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Predictive and State-of-the-art Machine Learning Models for Brain Tumors Prediction and Classification

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KEYWORDS

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ABSTRACT:
Brain tumors as part of complicated diseases impacting delicate functions of the brain, are generally caused by brain cell's uncontrolled proliferation or within locations such as the pituitary gland, the pineal gland, nerves, and the membranes covering the brain surface. Brain tumors are classed as critical diseases due to the brain's complex structure, and challenges related to early detection. In recent decades, machine learning (ML) has revolutionized medical imaging processing, innovating how healthcare professionals diagnose diseases and treat various conditions. This technique allows computers to learn to identify specific image features and patterns, and automatically classify different medical conditions. Several ML techniques are commonly used for image preprocessing in diverse domains.

This study aims to predict and classify brain tumors and analyze the performance of ML models: Support Vector Machine (SVM), XGBoost classifier, Light GBM (LGBM), and Random Forest (RF), using performance metrics: precision, recall, f1-score, and accuracy. This research paper reveals that the LGBM classifier outperforms other algorithms, achieving 91% accuracy.

Conclusively, this study illustrated that ML methods prove efficiency in brain tumor prediction at an early stage and provide a robust model for medical professionals to save patient lives.

1. Introduction

In the last decades, Brain tumors have emerged as sincere diseases having particular focus from healthcare professionals as they affect the most critical human body organ, controlling the whole-body functions. There are various types of brain tumors such as:

a) Glioma: This includes various types, including glioblastoma, astrocytoma, ependymoma, and oligodendroglioma, which are characterized by an abnormal growth of glial cells.
b) Embryonal tumors: affecting embryonal cells left after birth and often happen in babies and young children
c) Meningiomas: are the most popular types of brain tumors and generally impact the spinal cord and membranes surrounding the brain
d) Pituitary: is part of benign tumors and affects around the pituitary gland.

Machine learning has achieved widespread utilization in multiple fields, especially healthcare over the last few decades. This technique used advanced algorithms to analyze large datasets enhancing the efficiency and accuracy of medical image interpreting. Machine learning relies on automated analysis to improve medical diagnosis, reduces time processing, and increases patient outcomes through personalized treatment plans, in contrast to manual analysis, having limitations in accuracy, efficiency, and time consumption. Machine

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learning is an artificial intelligence subcategory and part of the prominent research domains [1] in computer science, classified under four major categories:

a) Supervised Learning: is a category of ML based on training the model using labeled data to make predictions and identify valuable patterns; this technique is commonly utilized for regression and classification problem-solving.
b) Unsupervised Learning: is an ML branch, generally utilized for clustering and association using unlabeled data and training algorithms without prior knowledge about data structure.
c) Semi-Supervised Learning: integrating both unsupervised and supervised learning and training unlabeled and labeled data.
d) Reinforcement learning: algorithms of this category are about decision-making, used to obtain the optimal decisions.

Figure 1 illustrates the commonly used machine learning algorithms per category:

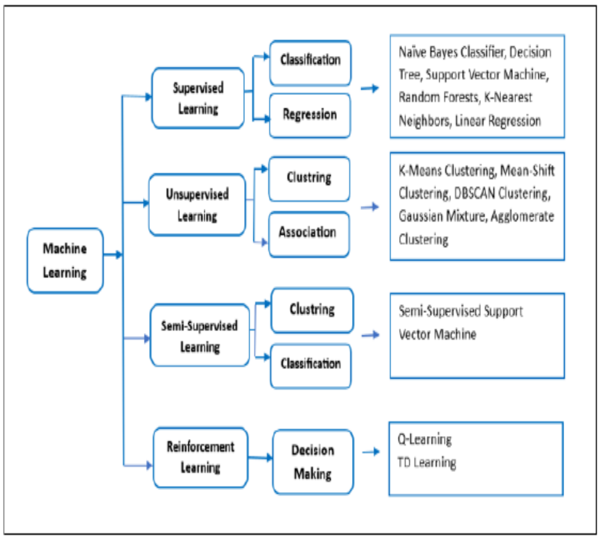

Figure 1. Classification of ML algorithms per category

The process of machine learning is iterative and based on five stages as shown in Figure 2:

a) Data Collection: gathering of data from different sources and formats
b) Data Processing: consists of data cleaning and feature extraction
c) Model Building: the machine learning algorithm is selected and the model is trained and tested
d) Model evaluating: evaluation of the model is based on every model methodology
e) Model Deployment: the model is integrated into the production environment to make decisions

