# Brain Tumor Detection by Incorporating Hyperparameter Optimization in Convolutional Neural Network

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***Abstract:***

In modern days, recognition of brain tumors has ended up being a breathtaking challenge in scientific endeavors. Because of its common image quality and the fact that it does not require ionizing radiation, MRI is frequently used. Diagnosis of a brain tumor is an extremely troublesome undertaking for specialists to distinguish at the beginning period. The objective is to recognize the brain tumor from MRI images utilizing Image processing strategies. The proposed work incorporates Extraction to assess tumor to be the noteworthy class that would be glioma, meningioma, and pituitary. The brain tumor earnestness has been assessed using Convolutional Neural Network figuring which gives us exact results by playing out the hyperparameter tuning components. Experimental findings demonstrate the superiority of our profound learning approach to the conventional condition techniques. Optimizing the hyperparameters in Convolutional Neural Networks (CNN) takes a lot of time for many researchers and professionals. Experts must configure a collection of hyperparameter options using tuning techniques to obtain superior performance hyperparameters. The best results of this configuration are thereafter modeled and implemented in CNN. Using the grid search tuning strategy the best hyperparameter for the dataset has been found by comparing three Optimizers and Batch size, learning rate, and momentum for Hyperparameter tuning. The system's performance and accuracy are enhanced by fine-tuning the parameters. When compared to other hyperparameters, the best optimizer, stochastic gradient descent (SGD), with a batch size of 64 and a learning rate of 0.001, achieved the maximum accuracy of 78.21%.

***Keywords***: Deep learning, glioma tumor, neural networks, tumor detection, convolutional neural network, hyperparameter.

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## 1. INTRODUCTION

The most important organ in the human body is the brain. For the most part, it is viewed as the administering point of the human body. Practically every single imperative movement of the human body is constrained by the cerebrum. The brain is viewed as answerable for overseeing feelings, development, insight, discourse, memory, detects, thought, actual work, taste, and innovativeness. Therefore, any incident or damage to this vital organ will interfere with how the body is supposed to function normally and result in an irregular daily schedule. It is along these lines pivotal to take the most extreme consideration of this valuable organ. Among the several problems that can affect the brain, the most well-known and dangerous problem these days is a brain tumor. Nearly 11,000 patients are being tested for brain tumors regularly. A brain tumor is an unusual piece of tissue that contains uncontrolled cell growth and duplication. There are roughly 130 different types of brain tumors depending on the cell type that the tumor begins with, where it is located inside the brain, and how quickly it grows and spreads. However, the broad classification divides brain tumors into two categories: primary and secondary brain tumors. The primary tumor arises from inside the cerebrum. Deep learning (DL) is a sub-field of AI and as of late showed an astounding exhibition, particularly in order and division issues. The motivation behind this work deals with Hyperparameter tuning which is primarily acquainted with an improvement of the exactness just as execution of the system. In this work, we have carried out the discovery of cerebrum tumors utilizing a Convolutional neural network, and the parameters are tuned utilizing the Grid search tuning procedure. After the identification of the tumor using CNN, the parameters have been tuned to improve the precision of the framework. Here the three Optimizers, Batch Size, and Learning rate has been taken to tune the boundaries. All the Optimizers and Batch size with learning rate has been tuned by utilizing the Grid Search tuning technique. With the help of this technique, we have improved the performance of the system by comparing it with other parameters.

## 2. RELATED WORKS

Fornseca et al. [2] propose a reliable detection method based on CNN that minimizes operators and mistakes. The Convolutional Neural Network (CNN) is used to gain function mappings by convolving a signal or a photo with kernelsImage - processing algorithms such as image conversion, feature extraction, and histogram equalisation have been developed for the extraction of the tumour in the MRI images of the majority of cancer patients. A Fuzzy Classifier is created to distinguish healthy tissue from most cancerous cells.

Dargan et.al [1] discussed the ideas of profound learning, its fundamental and progressed designs, methods, persuasive viewpoints, qualities, and impediments and also presented the significant contrasts between profound learning, old-style AI, and traditional learning drawing near and the significant difficulties ahead. The fundamental goal of this paper is to investigate and introduce sequentially, an extensive review of the significant uses of profound picking up covering an assortment of regions, investigate the strategies and designs utilized, and further the commitment of that particular application in reality.

