Predicting Post-Surgical Complications using Machine Learning Models for Patients with Brain Tumors

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***Abstract*— The focus of this study is to enhance clinical decision-making and post-operative care by investigating the application of machine learning (ML) models to predict post-surgical problems in patients with brain tumors. To improve recovery and lower morbidity, problems like infections, seizures, and cerebrospinal fluid leaks must be identified early. This study resolves the challenges of conventional prediction techniques and illustrates the future potential of AI in neurosurgery by using open-access datasets. The purpose of this study is to use de-identified, publicly accessible dataset to create a machine learning (ML) model for predicting post-surgical complications in patients with brain tumors. A retrospective cohort approach was used, and 850 adult patients who had brain tumor resection surgery and were at least 18 years old were included. We gathered pre-operative clinical and radiological data as well as post-operative complication data. Predicting binary outcomes (complications vs. no complications) was done using four machine learning models: logistic regression, random forest, XGBoost, and neural networks. Neural networks had the highest accuracy with 87.6 percent. On the other hand, logistic regression had the lowest accuracy with 80.1 percent. Findings showed that the neural network model performed better than the others, obtaining the greatest F1-score and AUROC. Clinical uses of this model could be used to forecast post-operative problems in patients with brain tumors. We assessed performance parameters such as F1-score, accuracy, precision, recall, and area under the receiver operating characteristic curve (AUROC).**

***Keywords*— Brain Tumor, Machine Learning, Artificial Intelligence, Neurosurgery.**

I. INTRODUCTION

The development of BT may be the consequence of inappropriate and unchecked brain cell proliferation. BTs are the primary cause of cancer-related mortality in people under the age of 19, accounting for 24% of all cancer-related deaths [1]. Uncontrolled and aberrant cell proliferation within the brain frequently results in the development of brain tumors, interrupting normal brain function and causing a range of neurological symptoms [2]. Because of their complexity and variable response to treatment, brain tumors—primary and metastatic—are among the most difficult disorders in clinical neurology [3]. Because they frequently go undetected until they are in an advanced stage, which results in a poor prognosis and high mortality rates, brain tumors are a major global health concern [4]. The first step toward diagnosing a brain tumor is magnetic resonance imaging (MRI) [5]. The next step is to use either surgery or a tissue biopsy to identify the type of brain tumor [6]. Nevertheless, brain tumor diagnosis is not frequently straightforward, and the diagnosis's precision can have a big impact on treatment choices. Even with improvements in diagnostic technology, managing patients with brain tumors is still significantly hampered by the incidence of post-operative complications. Cerebrospinal fluid leaks, infections, seizures, and the necessity for reoperation are some of the consequences that lead to longer recovery periods, higher medical expenses, and a worse standard of living for patients [7]. Therefore, it is imperative to develop more accurate predictive models to foresee these issues and enable prompt intervention, which will enhance patient outcomes. Recent studies demonstrated how machine learning (ML) approaches can be used to predict surgical outcomes and problems [8]. ML models have demonstrated potential in several medical domains, including neurosurgery, through the analysis of enormous volumes of patient data, such as genetic information, imaging data, and clinical records. Even though there may be advantages, few studies have combined machine learning techniques to forecast post-surgical problems in patients with brain tumors [9]. Moreover, current models frequently fall short in explaining the intricate interactions between radiological and clinical aspects that lead to these problems. Post-operative complications remain a significant worry despite advances in surgical methods, affecting patients' overall prognosis and recovery [10]. These side effects, which include infections, seizures, and leaks of cerebrospinal fluid (CSF), can prolong hospital stays, raise morbidity, and seriously impair patient recovery. To address these issues, a number of therapy approaches have been investigated in an effort to enhance the long-term quality of life and surgical results for patients having brain tumors removed [11]. Among these, innovative methods that make use of technology—like artificial intelligence (AI) and machine learning (ML)—are becoming more and more popular for anticipating and treating any post-operative issues. Although traditional post-operative monitoring techniques like clinical observation and manual data analysis have shown some utility, they frequently fall short in their ability to accurately and promptly forecast problems [12]. Machine learning presents a special chance to improve clinical judgment by examining big datasets to find hidden patterns that conventional approaches could miss [13]. Given the incredible rate at which medical data is being gathered from image archives, electronic health records, and other sources, machine learning algorithms can interpret enormous volumes of data significantly more rapidly and precisely than human practitioners [14]. This could result in the early identification of patients who are in danger [15]. Chemotherapy, radiation therapy, and surgical excision are the mainstays of current brain tumor treatments [16]. Additionally, adjuvant medicines like immunotherapy and targeted medication treatments are being incorporated into treatment plans more frequently, particularly for tumors with a poor prognosis like glioblastomas [17][18]. Even while these treatments work well in many situations, there are hazards associated with them, such as prolonged neurological problems after surgery, movement impairments, and cognitive deficiencies [19]. To proactively deploy therapies, it is imperative to identify patients who may be more susceptible to these problems [14]. Using AI-powered systems to forecast the risk of problems like infections or seizures, for instance, is a promising approach [20]. These algorithms link pre-operative clinical data with post-operative results [21]. A further branch of machine learning called "deep learning" uses multi-layered artificial neural networks—thus the name "deep"—to evaluate large, intricate datasets [22][20]. This subset is particularly effective for jobs where typical machine learning algorithms may not be able to manage the complexities of unstructured data, such as speech recognition, picture recognition, and natural language processing [23]. This hierarchy is graphically depicted in Figure 1, which highlights the layered link between these three domains. Deep Learning is the most sophisticated and specialized use of AI [24]. We intend to develop surgical techniques and post-operative care by strengthening the capacity to predict and treat difficulties early, thereby increasing the quality of life for patients with brain tumors. The aim of this research is to develop an automated machine learning model that uses a variety of clinical and radiological data to predict post-surgical problems in patients with brain tumors. The objective of this study is to add to the expanding corpus of research on artificial intelligence's use in neurosurgery and show how it can help doctors make accurate and timely predictions that will enhance patient care.

