

# A Survey On Overall Survival Prediction Of Brain Tumor Patients Using Machine Learning And Gradient Boosting Techniques

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## Abstract

Predictive analytics—the use of data to produce prediction or classification values for fresh observations—is the basis for this essay. By estimating the regression function, the purpose of prediction is to produce values with the least squared error. The purpose of classification is to provide values with the least amount of misclassification error possible by selecting the most likely class. Many strategies for automatic brain tumor classification have recently been presented, which may be divided into machine learning (ML) and deep learning (DL) techniques based on feature selection and learning process. For classification in ML techniques, feature selection and extraction are critical. DL techniques, on the other hand, directly extract and learn the features from the image. The objective of this research is to propose a hybrid model for predictive analysis of Brain Tumor and Overall Survival Prediction of the patients. The article contains literature survey of the related papers which gives the drawbacks of the existing techniques and directs the research to improve the accuracy of Brain Tumor prediction.

## Introduction:

Recent deep learning techniques, notably CNN, have shown to be accurate and are frequently employed in medical picture analysis. Furthermore, they have disadvantages over traditional approaches (ML) in that they require a big dataset for training, have a high time complexity, are less accurate for applications with a limited dataset, and require costly GPUs, all of which raise user costs. Selecting the correct deep learning tools is particularly difficult since it necessitates understanding of many parameters, training methods, and topology. Machine-learning techniques, on the other hand, have played an important role in medical imaging. Support vector machine (SVM), Naive Bayes (NB), Random Forest (RF), Decision Tree (DT), Convolutional Neural Network (CNN), and K-Nearest Neighbor are just a few of the learning-based classifiers that have been utilized for brain tumour classification and diagnosis (KNN).

CNN (Convolutional Neural Network) or ConvNet could be a deep machine learning algorithmic rule adopted to look at the Image. It utilizes varied multilayer perceptions framed to realize relatively reduced pre-processing time. Overall, these classifiers have received goodly analysis attention, as they need little dataset for training, low procedure time complexity, low value to the users, and might be simply adopted by less masterful people. XGBoost is an ensemble of gradient boosted call trees. A key side of XGBoost is that it uses a lot of regular model systematisation so as to manage overfitting. There are additional enhancements of XGBoost, like lightweight BGM and CatBoost which needs less coaching time and fewer prediction times than XGBoost.

Although both LightGBM and CatBoost require less training time, "LightGBM" excels when using non-category data and "CatBoost" outperforms when using categorical data. As a result, we may choose which categorization strategy to apply based on the type of data we have.

XGBoost provides good training accuracy, while "CatBoost" outperforms XGBoost in testing accuracy. The CatBoost Algorithm may be used in conjunction with CNN (Convolutional Neural Network) and Random Forest to increase the accuracy of overall survival prediction in brain tumour patients.

Overall, these classifiers have gotten a lot of study interest since they only require a small dataset for training, hav a low computational time complexity, are inexpensive for consumers, and can be quickly adopted by people with limited skills.

A brain tumour is a benign or malignant development of abnormal cells in the brain that can be cancerous or non-cancerous. The majority of researchers are working on primary tumours like Gliomas. Chemotherapy, radiation, and surgery are all options for treating gliomas. To gather the relevant clinical data, such as tumour existence, location, and type, computer-aided devices can be utilised to automate the process. However, determining their structure, volume, borders, tumour detection, size, segmentation, and classification remains a difficult problem. Furthermore, the severity of a brain tumour differs from person to person.

We get several types of MRI scans when we use different pulse sequences, such as (1) T1 weighted images that discriminate between tumour and healthy tissues. (2) T2 weighted scans result in the edoema region being delineated, resulting in a bright image region. (3) T4-Gd scans, which use a contrast agent to provide a strong signal at the tumour boundary. (4) FLAIR scans use a signal of water molecule suppression to distinguish between cerebrospinal fluid (CSF) and edoema regions. Manual annotation of brain tumours from MRI data is a tough undertaking. As a result, using computer vision and machine learning techniques to automate brain tumour segmentation and categorization is critical. Two researchers are now working on brain tumour segmentation and classification using

computer vision and machine learning methods. Clinicians' plans are quite expensive since they rely on a variety of imaging modalities including PET, MRI, and CT. The clinical approaches allow for the extraction of relevant data and a thorough study of photographs. Computational approaches aid in deciphering the nuances in medical imaging. The location of brain tumours can be determined using imaging techniques. In comparison to other imaging modalities such as CT, MRI delivers more useful information.