From voluminous appealing resonation imaging of human frontal area channels, six convolutional neural frameworks (CNN) models were created by Kalaiselvi et al. [3] for the purpose of determining the best cortical region tumour acknowledgment structure in high-grade glioma and inferiority glioma injuries. The cortical tumour that is most frequently recognized is a glioma. The models are created using a conventional CNN method that considers various combinations and settings of hyperparameters. The six models are: FLSC and dropout (FLSCD), FLSC and cluster normalization (FLSCBN), FLSC and dropout (FLSCBN), two layers of five ages, five levels of dropout, five layers of ending rules (FLSC), and FLSC and dropout (FLSCD).The models were created and tested using BraTS2013, as well as the entire brain map book's illuminating records. Among all, the FLSCBN model produced the most straightforward data for recognizing brain tumors. 7085

Mao et al. [4] used a convolutional neural architecture that included two sub-organizations: (1) a tumor limitation coordinate (TLN) and (2) an intratumor game plan organize (ITCN). The TLN, a fully convolutional mastermind (FCN) associated with trade learning, was initially utilized to deal with MRI data. The major sub-goal organization was to describe the tumor area using an MRI cut. The ITCN had been employed to stamp the reported tumor region into several sub-locations by that time. ITCN took advantage of a convolutional neural framework (CNN) with a larger plan and a smaller segment. The multimodal mind tumour division (BRATS 2015) datasets, which included 220 cases of high-grade glioma (HGG) and 54 cases of low-grade glioma (LGG), were used to validate the recommended technique .Shakers resemblance coefficient (DSC), positive insightful worth (PPV), and affectability were used as appraisal estimations. Our preliminary outcomes showed that our strategy could obtain promising division results and had a speedier division speed.

In their proposal, Kaur et al. [5] carry light to conceal designs that can aid in the reliable dynamic and also assess expectation frameworks for infections like heart diseases, breast cancer, diabetes, thyroid, dermatology, liver problems, and careful information using various info credits associated with that particular illness. A few AI computations taken into consideration in this research, including K-NN, SVM, DTD, RF, and MLP, are used to drive exploratory results. Malathi et.al [6] paper proposes a completely tweaked division of mind tumor utilizing a convolutional neural system. Further, it utilizes a high evaluation of glioma's mind picture from the BRATS 2015 database. The proposed work achieves cortical region tumor division utilizing tensor stream, during which the constrictor structures are wont to execute gigantic level legitimate cutoff points. The persistence velocities of patients are improved by an early finding of mind tumors.

Auto-Regressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM) are two information-driven evaluation methods that Kumar et al. [7] proposed for forecasting the overall number of COVID-19 cases and the overall number of COVID-19-related passings. Various fit integrity metrics, including the Akaike Information Criteria (AIC), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error, are registered for the ARIMA model (RMSE). Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error are the two bounds registered for LSTM (RMSE). The model is built with 80% of the available data and the remaining 20% is used for testing. To verify the accuracy of the forecast, the expected and actual values are compared.

Dargan et.al [8] explains the complete and profound overview that minimally and efficiently sums up the writing work done on unimodal and multimodal biometric frameworks and dissects the component extraction strategies, classifiers, datasets, results, productivity, and unwavering quality of the framework with high and multi-dimensional points of view and legitimizes exhaustively the traditional strategies, compelling techniques and scientific classification dependent on the biometric credits. The objective is to be mindful of the analysts of this space in regards to different measurements for the improvement of biometric frameworks to upgrade the security angles.

Kumar et al. [10] concentrated on images with facial obstruction and non-uniform illumination. The test images were collected from the AR face dataset and the Color FERET dataset, both of which are public datasets. A manual dataset has also been created for testing purposes. The images in this manual dataset were gathered from the internet. This includes making the machine sufficiently eager to gain human insight and information to identify, limit, and perceive the face in a discretionary picture as easily as people do, as well as proposing a proficient procedure for face identification from still pictures under impediment and non-uniform illumination.

