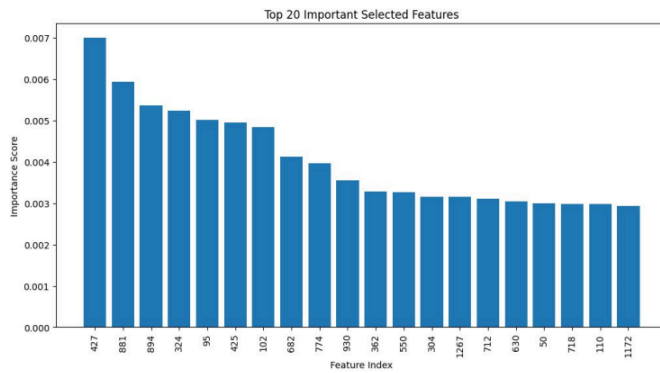


Figure 4.2: Top 20 Important Selected Features

4.2 Model Performance

All four model's performances were evaluated in terms of classification performance metrics, including precision, recall, accuracy and F1 Score. These metrics give insight into a model's efficient ability to classify brain tumor type into multiple categories. The model contains four categories of brain tumors: gliomas, meningionomas, pituitary tumors and no tumors.

Table 4.1 provides a comparison of different machine learning Classifiers. Both Linear SVM and Logistic Regression models perform better than the rest of the models in all the measures. The improvements are evident due to the importance of extracting deep features with feature selection, thus helping the models to learn patterns

Model	Accuracy	Precision	Recall	F1-Score
LR1_SAGA	0.9181	0.9249	0.9181	0.9161
LR2_NEWTON	0.9194	0.9267	0.9194	0.9172
LR3_LBFGS	0.9188	0.9260	0.9188	0.9166
LR4_LIBLINEAR	0.9144	0.9200	0.9144	0.9116
SVM_RBF	0.9075	0.9193	0.9075	0.9049
SVM_LINEAR	0.9031	0.9130	0.9031	0.9012
SVM_POLY	0.8956	0.9144	0.8956	0.8924
Decision Tree	0.7969	0.8147	0.7969	0.7919
KNN	0.8919	0.8958	0.8919	0.8891
Random Forest	0.8669	0.8779	0.8669	0.8606
Gaussian NB	0.7669	0.7729	0.7669	0.7578

Table 4.1: Performance Comparison of Machine Learning Models for Brain Tumor Classification

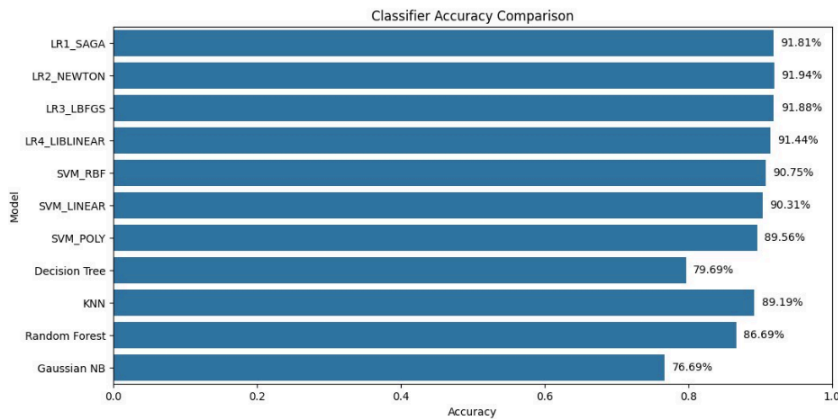


Figure 4.3: Machine Learning Model Accuracy Comparison

The evaluation performance for different model types was evaluated and compared through the subsequent figure which highlights the differences in Precision, Recall, Accuracy and F1-Score between the model types. The graphs illustrate distinct differences within the metric values further separating individual models from each other. Overall, linear models such as Logistic Regression and Support Vector Machines outperformed all of the other class of models. This increased level of performance was attributed to the use of deep feature extraction and/or selection techniques.