High variability and intrinsic MRI data properties, such as variability in tumour sizes or forms, tumour identification, area computation, segmentation, classification, and discovering ambiguity in segmented region, make Brain Tumor a difficult task. Picture segmentation is the most important work in image interpretation since it aids in feature extraction, area calculation, and importance in many real-world applications. It may be utilised for things like tumour volume estimate, tissue categorization, blood cell delineation, and tumour localization, as well as atlas matching, surgical planning, and image registration. The precise and morphology measurement of tumours is a vital job for monitoring oncologic treatment. Despite substantial scale work in this sector, physicians still rely on manual tumour diagnosis owing to a lack of communication between researchers and clinicians.

### **Literature Review:**

Various private international corporations, such as Siemens, Becton Dickinson, Medtronic, Accenture, GE Medical Systems, Atlantic Biomedical P. Ltd, and others, have performed brain tumour research. In the literature, there are both theoretical and experimental studies on the International arena.

### **Approaches**

For the diagnosis of a brain tumour, there are numerous methods for prediction and categorization. Each technique has its own set of advantages and disadvantages, as well as being domain specific. The ways that may be utilized to categorize Brain Tumor are as follows:

#### **1. Support Vector Machine (SVM):**

The Support Vector Machine, or SVM, is a common Supervised Learning technique that may be used to solve both classification and regression issues. However, it is mostly utilised in Machine Learning for Classification difficulties.

The SVM algorithm's purpose is to find the optimum line or decision boundary for categorising n-dimensional space into classes so that additional data points may be readily placed in the proper category in the future. A hyperplane is the name for the optimal choice boundary.

The extreme points/vectors that assist create the hyperplane are chosen via SVM. Support vectors are the extreme instances, and the method is called a Support Vector Machine. Consider the picture below, which shows how a decision boundary or hyperplane is used to classify two separate categories:

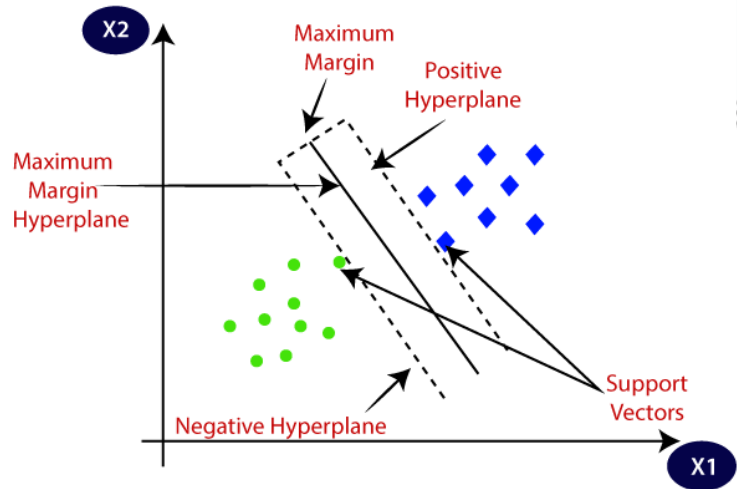


Fig 1: Support Vector Machine

## 2. Naïve Bayes Classifier:

The Naive Bayes method is a supervised learning technique for addressing classification issues that is based on the Bayes theorem. It is mostly utilised in text classification tasks that need a large training dataset. The Naive Bayes Classifier is a simple and effective classification method that aids in the development of rapid machine learning models capable of making quick predictions. It's a probabilistic classifier, which means it makes predictions based on an object's likelihood. Spam filtration, sentiment analysis, and article classification are all common uses of the Naive Bayes Algorithm.