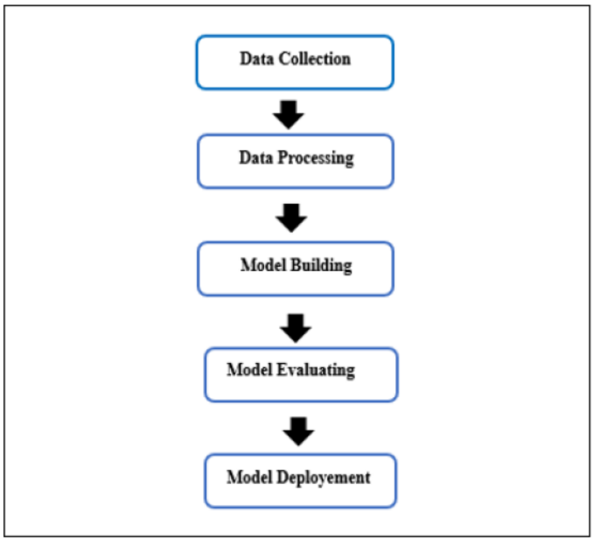

Figure 2. Process of Machine Learning

Machine learning application domains are vast such as economy, business, marketing, computer vision, and healthcare, and the most significant applications include image recognition, automatic language translation, online fraud detection, traffic prediction, healthcare, and more.

Examples of ML learning methods in the medical field are:

a) Medical Imaging: used for disease prediction and detection such as Alzheimer's prediction, breast tumor detection based on object detection, and image recognition techniques in Computed Tomography (CT) or Magnetic Resonance (MR)
b) Mental healthcare: consists of developing AI-based and ML-based applications with the ability to make realistic discussions with patients, an example of those applications is MoodTools for managing anxiety and depression
c) Treatment personalization: ML and IA algorithms can perform the personalization of treatments for each patient based on the medical history and symptoms of the patients
d) Healthcare Research Development: ML has recently contributed to healthcare research

development and medicament discovery, such as the pandemic field for instance useful tools were developed for the early detection of COVID-19

e) Fraud Detection: ML applications in healthcare fraud detection are various, especially medical insurance fraud, ML algorithms identify abnormal behavior in medical data based on many inputs such as medical records

Machine learning applications for classification in medical fields consist of extracting useful information and features to predict the correct medical label of a given input data.

2. Related Work

In the [2] study, the ML techniques: LGBM classifier, Extreme Gradient Boost classifier, Bagging classifier, SVM, Stochastic Gradient Descent classifier, Gaussian Naïve Bayes, DT, and RF, are used to predict brain tumors and reveal that all classifiers achieve good results.

The research paper [3] compares the interoperability and accuracy of brain tumor prediction using models BRL, EBM, RF, SVM, and LR. The ML techniques were applied to survival for one year and achieved 78,8% balanced accuracy for the RF algorithm as an excellent result.

The research paper [4], utilizes hybrid DL models for brain tumors detection and classification. The methods from EfficientNetB0 to EfficientNetB4 of the EfficientNets family are employed in this study, and the overall performance metrics results attain: 98.79%-F1-score, 99.13%-recall, and 99.06%-precision.

The brain tumors classification in [5] study employs the features selection and tuning hyperparameter, the methods used are Extreme Gradient Boosting, Categorical Boosting, Extra Trees RF, Nb, KNN, and SVM accomplish 98.0% accuracy.

The [6] study explores brain tumor classification automation using AlexNet, VGG16, and ResNet-50 methods. This study achieves an accuracy of 99.98%.

Brain tumors brain tumors using transfer learning algorithms: ResNet50V2, Xception, DenseNet201, and InceptionResNetV2 in [7] study, explores the efficiency of deep learning model and fine-tuning and reconstruction. The results of this research paper reveal that the ResNet50V2 method accomplishes 99.68% accuracy.