4.2.1 Model Performance Analysis

Based on the findings from our analysis, it becomes clear that algorithms such as SVM and Logistic Regression exhibit higher levels of performance than other types of models, with respect to metrics such as accuracy, recall, precision, and F1-score. Their proficiency with handling high dimensional feature spaces generated by DenseNet201 model of deep feature extraction is the cause of their exceptional performance. They are highly efficient in defining decision boundaries.

Additionally, linear algorithms like Logistic Regression take advantage of the structure of the deep feature set, thus simplifying any transformations that might be required otherwise. Likewise, Support Vector Machines provide good performance due to their margin maximization, which helps improve generalization even in high-dimensional space.

In contrast, K-Nearest Neighbor and Random Forest classification algorithms yield average results. Even though the KNN method computes the similarity based on distances, it depends heavily on how the features are distributed and scaled, and thus, it performs poorly in high dimensions. The Random Forest classifier outperforms the Decision Tree algorithm in that it addresses overfitting, but not all types of problems.

The use of Extra Trees Classifier for the process of feature selection proves to be effective, and it is yet another key finding of the study. In other words, the classifiers concentrate more on the important features that have been selected from the MRIs and exclude those which are not relevant enough to contribute to the decision-making process.

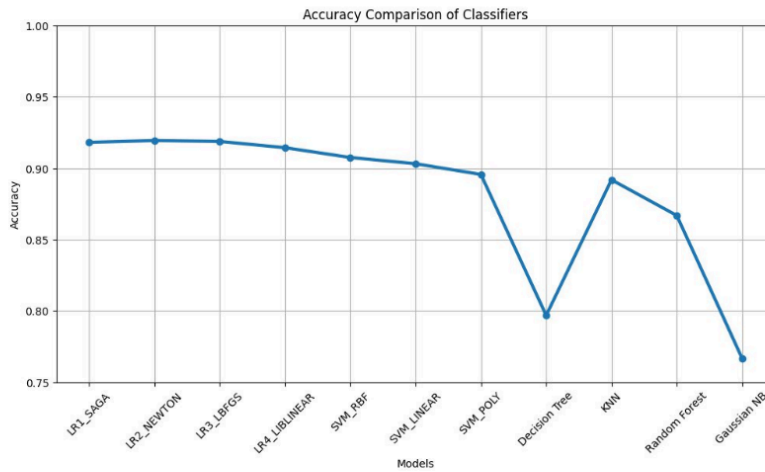


Figure 4.3: Accuracy Comparison

The decision tree model and the Gaussian Naive Bayes classifier show poor performances in relation to others. Decision trees have the problem of over-fitting since they are unable to generalize the interactions of features. The assumption of Gaussian Naive Bayes about independent features does not hold true.

Moreover, the confusion matrix from the best performing model (LR2_NEWTON) further confirms its efficiency in successfully categorizing all types of tumors. This model is efficient in classification tasks for all classes with very low levels of errors, thus making it a reliable and robust one.

4.3 Comparative Analysis

How well a particular machine learning model performs will largely depend on the type of features used to build the model. The logistic regression and SVM models have achieved a great deal of success because they can develop the ideal decision boundaries for the classification problem at hand in high dimensional feature space.

On the contrary, the Decision Tree model and Gaussian Naive Bayes perform poorly owing to their inability to process complex interactions of input features. While Random Forest helps solving the problem of overfitting for Decision Tree model, it is still inferior in performance to other classifiers.

However, the combination of DenseNet-based feature representation and feature selection allows increasing classifier performance.