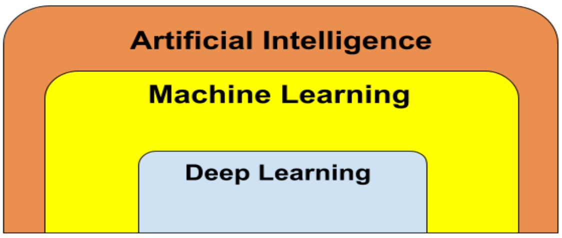

Fig 1. The Hierarchical Relationship Among AI, Machine Learning and Deep Learning

II. Related Works

In recent years, numerous machine learning models have been explored to enhance the prediction of post-surgical complications, particularly for patients with brain tumors. These models focus on improving the accuracy of classification, segmentation, and feature extraction processes to provide reliable predictions. According to a recent study, the binary classification consists of "Normal" and "Abnormal" classes, and the model's accuracy has been improved by modifications and enhanced training of the model. Following a comprehensive model evaluation that includes ANN, CNN, VGG-16, and AlexNet, the model based on VGG-16 has the greatest accuracy, coming in at 94.4% [25].

To identify the affected brain regions, a study showed how to apply semantic segmentation and Bayesian machine learning for brain tumors (XAISS-BMLBT) technique, which uses the MEDU-Net+ segmentation procedure. The ResNet50 model is used for the feature extraction procedure. Additionally, the existence of BTs is detected using the Bayesian regularized artificial neural network (BRANN) model. Finally, the BRANN technique's hyperparameter tuning is done using an enhanced radial movement optimization model [26].