## 3. Random Forest:

Random Forest is a well-known machine learning algorithm that uses the supervised learning method. In machine learning, it may be utilised for both classification and regression issues. It is based on ensemble learning, which is a method of integrating several classifiers to solve a complicated issue and increase the model's performance.

"Random Forest is a classifier that contains a number of decision trees on various subsets of a given dataset and takes the average to enhance the predicted accuracy of that dataset," according to the name. Instead of depending on a single decision tree, the random forest collects the forecasts from each tree and predicts the final output based on the majority votes of predictions. The bigger the number of trees in the forest, the more accurate it is and the problem of overfitting is avoided. The Random Forest's operation is depicted in the diagram below:

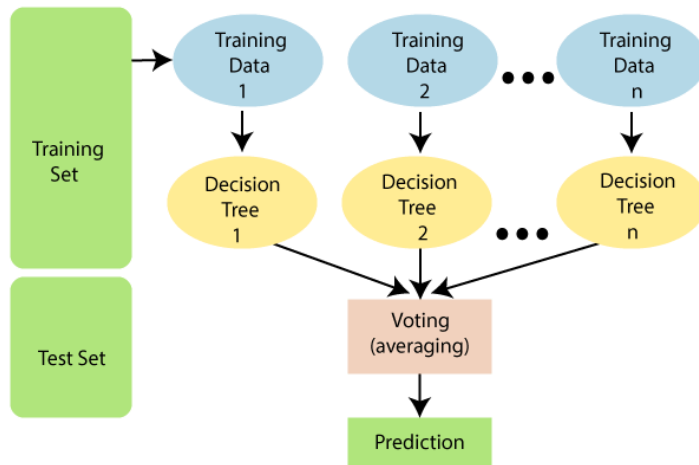


Fig 2: Random Forest

#### 4. Decision Tree:

Decision Tree is a supervised learning approach that may be used to solve both classification and regression problems, however it is most commonly employed to solve classification issues. Internal nodes contain dataset attributes, branches represent decision rules, and each leaf node provides the conclusion in this tree-structured classifier.

#### 5. K-Nearest Neighbor (KNN):

The K-Nearest Neighbour method is based on the Supervised Learning approach and is one of the most basic Machine Learning algorithms. The K-NN method assumes that the new case/data and existing cases are comparable and places the new case in the category that is most similar to the existing categories.

The K-NN method saves all available data and classifies a new data point based on its similarity to the existing data. This implies that fresh data may be quickly sorted into a well-defined category using the K-NN method. The K-NN approach may be used for both regression and classification, however it is more commonly utilised for classification tasks.

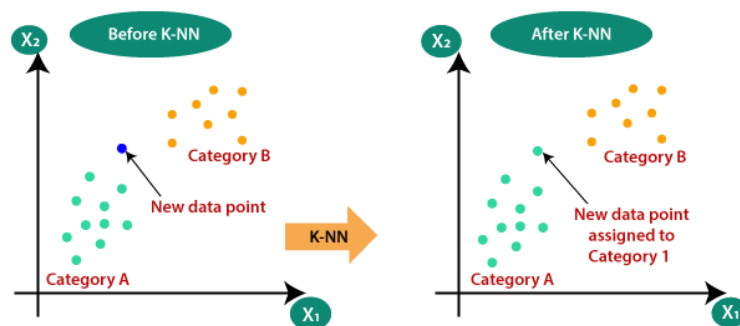


Fig 3: K-Nearest Neighbours

## **6. Convolutional Neural Network (CNN):**

Convolutional neural networks (CNNs, or ConvNets) are a type of artificial neural network used to evaluate visual information. Based on the shared-weight design of the convolution kernels or filters that slide along input features and give translation equivariant responses known as feature maps, they are also known as shift invariant or space invariant artificial neural networks (SIANN). Surprisingly, most convolutional neural networks are only equivariant under translation, rather than invariant.

## **7. XGBoost/ CatBoost/LightGBM:**

LightGBM is a Microsoft-developed boosting algorithm and framework. The LightGBM technique is implemented in the framework, which is accessible in Python, R, and C. LightGBM is unusual in that it can build trees using GOSS, or Gradient-Based One-Sided Sampling.