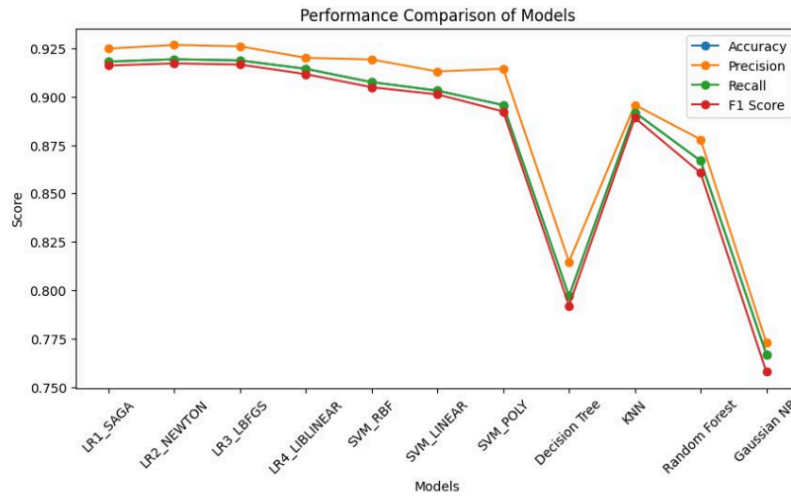


Figure 4.4: Performance Comparison

4.4 Discussion of Findings

It is clear from the results that the integration of deep feature extraction along with the classification techniques improves the efficiency of the proposed model in classifying brain tumors. With the use of DenseNet201, high-level structural and texture features can be extracted from the MRIs, which

contribute towards the discrimination power of the classifier models. From the models assessed, it was observed that logistic regression and SVMs outperform others because of their efficacy in dealing with high-dimensional feature space.

Another critical point of view is the success of feature selection through the use of the Extra Trees classifier. Though there are many informative features obtained from the deep learning model, it is beneficial to eliminate redundant and unrelated features for efficient computations without compromising on accuracy.