The element-based method for 2D face photos was introduced by Gupta et al. [11]. Include extraction is done using SURF (sped up strong highlights) and SIFT (scale-invariant component change). For testing purposes, five public datasets are used: Yale2B, Face 94, M2VTS, ORL, and FERET. In this study, different combinations of SIFT and SURF highlights were examined using two different layout methodologies, namely a choice tree and irregular forests. The developers used a combination of SIFT (64-parts) and SURF to get a maximum acknowledgment exactness of 99.7%. (32-segments).

## 3. PROPOSED METHODOLOGY

The point-by-point study made in the survey has been utilized to break down the current strategies and afterward decide on the discovery of brain tumors utilizing a classification procedure which is appeared in Figure 2. The Convolution Neural Network has been utilized for the tumor assessment and the hyperparameters are tuned for improving the accuracy of brain tumor.



### 3.1 Data Pre-Processing

A pre-preparing stage has been completed before organizing the photos into the suggested structure. The fundamental method comprises downscaling the main image from 512 * 512 * 1 to 128 * 128 * 1 pixels in order to decrease assessments and dimensionality and help the system display an unmatched exhibition in less time and with intelligently clear inspections. By that point, information has been altered before isolating it to keep the framework from anticipating unsorted data and ruining zeroing in on a small portion of the total dataset.

### 3.2 Data Augmentation

Last but not least, enlarging tumour photographs makes it easier to remember them as brand-new ones, which is occasionally employed to prevent overfitting and increase model liberality. Despite this numerical sequence of events, a grayscale bending (salt noise) effect is applied to the photographs. Despite this mathematical progress, a grayscale distortion affects the photos (salt noise). The movements for the dataset comprise a 45-degree film turn, a right/left reflecting salt noise, and an x-pivot rotation. The photos in the dataset have been expanded from the main image by an element of 5, resulting in an ever-increasing number of photos in the previous dataset.

### 3.3 Convolutional Neural Network

An frequently used feed-forward neural network for image identification is CNN. This includes neurons with predispositions and learnable loads. Each neuron receives information from a few sources, evaluates the information in its totality, initiates processing, and responds to the results. CNN works over volumes like neural frameworks where the info is a vector yet on the off chance that there ought to be an event of CNN the data is a multi-directed picture. CNN has defeated picture segmentation challenges through normally learning levels of leadership of dynamically complex highlights straightforwardly from the information. The CNN has been used in convolving the picture with the parts on the way toward getting the feature maps. The weights in the portion help in interfacing each unit of the component guide to the past layers. These weights of the kernels are utilized during the planning of the datasets for improving the quality of the data. CNN designs work in three primary kinds of succession layers: Convolutional Layer, Pooling Layer, and Fully-Connected Layer. The input layer will hang on the crude pixel worth of pictures. Next, the Convolutional will register the yield of the neurons. After the convolution, RELU represents Rectified Linear Unit is an enactment work that changes overall adverse pixel esteems to 0. Next comes the Pooling layer will disregard segments of the picture and pool them into the most noteworthy worth in the segment. The last layer is FC (completely associated) layer will ascertain the class.

Initialization is the most basic development for accomplishing convergence. This system helps in keeping up the inclinations at the important levels else there will be a chance blast of the slopes that are back propagated. The activation function is liable for the data change in a nonlinear manner. There are various kinds of actuation function of which the adjusted Rectifier linear units (ReLU) has been utilized. In the component maps, the path toward pooling joins the element that is nearby spatially. This course of action of excess highlights helps in making the portrayal invariant because of little changes and logically limited. The computation load for the reformist stages is in like manner diminished. The overfitting is lessened with the help of regularization. In every movement of planning, it will dispense with the hubs of the organization. Along these lines, every one of the nodes in the Fully Connected layer is constrained to learn better portrayals and forestall the co-transformation of nodes. In the proposed engineering shown in Figure 1, seven layers are connected by the CNN structure, starting with the information layer, which stores the expanded images from the previous pre-taking care phase, and moving on to the convolution layers and their implementation task. In order to avoid overfitting, a dropout layer was used. This was followed by a fully related layer, a Softmax layer to predict the yield, a solicitation layer to pass on the expected class, and finally a solicitation layer. The following shows how each layer is represented; nevertheless, the data layer has been utilised to specify the size of information pictures and implement an information standardization. A 2D convolutional layer moves K convolutional channels of size (M * N) along the data and affiliation spot implications of the hundreds (bits loads), as well as the data.