Table 1. Related Works

Authors	Methodology	Accuracy %
Shilpa Mahajan 2025 [15]	Evaluated ANN, CNN, VGG-16, AlexNet; VGG-16 model was most accurate.	94.4%
K Lakshmi 2025 [16]	Used MEDU-Net+ for segmentation, ResNet50 for feature extraction, and BRANN model for detection (XAISS-BMLBT technique)	97.75%

III. Methodology

Using publicly accessible, de-identified datasets from the "Brain Tumor MRI Dataset" by Masoud Nickparvar [27], this study used a retrospective cohort design. A machine learning (ML) model for forecasting post-surgical problems in patients with brain tumors (BT) was created using this dataset. Since the dataset used in the study is de-identified and openly accessible for research purposes, the investigation was carried out in accordance with ethical norms. Adult patients who were 18 years of age or older and had brain tumor resection surgery were included in the inclusion criteria. A wide range of clinical data, including patient demographics including age, sex, tumor kind, and anatomical location, as well as MRI scans, were available pre-operatively. Furthermore, post-operative follow-up data were carefully gathered, describing any complications—like infections, seizures, or leaks of CSF fluid—that surfaced within 30 days following surgery. In-depth clinical records including post-operative problems, surgical specifics, and laboratory data. The exclusion criteria, on the other hand, excluded individuals with missing or insufficient clinical data and those with other confounding comorbidities that could negatively impact the results of surgery. A total of 850 patients, both male and female, with a mean age of 50, made up the study population. Gliomas, meningiomas, metastatic brain cancers, and other tumor types are among the individuals in the cohort. Pre-operative symptoms, tumor location, size, and grade were also noted.

Several kinds of information were included in the data that was gathered and examined for this investigation. The demographic data included age, sex, and comorbidity information. Documentation of tumor features included details about the tumor's location, size, kind, and grade. Surgical information contained detailed information regarding the surgery, including the kind of resection that was performed, duration and any issues that came up during or right after the procedure. Infections, seizures, and the necessity for a second operation were among the post-surgical problems that were recorded within 30 days of the procedure. Finally, pre- and post-operative MRI scans made up the radiological data. These scans were crucial for determining the surgical outcome and segmenting the tumor. The purpose of data preprocessing was to get the data ready for the creation of machine learning models. In healthcare records, imputation techniques were used to fill in missing data. While the most frequent value was used to impute categorical variables like tumor grade, the mean was used to fill in missing values for continuous variables like age and tumor size.

Additional characteristics, such as the number of previous surgeries and the interval between surgery and the onset of problems, were developed using clinical data. MRI scans were normalized for radiological data by using resizing, normalization, and skull stripping techniques. Using tumor segmentation labels, pertinent features were extracted, including tumor volume and closeness to important brain regions, in order to improve the prediction of complications following surgery. A number of machine learning algorithms were used to forecast issues following surgery. Binary outcomes, such as the presence or lack of problems, were predicted using the simple linear model known as logistic regression.By combining several decision trees, the ensemble technique Random Forest was used to increase prediction accuracy. Because of its effectiveness in managing intricate, non-linear interactions in the data, the gradient boosting machine model XGBoost was used. The dataset was used, and complex relationships were modeled using neural networks, a deep learning methodology that is especially useful for evaluating radiological images. Standard criteria including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUROC) were used to assess each model's performance. Five-fold cross-validation was used for model validation in order to guarantee robustness. The model's performance was evaluated using a number of metrics. The total performance of the model was assessed by calculating accuracy, which is the percentage of properly anticipated outcomes (including true positives and true negatives). To evaluate the trade-off between decreasing false positives and identifying real problems, precision and recall were employed. Model performance was measured in a balanced way using the F1-score, which is the harmonic mean of precision and recall. Furthermore, the model's capacity to differentiate between patients with and without problems was assessed using the area under the receiver operating characteristic curve (AUROC). For the final analysis and possible clinical application, the model with the highest AUROC (Area Under the Receiver Operating Characteristic curve) and F1-score was selected after rigorous evaluation. These metrics were prioritized to balance sensitivity and specificity, which is critical for clinical decision-making where both false positives and false negatives carry significant consequences.