GOSS examines the gradients of various cuts that impact a loss function and updates an underfit tree based on a sample of the greatest gradients and a random sample of tiny gradients. LightGBM can rapidly locate the most influential cuts thanks to GOSS.

XGBoost was created by academics at the University of Washington and is now maintained by open-source contributors. Python, R, Java, Ruby, Swift, Julia, C, and C++ are all supported by XGBoost. XGBoost employs the gradients of distinct cuts to determine the next cut, similar to LightGBM, but it also includes the hessian, or second derivative, in its cut ranking. This next derivative has a little cost, but it allows for a more accurate calculation of the cut to utilise.

Finally, the Russian search engine Yandex created and maintains CatBoost, which is accessible in Python, R, C++, Java, and Rust. CatBoost differs from LightGBM and XGBoost in that it focuses on improving decision trees for categorical variables, or variables with many values that may or may not be related (eg. apples and oranges).

In XGBoost, you'd have to separate apples and oranges into two one-hot encoded variables denoting "is apple" and "is orange," while CatBoost automatically finds distinct categories without the need for preprocessing (LightGBM does support categories, but has more limitations than CatBoost).

## **Related work**

This section focuses mostly on existing relevant work in the field of Brain Tumor Prediction and Classification. On the one hand, numerous writers gave reviews of various Classification techniques for categorising Brain Tumor in order to better understand their application. Such in-depth analyses focused mostly on implementation principles, as well

as the strengths and weaknesses of current techniques. The following are some of the most important works concentrating on improving categorization and prediction accuracy.

**S. Krishnakumar, K. Manivannan, 2020 [1]**, In MR images, researchers used a crude K-means algorithm and a Multi-Kernel Support Vector Machine to segment and categorise brain tumours. The goal of the study is to use brain MR image segmentation to align and enhance the technique for tumour identification. The author employed the Multi-kernel SVM approach to create tumour segmentation pictures that were fast, accurate, and repeatable. We got a maximum accuracy rate of 0.997200012. However, the classification in this article is not done by category.

**Candice Bentéjac • Anna Csörgő • Gonzalo Martínez Muñoz, 2020, [2]**, A study of gradient boosting techniques in comparison. The goal of this study is to conduct a practical examination of how these new gradient boosting variations perform in terms of training time, generalisation performance, and hyper-parameter configuration. After comparing Random Forest, Gradient Boosting, CatBoost, and LightGBM, the author found that LightGBM is the quickest. For non-categorical data, LightGBM outperforms, whereas for categorical data, CatBoost outperforms.

**MansiLathera, Dr. Parvinder Singh, 2020 [3]**, Brain tumor segmentation and detection strategies were examined. The major goal of this research is to build on previous efforts by various academics to partially or completely automate the task of segmenting brain tumors. The author conducted a comparative examination of segmentation approaches and came to the conclusion that existing work that includes other stages such as feature extraction and classification can categorize the extracted region as normal or abnormal, but with less accuracy. There is a need to model sophisticated techniques for automating the work of identifying brain tumors, which will produce better outcomes than current methods.

**Jinjing Zhang, Jianchao Zeng, Pinle Qin, Lijun Zhao, 2020 [4]**, explored the use of triple intersecting U-Nets to segment brain tumours using Multi-Modality MR Images. The work's major purpose is to offer a triple intersecting U-Nets (TIU-Nets) approach to brain glioma segmentation. Using TIU-nets, the author determined that the suggested technique produces the best segmentation results. The research focuses on deep neural network-based multi-modality MR image segmentation and fusion.

**SetthanunThongsuwan ,SaichonJaiyen, AnantachaiPadcharoen, Praveen Agarwal, 2020 [5]**, ConvXGB is a novel deep learning model based on CNN and XGBoost for classification challenges. The goal of this study is to explain a novel deep learning model for classification tasks called Convolutional eXtreme Gradient Boosting (ConvXGB), which is based on convolutional neural networks and XGBoost. ConvXGB was built on CNN and XGBoost, according to the author, however testing results show that it was always somewhat better and generally much better than these two models, as well as other

models. However, XGBoost requires more training and processing time, lowering its total performance.