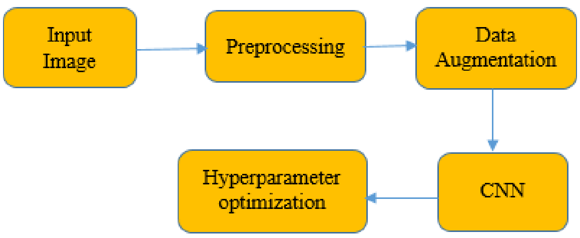


**Fig. 1.**Flowchart of the system

With vertical and level advances known as steps, the channels slide over the image. Before sliding the channels to keep data up along the edges, cushioning of the important photographs may occur. These channels are employed as highlight identifiers; heaps of that portion inside the early layers view mostly low-level highlights such as (edges, lines, and masses), whilst progressed ones are utilized to recognize an ever-increasing amount of complicated highlights. Each convolutional layer is followed by a submerged start-up operation called ReLU, which is on a fundamental level adapted to reduce the look time while still performing other activation functions. The ReLU model is represented as a piece of x where the yield is 0 for various features in condition 1 and travels in the direction of the information when x is positive.

$f(x) = max(0, x)$(1)

Concerning the greatest Pooling layer, it's a method for down inspecting accustomed achieve spatial invariance by separating the full picture into little square shapes that are moving absurd with a decision and afterward give some thought to just the foremost extreme worth of the four components. The pooling layer is employed to diminish amounts of boundaries and in this way estimations within the framework. Concerning the most limited Pooling layer, it's a method for down inspecting accustomed accomplish spatial invariance by isolating the complete picture into minimal square shapes that are moving crazy with a choice and a long time later consider only the simplest worth of the four segments. The pooling layer is used to reduce limitations measurements and, consequently, calculations inside the structure. Utilizing a dropout layer may be the first widely used approach to reduce overfitting. During this layer, a pair of activations (hubs) are left discretionarily which fundamentally helps likewise in accelerating the readiness stage. At last, the Fully Connected layer (FC) has been utilized, the softmax layer and characterization layer. The preceding one was used to connect every neuron in one layer to every neuron in another, yielding three classes in this layer. Softmax layer is used to crush each one of the anticipated classes somewhere within the range of 0 and 1, and additionally, the total number of those qualities is 1 (100 percent). Equation 2 can be used to calculate this layer's output as follows

$$y(z_j) = e^{z_j} \Big/ \textstyle\sum_{k=1}^{k} e^{z_k} \qquad (2)$$

As a function of y (z), over (k) different classes, the probability of any class (j) can be approximated and their total summations are equal to 1.

### 3.4 Hyperparameter Optimization

To increase the accuracy, Hyperparameter Optimization has been implemented in the proposed system. Hyperparameters are important because they influence the training algorithm's actions directly, having a significant impact on the model's output under training. Given the effect on the trained model, choosing suitable hyperparameters plays a key role in the performance of neural network architectures. The variables in the setup are known as hyperparameters since they are outside of the model and their value cannot be determined from the data. Hyperparameters can be divided into two categories: Kernel Size, Kernel Type, Stride, Padding, Hidden layer, and Activation function are examples of hyperparameters that determine network design.

b) Learning rate, momentum, number of epochs, and batch size are hyperparameters that govern how the network is trained.

### 3.5 Hyperparameter Tuning

In the proposed system hyperparameters are tuned for improving the accuracy. The hyperparameter that has been taken for tuning are Batch size, learning rate, momentum, and Optimizers using a grid search mechanism. Grid search is a technique for hyperparameter tuning that builds and methodically assesses a model for each combination of algorithmic parameters provided in a grid. By allowing you to select the ideal parameters for your optimization problem from a list of parameter options you provide, the grid search optimization method automates the "trial-and-error" procedure.