In [8] brain tumors classification is combining ML models Light GBM algorithm, gradient boosting, AdaBoost, Quadratic Discriminant Analysis, Random Forest, logistic regression, transfer learning algorithms, and Linear Discriminant Analysis. This study outcome revealed that the algorithm Light GBM achieves 95.7% and the GoogLeNet model attains an accuracy of 99.3%. This research paper showed the ML technique efficiency combined with transfer learning methods.

The research paper [9] built a model for brain tumors classification using Local Cascade Ensemble, XGBoost, LGBM, and CatBoost classifiers, Histogram-based gradient boosting. This study is focused on 422 patients summaries and classified the dataset into Craniopharyngioma, Meningioma, and Pituitary adenoma tumors. This model is analyzed using the Python package: ELI5 tool and the output for this study demonstrated that this model performs well in classification.

In [10], the automatic detection of brain tumors is based on the EfficientNet method including three models of its family: EfficientNet-B4, EfficientNet-B3, and EfficientNet-B2. This research outcome showed that the model EfficientNet outperforms the traditional CNN because of the scaling of all depth dimensions, resolution, and width.

In the study [11], the authors explore the role of IA and ML techniques in detecting brain tumors, especially for pediatric patients. The study employed the Artificial Neural Network method and a dataset of 4493 images and the outcome revealed that the accuracy results for this study matched the radiologist's report.

3. Methods

3.1 Research Approach

This paper's objective is to predict and classify brain tumors using supervised machine-learning models: XGBoost classifier, Light GBM(LGBM), SVM, and Random Forest (RF), using brain tumors MRI dataset, and to compare the ML state-of-the-art performance techniques: LGBM and XGBoost with the predictive models: SVM and RF utilizing metrics: accuracy, precision, f1-score, and recall.

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Classification is a machine learning method performed on labeled or unlabeled data, and splitting input data into training and testing. This technique is classified under supervised ML learning and categorizes a set of data into classes by mapping approximately the input data features to the resulting output.

In the biomedicine field classification is generally used for the prediction of specific categories of medical conditions such as viral diseases; however; regression is for real values of inputs, for instance, therapy response. [12]

The objective of the classification is to predict the target class with high precision [13], and the process for the classification is based on the classification model through many steps:

a) Pre-processing: This step focuses on cleaning and filtering data to improve data quality. The dataset is partitioned into testing and training data.
b) Feature extraction: consists of extracting valuable patterns such as edges, shapes, and others to transform data rows into digital features compatible with the ML algorithm. This stage aims to optimize the trained model's efficiency and accuracy.
c) Feature selection: in this step, the feature selection contributes to optimizing the ML model by finding the best set of patterns within used items
d) Classification: is based on model training, using models: SVM, RF, XGBooster, and LGBM. Those algorithms are implemented using the Python programming language, which is the most useful in the machine learning domain.
e) Predictions: predicts the classification results, for this study tree output classes: Normal (No Tumor), Pituitary Tumor, and Meningioma Tumor
f) Evaluation: the trained model performance evaluation utilizes metrics: F1-score, accuracy, precision, and Recall.

Figure 3 shows the classification workflow for medical images for this study:

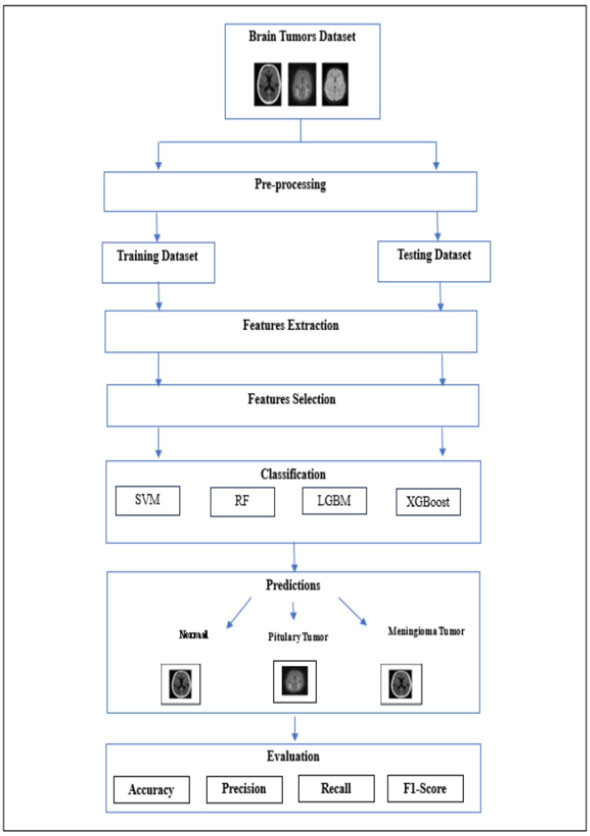

Figure 3. Classification workflow for this study

3.1.1 Evaluation Metrics

There are many performance metrics used to evaluate machine learning methods. The metrics used for that research to compare machine learning classifies are: [14]

a) Accuracy: is the fraction of classes classified correctly compared to the total items evaluated

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

b) Precision: calculates positive items that are correctly predicted by all predicted items:

$$\text{Precision} = \frac{TP}{TP + TF}$$

c) Recall or Sensitivity: represents the portion of the positive samples correctly classified

$$\text{Sensitivity} = \frac{TP}{P} = \frac{TP}{TP + FN}$$

d) F1-Score: is calculated as shown in the equation below:

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

3.1.2 Data Set

In this research, we performed classification using a brain tumor medical MRI dataset, which includes 409 images. This dataset is outsourced from Kaggle's repository.

The dataset is segmented into two main sets:

a) Training dataset: representing 80% of dataset size, and used in training of the model
e) Testing dataset: having 20% size, used for testing and validating the model

3.2 Machine Learning Algorithms

This study will focus on the supervised learning techniques commonly used in classification, including LGBM, XGBoost, SVM, and RF.

3.2.1 Support Vector Machine

Support Vector Machine (SVM) is a supervised machine learning method that makes classifications accurate [15]. This ML model is centered on the statistical learning theory and is a reliable tool for solving problems with limited samples, nonlinearities, high dimensions, and local minima.

The strategy for the SVM algorithm is based on finding a max-margins separation in the n-dimension feature space. SVM linear is used to solve linear problems however for no linear data the kernel functions are usually more adapted. Many hyperparameters can greatly impact the SVM performance for instance:

a) Regularization: showed as 'C' controlling the balance between low training and testing error;
b) Kernel function: can be either linear or polynomial, defines the transformed space decision limit;
c) Kernel specific: determining kernel polynomial level.

3.2.2 Random Forest

Random Forest (RF) is an ML algorithm for classification that creates several decision trees by choosing a group of training items and learning variables [16].

RF is a supervised ML technique, for which every node represents an attribute constraint and the branch stands for decision results. [17]

Figure 4 illustrates a decision tree structure: [13]

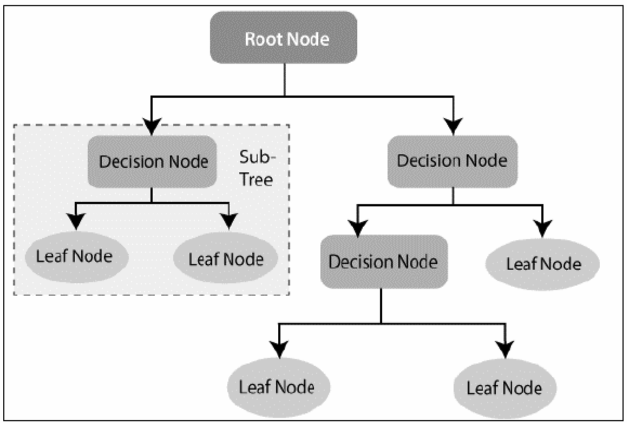

Figure 4. DT structure

There are various types of DT algorithms, the most significant of which are: [13].

a) Multivariate Adaptive Regression Splines (MARS),
b) Chi-squared Automatic Interaction Detector (CHAID),
c) Classification and Regression Tree (CART).

Entropy and Information Gain are the main metrics used in the DT algorithm:

a) Entropy: utilized to calculate the dataset randomness or impurity, this metric always has values between 0, and the best performance is when the entropy value is 0.
b) Information Gain: this metric is utilized for segmentation, and informs about the degree of knowledge of random variable values. It is the entropy opposite, the higher its value is, the better the performance the model has.