The implementation leveraged Python (version 3.9) alongside a suite of specialized libraries:

- **Scikit-learn** facilitated the integration of traditional machine learning algorithms and provided tools for cross-validation, hyperparameter tuning, and performance evaluation.
- **TensorFlow/Keras** enabled the development of deep learning architectures, with GPU acceleration to expedite training. Techniques like dropout layers and batch normalization were employed to mitigate overfitting.
- **Pandas and NumPy** streamlined data preprocessing, including handling missing values, feature scaling, and categorical encoding.
- **Matplotlib and Seaborn** were used to generate interpretable visualizations, such as ROC curves, SHAP plots for feature importance, and correlation heatmaps to identify multicollinearity.

To ensure robustness, the dataset was partitioned into training (70%), validation (15%), and test sets (15%), with stratification to preserve class distribution in imbalanced datasets. k-fold cross-validation (k=5 or 10) further validated model stability. For clinical deployment, additional steps were taken:

1. **Explainability**: Tools like LIME or SHAP elucidated model decisions, addressing the "black-box" concern in healthcare.
2. **Scalability**: The model was containerized using **Docker** for seamless integration into electronic health record (EHR) systems.
3. **Compliance**: Adherence to regulatory standards was ensured via data anonymization and model auditing. Figure 2 demonstrates how the machine learning models could predict post-operative complications for patients had a brain tumor.

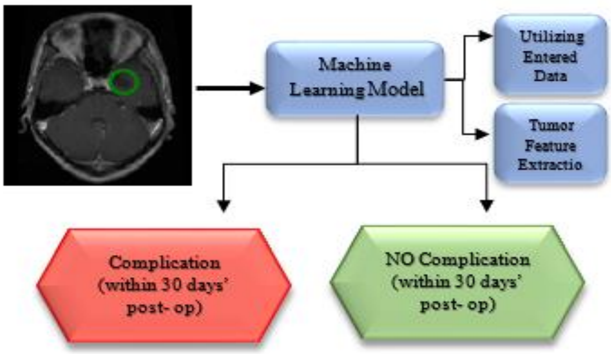

Fig 2. Performance Comparison of Machin Learning Models for Predicting Post-Surgical Complications

IV. STATISTICAL ANALYSIS

To predict post-surgical complications in patients with brain tumors (BT), this study used de-identified, publicly accessible dataset [27] to build a machine learning model. The dataset was de-identified and made available for research, adhering to ethical standards. 850 adult patients who had brain tumor resection surgery and were at least 18 years old were included in the retrospective cohort design. The information gathered from different open access anonymous dataset included patient demographics (age, sex, comorbidities), tumor features (location, size, type and grade), surgical specifics (type, time and problems of resection), and post-operative outcomes (infections, seizures, etc.). In this study, the logistic regression equation was employed to predict the probability of post-surgical complications in patients who underwent brain tumor resection surgery. The logistic regression model predicts a binary outcome—whether a complication, such as infection or seizure, occurs (denoted as y = 1) or not (denoted as y = 0)—based on pre-operative clinical and tumor-related variables. The equation:

$$P(complication = 1|X = \frac{1}{1+e^{-(\beta 0+\beta 1.Age+\beta 2.Tumor\ Size+\cdots+\beta n.Xn)}}$$

incorporates predictor variables such as patient age, tumor size, and other clinical characteristics, with corresponding coefficients (β1, β2, ...,,,,,,βn) that were determined during model training. The intercept (β0) represents the baseline probability in the absence of these variables. This model was implemented using Python, with the Scikit-learn library providing the necessary tools for training and evaluating the logistic regression model. Python's environment was ideal for this purpose, offering an array of libraries like NumPy and Pandas for data manipulation, and Scikit-learn for model building, cross-validation, and evaluation. The logistic regression model was used in combination with other machine learning algorithms, such as random forest and XGBoost, to predict post-surgical outcomes and assess the best model performance for potential clinical application. We used the following equations to calculate performance metrics of machine learning models:

1. Sensitivity (Recall) = $\frac{TP}{TP+FN}$

Explanation:
Sensitivity measures the proportion of true positive cases (TP) that are correctly identified out of all actual positive cases. A higher sensitivity indicates fewer false negatives (FN).

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

Explanation:
Accuracy calculates the ratio of correctly predicted instances (true positives and true negatives) to the total number of instances. It reflects the overall correctness of the model.