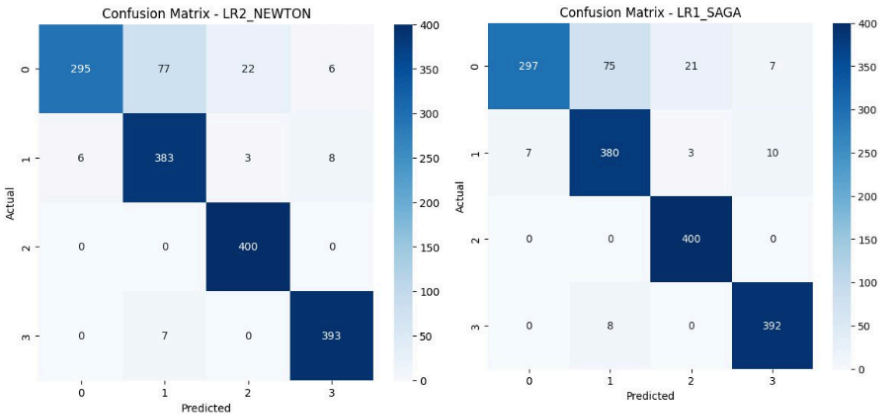


Figure 4.5: Confusion Matrix for LR2_NEWTON And LR1_SAGA

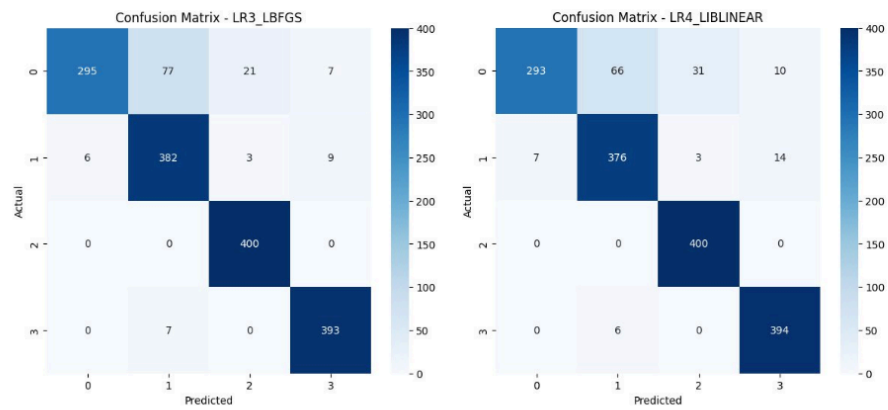


Figure 4.6: Confusion Matrix for LR3_LBFGS And LR4_LIBLINEAR

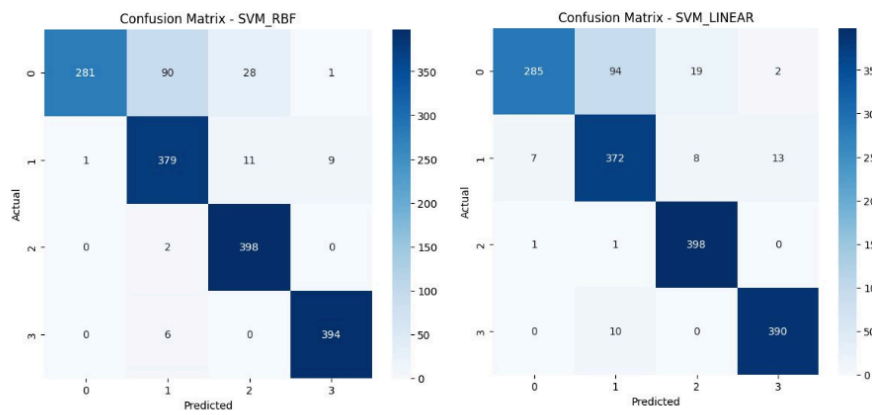


Figure 4.7: Confusion Matrix for SVM_RBF And SVM_LINEAR

Additionally, the best-performing model's confusion matrix shows little misclassification between classes and balanced categorization across all tumor types. This illustrates how resilient the suggested strategy is.

In conclusion, the combination feature extraction and classifiers can be used effectively for brain tumor classification.

CONCLUSION and FUTURE WORK

5.1 Summary of Findings

Hybrid methods were created to classify MR brain tumor image data from MRI scans into associated categories. A trained, DenseNet201 neural network was utilized to extract large amounts of visual features from the data set. The other half of the analysis process consisted of classifying the features based on diagnoses made by the other half of the analysis process. Several different classifiers were created as part of the evaluation process and included logistic regression, KNN, support vector machines (SVMs), decision trees, random forests, and naive Bayes classifiers. Each of these classifiers was evaluated based on their accuracy in predicting results and compared to each other to see how well they performed overall.

Experimentation determined that the linear classifiers, which consist of Logistic Regression and SVM models, showed the best accuracy across all four performance evaluations; accuracy, recall, precision, and F1 Score. The method of feature selection performed very well in reducing redundancy yet keeping the selected features discriminative.

From the results, we can see that using both transfer learning and a machine-learning model is an efficient method for detecting brain tumors, especially due to its speed over fully trained deep learning models while still being an accurate method of predicting results.

5.2 Limitations

Although the above-mentioned approaches ensure high accuracy in classifying brain tumors, there are several disadvantages associated with their use:

- **Dependency on the data:** The framework is built upon a certain MRI dataset available publicly and therefore cannot be generalized to different data characteristics, machines, and imaging protocols used by clinics.
- **Imbalanced classes:** Even though this research used a rather evenly divided dataset in terms of classes, many healthcare data collections include a significantly smaller number of abnormal cases.
- **Lack of transparency:** Using dense features from a DenseNet201 network in a hybrid architecture reduces transparency. The difficulty of comprehending this technique is immense.

- **Absence of the localization component:** While this technique helps us to classify the MRI in one of the classes, it does not give us information regarding its location.
- **Resource consumption:** Although this particular model uses energy less than the end-to-end model, energy utilization is not small.

5.3 Future Work

Some of the potential areas for future research ¹⁶ in order to enhance the effectiveness of proposed classification model include following:

- **Multimodal Integration:** In the course of future research, additional modalities such as patients' data and/or CT scan may be considered in order to augment the present database which is built from MRI images.
- **Transparency:** It would be possible to highlight key information from an MRI image and hence enhance transparency through techniques like Grad-CAM, LIME, and SHAP.
- **Feature Selection Algorithms:** Further studies involving different techniques of feature selection such as MRMR can aid in boosting accuracy by making sure that all features are considered.
- **Transformer Networks:** By permitting contextualization of the entire image rather than isolated patches, research utilizing transformer networks (ViT), hybrid CNN-transformer models, or similar models could enhance feature extraction.
- **Real-Time Clinical Applications:** Implementing the algorithm in a clinical setting, providing support in real-time, could assist radiologists in making more accurate diagnoses.

In summary, the results of this study demonstrate that deep feature extraction in conjunction with classification algorithms is highly effective in brain tumor discrimination. Intelligent medical systems that improve diagnostic accuracy are made possible by the successful use of hybrid models.

An Integrated Approach for Brain Tumor Detection using Deep Feature Extraction and Machine Learning Classifiers.

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