**C. Narmatha, Sarah Mustafa Eljack, Afaf Abdul Rahman Mohammed Tuka, S. Manimurugan, Mohammed Mustafa, 2020 [6]**, proposed A hybrid fuzzy brain storm optimization method for the categorization of brain tumour MRI images. The major purpose of the study is to build the fuzzy brain-storm optimization method for medical picture segmentation and classification was suggested, a mix of fuzzy and brain-storm optimization approaches. The author employed Fuzzy Brain-Storm optimization and got a 93.85 percent accuracy, 94.77 percent precision, 95.77 percent sensitivity, and 95.42 percent F1 score. This algorithm can be utilised for classification and detection in the future.

**GinniGarg, RituGarg, 2020 [7]**, Brain Tumor Detection and Classification Using a Hybrid Ensemble Classifier was described. The major goal of this paper is to present a hybrid ensemble approach based on the Majority Voting Method that uses Random Forest (RF), K-Nearest Neighbour, and Decision Tree (DT) (KNNRF-DT). Its goal is to determine the tumor's area and categorise benign and malignant brain tumours. The suggested technique obtained accuracy of 97.305 percent, precision of 97.73 percent, specificity of 97.60 percent, sensitivity of 97.04 percent, Youden-index of 94.71 percent, and F1-score of 97.41 percent using Ensemble modelling (KNNRF-DT), indicating its authenticity across medical pictures. Other hybridization techniques will need to be used in the future to enhance accuracy.

**G.Hemanth, M.Janardhan,L.Sujihelen, 2019 [8]**, Brain tumour detection was devised and executed utilising a machine learning technique. The work's major goal is to offer an automated segmentation approach based on CNN (Convolutional Neural Networks) that determines tiny 3 x 3 kernels. The author employed a Convolutional Neural Network and came to the conclusion that the CNN technique is effective in detecting brain tumours. The suggested method is tested on a variety of photos, and the results are the best and most effective. However, in the future, the accuracy can be enhanced by utilising an ensemble classifier.

**Tiejun Yang, Jikun Song, Lei Li, 2019 [9]**,proposed A deep learning model for brain tumour segmentation on MRI that combines SK-TPCNN and random forests. The study's goal is to come up with a new design. The feature extraction capacity of the SK-TPCNN and the joint optimization capability of the model are shown, and an automated segmentation approach combining the small kernels two-path convolutional neural network (SK-TPCNN) and random forests (RF) is provided. The author found that the SK-TPCNN model has a high feature extraction capacity and gets generally accurate results using CNN + Random Forest. The SK-TPCNN model, on the other hand, is over-segmented; this may be corrected by increasing the quantity of training data.



**Po-Yu Kao ,Thuyen Ngo , Angela Zhang, Jefferson W. Chen, and B.S. Manjunath 2019 [10]**, Brain Tumor Segmentation and Tractographic Feature Extraction for Overall Survival Prediction from Structural MR Images were addressed. The goal of this study is to present a new approach for brain tumour segmentation and survival prediction that integrates human brain connectomics with parcellation. The suggested ensemble resulted in a more robust tumour segmentation, according to the author, who employed Ensemble Modelling. The unique use of tractographic characteristics for overall survival prediction appears to be beneficial for brain tumour patients. However, the model's accuracy can be improved in the future.

**Eric Carver, Chang Liu, Weiwei Zong, Zhenzhen Dai, James M. Snyder, Joon Lee, Ning Wen 2019 [11]**, Machine Learning Algorithms for Automatic Brain Tumor Segmentation and Overall Survival Prediction The goal of this study is to see how well a U-net neural network and an ELM can correctly identify three locations of a brain tumour and predict patient overall survival following gross tumour removal using preoperative MR data. The U-NET model was efficient in determining the location of the complete tumour and segmenting the whole tumour, enhancing tumour and tumour core, and also the prediction accuracy needs to be improved, according to the author (it is 60.7 percent only).