#### *3.5.1 Stochastic Gradient Descent*

It is perhaps the most direct smoothing out estimations. It uses just a single static learning rate for all limits during the entire planning stage. The static learning rate doesn't recommend an identical update after each minibatch. As the smoothing out specialists approach an ideal value (sub), their points start to lessen.

#### *3.5.2 RMSProp*

It is Root Mean Square Propagation that attempts to choose Adagrad's certainly diminishing learning rates by utilizing a moving common of the squared point. It utilizes the significance of the new slant falls to normalize the tendency. The learning rate gets changed normally and it picks another learning rate for each limit and parcels the learning rate by the ordinary of the remarkable decay of squared tendencies.

### *3.5.3 Adam*

It is Adaptive Moment Estimation that processes the individual flexible taking in rate for each limit from assessments of first and second previews of the points. It is computationally beneficial and has close to no memory essential.

## 4. Implementation

### *4.1 Dataset Description*

The information was obtained from The Cancer Imaging Database (TCIA), a public database of 233 people with meningioma, glioma, and pituitary tumours, three major forms of brain tumours. It contains the first image of the condition and the locale of interest, which is a region covered by three different types of brain cancers: meningioma, glioma, and pituitary tumours.

### *4.2 Grid Search*

In the proposed framework, Hyperparameters are tuned for improving accuracy. The Hyperparameter that has been taken for tuning are Batch size, learning rate, momentum, and the Optimizers are shown in Table 1. The analyzers like Stochastic angle plunge, RMSProp, and Adam are contrasted and batch size sizes of 16, 32 and 64 with the assistance of utilizing Grid search calculation. This search deals with hyperparameter tuning that will systematically fabricate and assess a model for every mix of calculation boundaries determined in a matrix. Grid search is an enhancement calculation that allows you to choose the best boundaries for your advancement issue from a rundown of boundary choices that you give, thus computerizing the 'experimentation' technique.

## 5. Discussion

Hyperparameter tuning is mostly used to increase the system's accuracy and performance. In this study, we used a convolutional neural network to detect brain cancers, and we used the Grid search tuning method to fine-tune the parameters. After the tumor was identified, the parameters were fine-tuned to improve the system's accuracy. To tune the parameters, the three Optimizers, Batch Size, and Learning Rate were used. The Grid Search tuning approach was used to tune and compare all of the Optimizers and Batch sizes with learning rates. As a result, the best accuracy suited for the dataset is 78.21% with Optimizer with a batch size of 16, a momentum of 0.9, and a learning rate of 0.001, stochastic gradient descent (SGD) is used. Thus it improves the accuracy of the system by tuning with the grid search technique.

## 6. Results

Utilizing Google Colab, the exploratory consequence of brain tumor recognition utilizing a Convolutional neural network has been done. The estimation has been executed for classification precision which prompts a data-based data picture. The test input image is checked for tumor affirmation, for instance, non-tumor and tumor images, from the picked data set. It examines the outcome by contrasting the exactness of three Optimizers and Batch size, learning rate, and momentum for Hyperparameter tuning. The three optimizers were tried on the brain tumor dataset acquired from TCIA. The accuracy for brain tumor identification using Stochastic gradient descent with a learning rate of 0.001 is 78.21% which is tabulated in Table 2. And for Adam with a learning rate of 0.001 is 75.40% which is shown in Table 3. Similarly, for the RMSProp optimizer, it is 76.60% as shown in Table 4. The calculated parameters of test MRI brain image are highlighted as Accuracy. Thus three optimizers are compared and the best optimizer is stoachastic gradient descent with batch size of 64 has attained highest accuracy of 78.21% which is shown in Figure 2 and Table 6.