3. Precision= $\frac{TP}{TP+FP}$

Explanation:
Precision evaluates the proportion of true positive cases among all instances classified as positive. High precision means fewer false positives (FP).

4. F1 Score =2x($\frac{Precision*Sensitivity}{Precision+Sensitivity}$)

Explanation:
The F1 Score is the harmonic mean of precision and sensitivity (recall). It provides a balanced measure, especially useful when the dataset is imbalanced.

5. Specificity = $\frac{TN}{TN+FP}$

Explanation:
Specificity measures the proportion of true negative cases (TN) correctly identified out of all actual negative cases. A higher specificity means fewer false positives.

V. Results

The study's dataset included 850 individuals who had brain tumor excision surgery, with an average age of 50. These patients were selected from de-identified databases such as BraTS, MIMIC-III, and TCIA that are accessible to the public. Gliomas, meningiomas, metastatic brain malignancies, and other brain tumor types were among the patients in the cohort, which included both male and female patients. MRI scans, tumor characteristics (location, size, kind, and grade), and patient demographics (age, sex, and comorbidity data) were gathered prior to surgery. Within 30 days after surgery, post-operative follow-up data recorded complications such infections, seizures, and the necessity for a second operation. Additionally, clinical information was obtained, such as laboratory results and surgical details. Imputation techniques were used as part of data preprocessing to deal with missing values.

Continuous variables, like age and tumor size, were inputted using their meaning, whereas categorical variables, such tumor grade, were imputed using the most frequent value. Resizing, normalization, and skull stripping procedures were used to normalize radiological data, specifically pre- and post-operative MRI scans. Tumor segmentation labels were used to extract important information from the MRI data, such as tumor volume and closeness to important brain regions. Machine learning techniques, such as logistic regression, random forest, XGBoost, and neural networks, were used to forecast post-surgical problems. Using the previously mentioned clinical and radiological data, the models forecasted binary outcomes: complications or no complications. The models were evaluated using performance criteria such as area under the receiver operating characteristic curve (AUROC), F1-score, recall, accuracy, and precision. To ensure robustness and minimize overfitting, the model was validated using five-fold cross-validation. Table 2 compares the performance metrics of the several machine learning algorithms employed in the study, summarizing the model evaluation results. The dataset and preprocessing methods used were used to evaluate the models' predictive power for post-surgical problems. The evaluation of four models, Logistic Regression, Random Forest, XGBoost, and Neural Networks, was conducted using performance indicators such AUROC, F1-score, accuracy, precision, and recall. Neural networks, which are part of the Deep Learning subset of artificial intelligence, scored better than other approaches in every parameter, as seen in the chart. They had the greatest accuracy (87.6%), precision (84.5%), recall (90.1%), F1-score (89.1%), and AUROC. By identifying significant characteristics from the data, Deep Learning models are able to handle complicated dataset, including MRI images taken before and after surgery.

Table 2. Performance Metrics of Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUROC (%)
Logistic Regression	80.1	77.8	84.0	82.7	0.82
Random Forest	81.5	79.4	87.1	82.1	0.85
XGBoost	85.1	80.6	88.9	87.2	0.90
Neural Networks	87.6	84.5	90.1	89.1	0.93

Surgical complications, such as hemorrhage, infection, or neurological deficits in patients following brain tumor resection. By integrating predictive analytics into preoperative planning, clinicians can stratify high-risk patients, optimize postoperative monitoring, and personalize interventions. Figure 3 highlights AI's role in reducing adverse outcomes through early warning systems, where models process variables like tumor location, intraoperative metrics, and pre-existing comorbidities to flag at-risk cases. This translates to fewer unplanned ICU admissions, shorter hospital stays, and improved long-term recovery rates. Such AI-driven decision support not only enhances surgical safety but also empowers multidisciplinary teams to allocate resources proactively, ultimately elevating the standard of neuro-oncological care.