The Random Forest algorithm is regarded as a highly accurate algorithm to solve problems of regression and classification focused on the selection of the features from top to bottom in the tree and a few evaluation parameters like information gain, Gini index, chi-square, etc. [17]

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3.2.3 XGBoost Classifier

XGBoost belongs to the ensemble learning algorithms, employs a decision tree as a learner base, and is used to handle classification and regression issues. XGBooster Classifier defines three categories of parameters: [18]

a) General parameters: used to define the booster type for boosting, generally a linear model or a tree.
b) Booster parameters: depend on the selected booster
c) Task parameters: to choose a learning situation. For example, tasks of ranking and regression use different parameters.

XGBoost algorithm has several advantages such as handling large amounts of data, and running on multiple computing systems Additionally, XGBoost utilizes several regularization techniques for overfitting problem prevention, which is common in classification, and increases performance in terms of efficiency and scalability.

3.2.4 LGBM Classifier

Light GBM (LGBM) is an ensemble learning classifier renowned for its efficiency. The LGBM classifier is based on a decision tree and its working process relies on gradient boosting technique. This technique combines several weak decision trees representing learners to construct a stronger predictive model.

The workflow of trees creation in the LGBM classifier is bottom-up, where selected leaves will have increased loss reduction which has a significant impact on efficiency and memory usage improvement. [19]

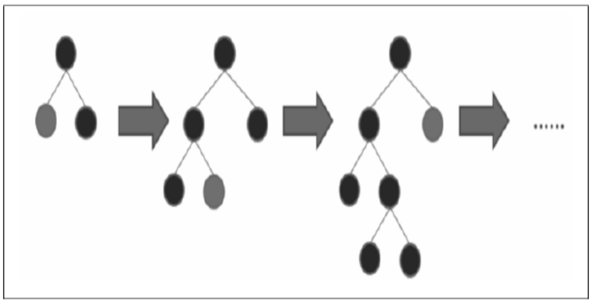

Figure 5. Workflow of tree creation in the LGBM algorithm

4. Results

The experimental results for classifying brain tumors using the machine learning methods: LGBM, XGBoost, SVM, and RF are evaluated based on various performance metrics already explained.

Figure 6 shows a sample of the classification output using the XGBoost algorithm:

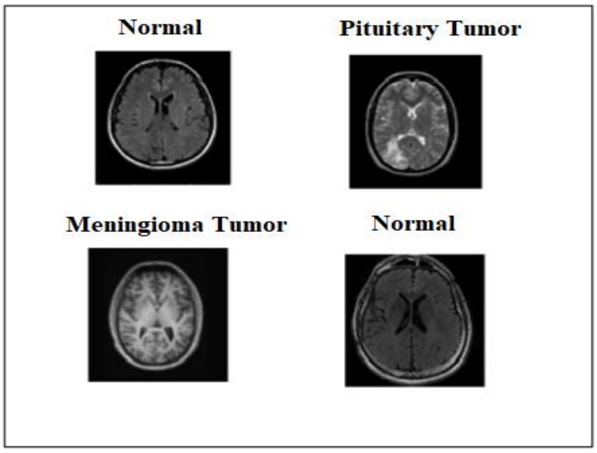

Figure 6. Classification output sample for Brain Tumor MRI images using XGBoost Algorithm

The next tables show the results and performance metrics comparison for various ML classifiers:

Classifier	Correctly Classified (%)	Misclassified (%)
LGBM	91.3	8.7
XGBoost	90.98	9.02
SVM	89.00	11.00
Random Forest	90.96	9.04

Table 1: correctly classified and misclassified items in (%)

Classifier	Execution Time (Sec)	Testing Size	Training Size
LGBM	30.5	20	80
XGBoost	31	20	80
SVM	147.86	20	80
Random Forest	31.45	20	80

Table 2: execution time(s), testing and training dataset size

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Figure 7 and Figure 8 are graphs representing execution time, and the correctly classified and misclassified items, respectively:

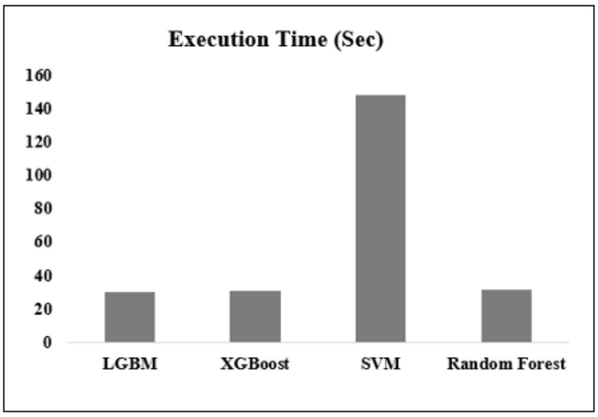

Figure 7. Execution time of classifiers for brain Tumors MRI dataset

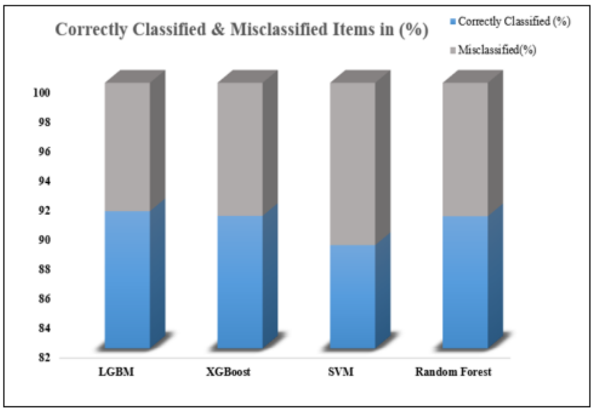

Figure 8. Correctly Classified and Misclassified items for brain Tumors MRI dataset

Classifier	F1-score	Recall	Precision	Accuracy
LGBM	89	91	92	91
XGBoost	89	91	91	90
SVM	88	88	90	89
Random Forest	89	90	90	90

Table 3: Performance metrics comparison of ML classifiers

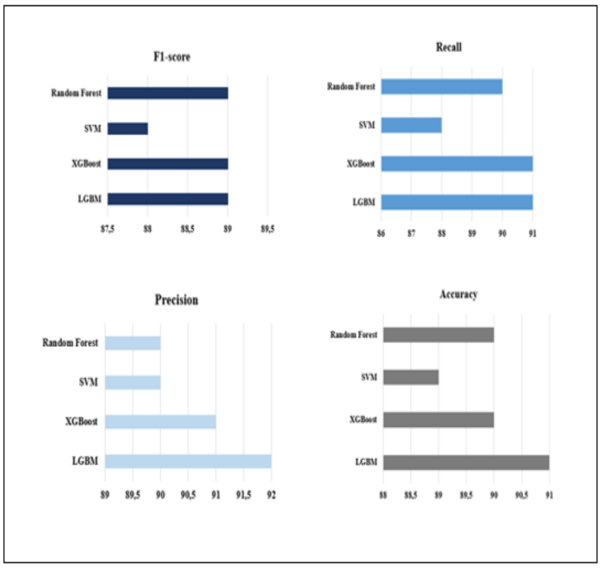

Figure 9. Graph of performance metrics for various classifiers

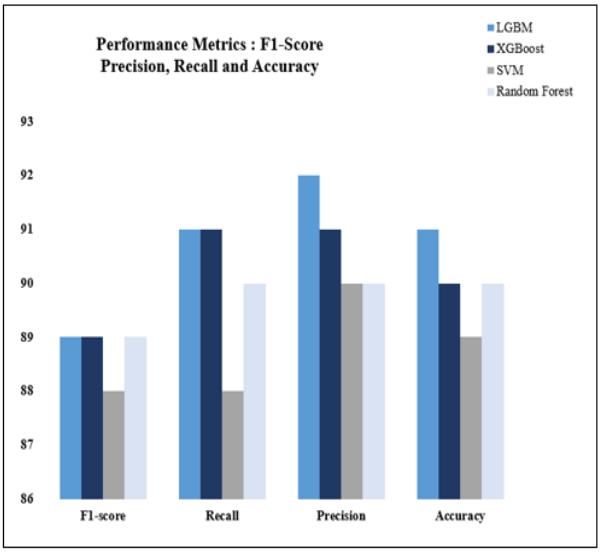

Figure10. Performance metrics: f1-score, recall, precision, and accuracy graph comparison of ML classifier

The graphic illustrates that the LGBM stands out as the most effective classifier, achieving 91% accuracy. The SVM model has 89% accuracy and the lowest performance metrics compared to other models.