**Muhammad Nazir, Muhammad Attique Khan, Tanzila Saba, AmjadRehman 2019 [12]**,Brain Tumor Detection from MRI Images Using Multi-level Wavelets was explored. The goal of this study is to develop a system for segmenting brain tumours that is both computationally efficient and accurate. The author employed DCT and K-Means and found that the suggested algorithm's effectiveness is demonstrated by its low computing complexity and accurate tumour region segmentation. The author also proposed that future research incorporate more variables for classifying tumours in order to better classify tumour types.

**Rupal R. Agravat; Mehul S. Raval 2019 [13]**,revealed how to estimate overall survival in patients with brain tumours. The goal of this study is to use the BRATS 2018 benchmark dataset to segment tumours and use age, shape, and volumetric parameters to predict patient overall survival. The author employed CNN and Random Forest to get to the conclusion that the suggested work outperforms state-of-the-art technologies in terms of accuracy. Improved segmentation can help improve accuracy. To increase overall survival prediction, the model may be improved by enhancing segmentation and adding characteristics from MRI modalities.

**Mamta Mittal, Lalit Mohan Goyal, Sumit Kaur, Iqbaldeep Kaur, Amit Verma, D. Jude Hemanth 2019 [14]**, deep learning-based better tumour segmentation for MR brain images was explored. The goal is to present a deep learning-based technique for segmenting brain tumour images. The suggested solution incorporates the Stationary

Wavelet Transform (SWT) principle as well as a novel Growing Convolution Neural Network (GCNN). The author employed SWT and GCNN to get to the conclusion that the suggested method outperformed the standard CNN strategy by around 2% in terms of PSNR and SSIM. To increase the performance of the suggested system, more combinations of various classifiers might be employed.

**ZarNawab Khan Swati, Qinghua Zhao, Muhammad Kabir, Farman Ali, Zakir Ali, Saeed Ahmeda, Jianfeng Lu 2019 [15]**,described Transfer learning and fine-tuning are used to classify brain tumours on MR images. The goal is to offer a block-wise fine-tuning technique based on transfer learning using a pre-trained deep CNN model. The suggested approach is tested using a benchmark dataset of T1-weighted contrast-enhanced magnetic resonance imaging (CE-MRI). The study employed CNN and found that under five-fold cross-validation, the average accuracy was 94.82 percent, and that additional pictures should be used to differentiate tumour categorization in a broader approach..

**NileshBhaskarraoBahadure, Arun Kumar Ray, Har Pal Thethi 2018 [16]**,MRI-Based Brain Tumor Segmentation and Classification Using Genetic Algorithm was explored in Comparative Approach. The goal is to increase tumour detection performance, thus researchers looked at numerous segmentation algorithms and compared their segmentation scores to find the best one. Furthermore, the genetic algorithm is used for the automated categorization of tumour stage to increase classification accuracy. The author attained 92.03 percent accuracy, 91.42 percent specificity, 92.36 percent sensitivity, and an average segmentation score of 0.82 to 0.93 in a comparative examination of segmentation methodologies. Accuracy and the Dice Coefficient Index, according to the author, both need to be improved.

**HimajaByale ,DrLingaraju G M and ShekarSivasubramanian 2018 [17]**,Machine Learning Techniques for Automatic Segmentation and Classification of Brain Tumors were reported. The goal of this project is to create an automated system that can help determine if a lump (mass of tissue) in the brain is benign (clump thickness) or malignant (marginal adhesion) based on categorization. The study was done with K-Means, GMM, GLCM, and Neural Networks, and the results showed that the suggested model has 93.33 percent accuracy, 96.6 percent specificity, 93.33 percent sensitivity, and 94.44 percent precision. This technique will be improved to identify different types of cancer (Glioma, Meningioma) among the benign and malignant categories.

**Sasikaladevi V, Mangai V 2018 [18]**,Color-based image segmentation utilising hybrid kmeans and watershed segmentation was explored. The goal is to utilise a hybrid k-means algorithm with a watershed segmentation technique to segment the photos. The work was completed using the K-Means with watershed algorithm, and it was concluded that the proposed system accurately describes quality measurement when compared to other systems that do not use a filter technique, and that the filter technique produces a better

result for the k-means with watershed algorithm. The median filter is more accurate than the wiener filter in terms of filtering approaches.