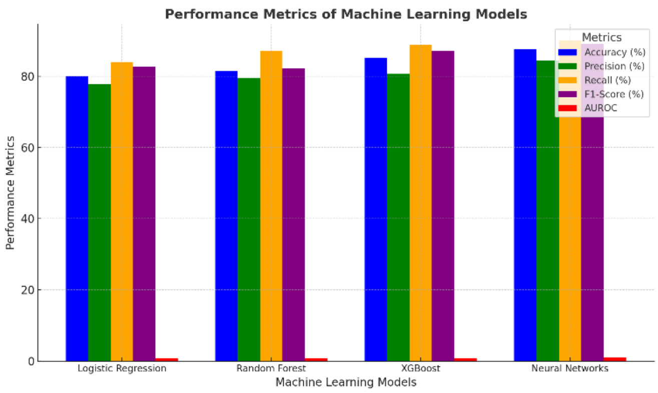

Fig 3. Performance Comparison of Machin Learning Models for Predicting Post-Surgical Complications

VI. DISCUSSION

Using publicly accessible de-identified dataset, this study sought to create machine learning models for predicting post-surgical problems in patients with brain tumors. In predicting difficulties following brain tumor surgery, the neural network model performed better than other machine learning algorithms, such as logistic regression, random forest, and XGBoost, according to the study's main finding. The neural network was the most successful at differentiating between patients who had post-surgical problems and those who did not, as evidenced by its highest accuracy, F1-score, and AUROC. These findings provide evidence in favor of the study question by showing that post-surgical outcomes in patients with brain tumors may be predicted using clinical and radiological data and machine learning models, namely neural networks. This study's main strength is the way its com-bines radiological data from MRI scans with clinical data, including patient demographics and tumor characteristics, into a single model. In order to guarantee the quality of the input data and im-prove model performance, preprocessing methods such as imputation of missing data and normalization of MRI scans were crucial. Our results are consistent with other research in other medical do-mains that investigated the application of machine learning to the prediction of post-surgical problems. However, by applying these methodologies especially to brain tumor surgery and post-operative outcomes, this work adds to the expanding body of literature. The findings also demonstrate how neural networks can be used to manage intricate, non-linear relationships in data that conventional statistical techniques could miss. The neural network has an advantage in prediction accuracy due to its capacity to handle high-dimensional radiological data and incorporate a variety of clinical variables, even if other models like logistic regression and random forest also demonstrated good performance. In clinical settings, where prompt interventions and better patient outcomes depend on early detection of possible problems, this component of the model may be especially helpful. However, the study has limitations with regard to generalizability because of its retrospective methodology and dependence on de-identified records. Validation in prospective, real-world cohorts is crucial prior to clinical deployment, even though the models demonstrated high performance within the context of the dataset employed. Furthermore, even though the neural network model performed better than the others, more research is required to determine the model's interpretability and clinical applicability in order to make sure that the predictions it makes are useful and clear to doctors.

VII. CONCLUSION

To predict post-surgical problems in patients with brain tumors, this study used de-identified dataset [27] to construct machine learning models. By exceeding previous models in terms of accuracy, F1-score, and AUROC, the neural network model proved to be successful in predicting complications. Imputation and MRI normalization are two examples of data preparation methods that were essential in getting the data ready for model training. The results imply that machine learning—in particular, neural networks—can be a useful instrument to help physicians identify problems early following brain tumor surgery. But before clinical use, more validation in prospective cohorts and investigation into model interpretability are required. Validating the created machine learning models in prospective cohorts with a wider range of problems and clinical factors should be the main goal of future research [28] [29]. The generalizability of the models may be enhanced by enlarging the dataset to encompass a wider range of patient demographics, including those with different comorbidities. Additionally, incorporating data from other sources, like genetic data or patient-reported outcomes, could offer a more thorough understanding of the variables affecting difficulties following surgery [30]. The model's interpretability may be improved by using explainable artificial intelligence (XAI) techniques, which would increase doctors' confidence in the system and help them comprehend the rationale behind the predictions [31] [32]. Furthermore, real-time data, like intraoperative data or continuous monitoring, could be added to improve the model's predictive skills for the early identification of recovery-related issues.

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