**Table 1** : Network Trained Hyperparameters

| Hyperparameter | Range |
|---|---|
| Learning rate | [0.001,0.003] |
| Batch Size | [16,32,64] |

| | |
|---|---|
| Momentum | [0.9] |
| Optimizers | [SGD,Adam,RMSProp] |

**Table 2**: Tuning Accuracy of SGD optimizer

| Hyperparameter | | | | | Accuracy |
|---|---|---|---|---|---|
| **Epochs** | **Optimizers** | **Batch Size** | **Momentum** | **Learning rate** | |
| 10 | SGD | 16 | 0.9 | 0.001 | 77.00% |
| | | 32 | 0.9 | 0.001 | 78.00% |
| | | 64 | 0.9 | 0.001 | **78.21%** |
| 10 | SGD | 16 | 0.9 | 0.003 | 76.20% |
| | | 32 | 0.9 | 0.003 | 76.60% |
| | | 64 | 0.9 | 0.003 | 76.00% |

**Table 3**: Tuning Accuracy of Adam Optimizer

| Hyperparameter | | | | | Accuracy |
|---|---|---|---|---|---|
| Epochs | Optimizers | Batch Size | Momentum | Learning rate | |
| 10 | Adam | 16 | 0.9 | 0.001 | 72.00 % |
| | | 32 | 0.9 | 0.001 | 72.60 % |
| | | 64 | 0.9 | 0.001 | **75.40 %** |
| 10 | Adam | 16 | 0.9 | 0.003 | 75.38 % |
| | | 32 | 0.9 | 0.003 | 60.65 % |
| | | 64 | 0.9 | 0.003 | 47.20 % |

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**Table 4**: Tuning Accuracy of RMSProp Optimizer

| Hyperparameter | | | | | Accuracy |
|---|---|---|---|---|---|
| Epochs | Optimizers | Batch Size | Momentum | Learning rate | |
| 10 | RMSProp | 16 | 0.9 | 0.001 | 75.80% |
| | | 32 | 0.9 | 0.001 | **76.60%** |
| | | 64 | 0.9 | 0.001 | 75.23% |
| 10 | RMSProp | 16 | 0.9 | 0.003 | 69.12% |
| | | 32 | 0.9 | 0.003 | 74.24% |
| | | 64 | 0.9 | 0.003 | 65.20% |

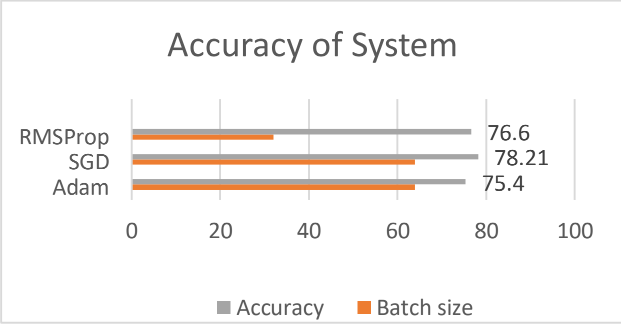


**Fig. 2.** Accuracy of the brain tumour classification.

**Table 6**: Accuracy of the Proposed system using Grid Search

| **Hyperparameter** | | | | | **Accuracy** |
|---|---|---|---|---|---|
| Epochs | Optimizers | Batch Size | Momentum | Learning rate | |
| 10 | SGD | 64 | 0.9 | 0.001 | **78.21 %** |

## 7. CONCLUSION

Utilizing an MRI picture, the identification of brain tumor was executed by utilizing a Convolutional Neural Network to a significant class that would be glioma, meningioma, and pituitary, giving us exact outcomes by playing out the framework search tuning components of the hyperparameter. The hyperparameter-like optimizers, momentum, and batch size was taken and contrasted to give the correct one to improve the exactness. From the perceptions, it is derived that to improve the performance of the system, the best hyperparameter for the dataset was found by grid search tuning strategy.

***Declarations:***

**Conflict of interest:** The authors declare that they have no conflict of interest.

**Ethical approval:** This article does not contain any studies with human participants or animals performed by any of the authors.

**Consent of publication:** Not applicable.

**Availability of data and materials**: Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

**Competing interests:** The authors declare that they have no competing interests

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**Informed consent:** This articles does not contain patient data.

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