**Mohammadreza Soltaninejad ,Lei Zhang Tryphon Lambrou Guang Yang NigelAllinson Xujiang Ye 2018 [19]**,Random Forests and Fully Convolutional Networks were used to segment MRI brain tumours and predict patient survival. The goal is to present a learning-based system for automatic brain tumour segmentation in multimodal MRI images that combines two sets of machine-learned and hand-crafted characteristics. The classification accuracy scores for the training, validation, and testing datasets were 0.638, 0.485, and 0.411, respectively, according to the work done using FCN+RF. This suggested model's accuracy will need to be enhanced in the future.

**Lina Chato Shahram Latifi 2017 [20]**,Machine Learning and Deep Learning Techniques for Predicting Overall Survival of Brain Tumor Patients Using MRI Images were addressed. The study proposes a technique for automatically predicting the survival rate of patients with glioma brain tumours using machine learning (ML) algorithms to identify the patient's MRI picture. The study was completed using SVM, KNN, and CNN, and it was determined that deep feature extraction based on pre-trained AlexNet and trained by Linear Discriminant provided the best classification accuracy. The accuracy of overall survival prediction was not higher than 46%, according to this study. As a result, there is a lot of room to improve overall survival forecast accuracy.

**AmrutaHebli, Dr. Sudha Gupta 2017 [21]**, Support Vector Machine was used to predict and classify brain tumours. This work proposes a method that uses image processing in conjunction with machine learning to detect tumours and categorise them as benign or malignant. With real clinical data, the step-by-step technique for image pre-processing, segmenting brain tumours using morphological operations, extracting tumour features using DWT, and classifying the tumour using SVM is completed. DWT, PCA, and SVM were used to complete the project. The suggested approach effectively segmented tumours and identified them as benign or malignant, according to the author. Three databases were used to examine the methods. Tumor stages can be classified further, and the specific location of the tumour can be approximated.

**Xudie Ren, HaonanGuo, Shenghong Li(&), Shilin Wang, and Jianhua Li 2017 [22]**, The CNN-XGBoost Model was used to create a novel image classification method. The major purpose of this research is to offer a new image classification approach that combines the Convolutional Neural Network (CNN) and the eXtreme Gradient Boosting (XGBoost), two excellent classifiers. This article used CNN+ XGBoost and found that by combining the CNN and XGBoost classifiers, this model provides more precise output by integrating CNN as a trainable feature extractor to automatically obtain features from input and XGBoost as a recognizer in the network's top level to produce results. The author also

found that tweaking the CNN structure to extract even more high-quality features will help the model perform even better.

**S.K. Shil, F.P Polly, M.A. Ifthekar, M.N Uddin and Y.M jang 2017 [23]**, Improved Brain Tumor Detection and Classification Mechanism was described. The goal of this study is to develop an automated technique for detecting and segmenting tumours from MRI images. The suggested system achieved a classification accuracy of 99.33 percent, sensitivity of 99.17 percent, and specificity of 100 percent after employing K-Means, DWT, PCA, and SVM. The model may be tweaked further to enhance accuracy and speed up processing.

### **Conclusion**

After the extensive literature review, it is concluded that there are many techniques that can be implemented to predict brain tumor and classify the tumor into broader category. The overall survival prediction of a patient is a very crucial task. The article contains literature survey of the related papers which gives the drawbacks of the existing techniques and directs the research to improve the accuracy of Brain Tumor prediction. Overall survival prediction accuracy is relatively low. To make the brain tumour prediction model more successful, this has to be enhanced. To enhance this model, several prediction approaches can be merged to create a hybrid methodology that will improve forecast accuracy. LightGBM and CatBoost both need shorter training time, however "LightGBM" excels with non-categorical data while "CatBoost" outperforms with categorical data. As a consequence, depending on the type of data we have, we may pick which classification technique to use. XGBoost has strong training accuracy, however "CatBoost" has better testing accuracy than XGBoost. The CatBoost Algorithm may be used with CNN (Convolutional Neural Network) to improve overall survival prediction in patients with brain tumours.

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