Confusion matrix of algorithms SVM and RF is shown in the next figures:

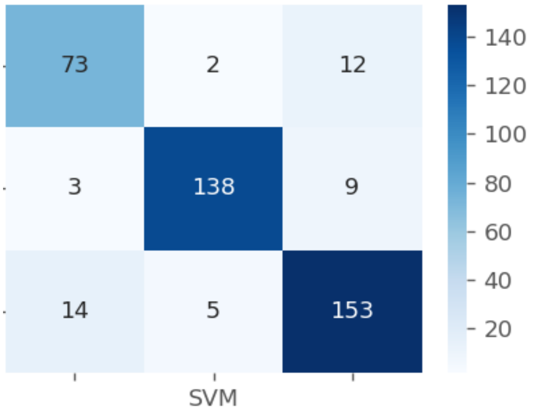

Figure 10. SVM algorithm Confusion matrix

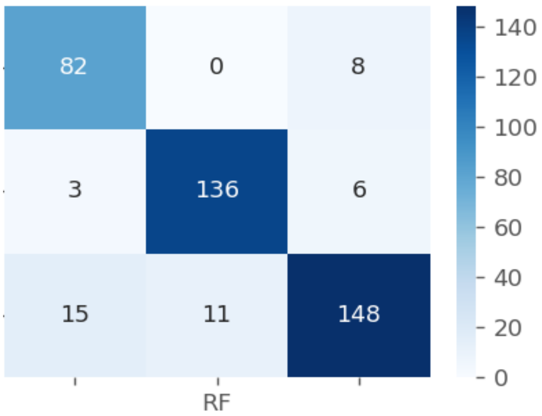

Figure. 11. RF algorithm Confusion matrix

The classification reports of the LGBM and SVM algorithms are shown in the figures below:

	precision	recall	f1-score	support
0	0.94	0.78	0.85	97
1	0.97	0.95	0.96	174
2	0.83	0.93	0.88	138
accuracy			0.91	409
macro avg	0.91	0.89	0.90	409
weighted avg	0.91	0.91	0.91	409

Figure. 12. Classification report of LGBM algorithm

	precision	recall	f1-score	support
0	0.81	0.84	0.82	87
1	0.95	0.92	0.94	150
2	0.88	0.89	0.88	172
accuracy			0.89	409
macro avg	0.88	0.88	0.88	409
weighted avg	0.89	0.89	0.89	409

Figure. 13. Classification report of SVM algorithm

The overall distribution for various classifiers per class is illustrated in the next table:

Classifier	**Distribution in (%)**		
	Normal	**Pituitary Tumor**	**Meningioma Tumor**
LGBM	24	42	34
XGBoost	22	43	35
SVM	21	37	42
Random Forest	25	36	39

Table 4: The overall distribution for various classifiers

5. Discussion

In this research, we evaluated the ML techniques LGBM, XGBoost, SVM, and RF for predicting and classifying brain tumors based on feature extraction and selection and using metrics F1-score, precision, accuracy, and recall.

The experimental outcome of this study demonstrated that the LGBM algorithm achieves high performance with an 89% F1 score, 91% recall, 92% precision, and 91% accuracy.

LGBM, XGBM, and RF algorithms have the best performance regarding execution time; however, the SVM is the slowest compared to other models.

Overall, the evaluated ML models used for this study have achieved good results contributing to enhanced efficiency and accuracy. Furthermore, results reveal that ensemble learning algorithms LGBM and XGBoost outperform predictive algorithms: SVM and RF models.

Regarding the limitations of this study, the study revealed the considerable time required for the SVM algorithm as it is the slowest one trained among other algorithms, on the other hand, the training of the XGBoost algorithm requires higher computing resources.

6. Conclusion

Machine learning techniques have revolutionized medical image analysis by improving overall performance and automating the detection process of various diseases. This research paper is centered on a multi-class classification utilizing machine learning models LGBM, XGBoost, SVM, and RF, demonstrating the best results in predicting and classifying brain tumor diseases.

Future work will use ensemble learning models combining boosting, bagging, and stacking to make predictions based on large amounts of medical data and high-quality medical images.

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