# *BRAIN TUMOR CLASSIFICATION USING RESNET50: A LITERATURE REVIEW*

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***Abstract— A precise classification is necessary for brain tumors to be treated effectively since they pose serious health risks. It is essential to identify tumors with magnetic resonance imaging (MRI), which provides comprehensive information. Newer research emphasizes how MRI can be enhanced in classification accuracy by integrating SVM with ResNet50. SVM's classification prowess is matched by ResNet50's superiority at feature extraction. The approaches of feature extraction, preprocessing, model evaluation, and dataset collecting are summarized in this paper. Enhancing patient care in neuro-oncology, the ResNet50-SVM integration provides a powerful pipeline for accurate tumor categorization. Upcoming studies could improve clinical results in the treatment of brain cancer by validating techniques and refining integration.***

***Keywords— ResNet50, MRI, Deep learning, SVM, brain tumor classification, and medical image analysis..***

## I. INTRODUCTION

Brain tumors are anomalous growths of brain tissue that pose serious worldwide health implications. They can be roughly classified as benign, with slower growth rates and non-invasiveness, or malignant, with fast cell proliferation. Planning and prognosis of brain tumors effectively depend on their accurate classification. Since magnetic resonance imaging (MRI) provides both soft tissue contrast and great spatial resolution, it has emerged as the technique of choice for the identification of brain tumors[3]. Tumor form, location, and size can all be used to characterize the tumor with the use of MRI's comprehensive images of the brain's architecture[6]. Using characteristics taken from MRI scans, Support Vector Machine (SVM) classifiers common in medical image analysis distinguish between tumor types and grades. SVMs use the largest separation margin to identify the best hyperplanes for classifying data points.For the purpose of classifying tumors, deep learning methods, specifically the ResNet50 convolutional neural network (CNN) architecture, extract intricate information from MRI scans[12]. The deep structure of ResNet50 is optimized for efficient feature extraction, improving the brain tumor classification accuracy of SVM classifiers. This study of the literature looks at how brain tumor classification has advanced recently using deep learning methods like ResNet50, SVM classifiers, and MRI imaging. To improve patient care in neuro-oncology, the review attempts to provide insights into present approaches, obstacles, and prospects in automated brain tumor diagnosis by synthesising recent discoveries[18].

## II. LITERATURE SURVEY

Deep learning techniques have become highly effective tools for correctly classifying medical pictures, especially when it comes to the identification and categorization of brain tumors. ResNet50, a deep convolutional neural network (CNN) architecture, has proven effective in this setting in a number of investigations [2].

Convolutional block attention mechanism (CBAM) is one attention mechanism that researchers have used with ResNet50 to improve feature extraction and brain tumor classification accuracy. Remarkable 99.43% classification accuracy has been reported in these trials [1]. But these models' persistent computational complexity makes them difficult to use, thus more work is needed to create lightweight ResNet50 versions with attention methods. The use of pre-trained ResNet50 models in transfer learning techniques has also been investigated for the classification of brain tumors [1]. Comparative studies with alternative CNN designs have consistently demonstrated ResNet50's superior performance in more precisely and computationally efficiently classifying brain cancers [24]. These models have minimized computing time and achieved optimal classification accuracy by augmenting data with support vector machine (SVM) classifiers. Additionally, research has shown that using pre-trained ResNet50 models is crucial for cutting down on training time and avoiding overfitting. The creation of intuitive user interfaces makes it easier for medical personnel to diagnose and arrange treatments, which improves patient care in neuro-oncology.

Based on MRI data, ResNet50 proves to be a reliable and efficient technique for classifying brain tumors. By accurately diagnosing and classifying different types of brain tumors, its integration with deep learning techniques and attention mechanisms enhances clinical decisionmaking and improves patient outcomes in neuro-oncology [3]. To further improve brain tumor classification accuracy and computing efficiency, future research may concentrate on creating lightweight ResNet50 variations and investigating sophisticated augmentation approaches.

### 1. Dataset Collection

The MRI scans of brain tumors that were collected from medical facilities and publicly accessible repositories make up the dataset as shown in Fig 1 [4]. The photos in the dataset, which includes normal brain scans and images of pituitary tumors, gliomas, meningiomas, and other tumor forms, have been carefully selected. With a substantial amount of photos, the dataset is large enough to guarantee reliable model training and validation [30]. In order to enable thorough analysis and classification, further efforts are made to guarantee variation in tumor features, such as tumor size, location, and morphology.

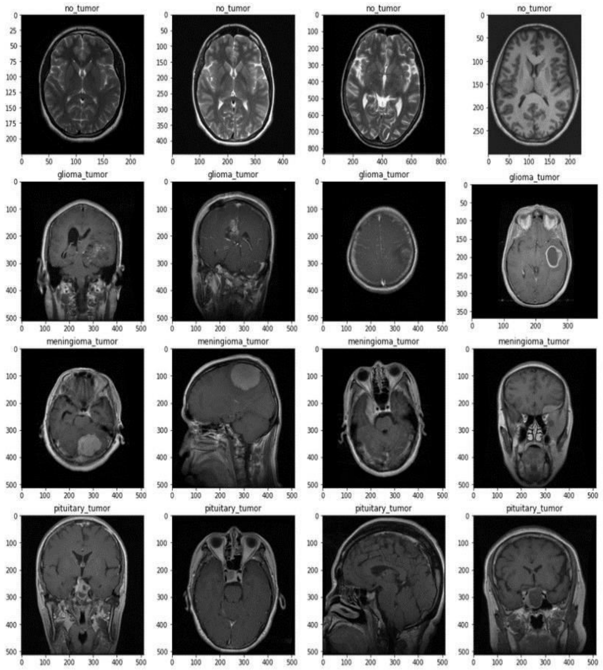


Fig 1.Samples of the datasets

2. Data Preprocessing

Preprocessing processes are applied to the obtained MRI images to improve and standardize their quality prior to training the classification model [29]. One of the preprocessing methods used to guarantee consistency throughout the collection is resizing each image to the same resolution [7]. Additionally, pixel intensity values are standardized through the use of normalization techniques like min-max normalization, which helps to avoid overfitting and model bias [23]. In addition, image contrast and clarity can be increased by using image enhancement techniques like dynamic histogram equalization (DHE), which strengthens the discriminative characteristics for tumor classification [28].

## III. PROPOSED METHODOLOGY

*1. ResNet50 Feature Extraction*

Preprocessed MRI images are used to extract features using the ResNet50 architecture as shown in Fig 2[3]. The ResNet50 model is initialized with pre-trained weights from the ImageNet dataset, allowing for the effective extraction of high-level features from images of brain tumors [16]. Accurate categorization is made possible by ResNet50's deep architecture, which captures complex patterns and structures suggestive of many tumor kinds.

*2. 2. Support Vector Machine (SVM) Classification*

Tumor classification is achieved by utilizing a Support Vector Machine (SVM) classifier in conjunction with feature extraction with ResNet50[8]. The SVM classifier learns to distinguish different tumor types based on the feature representations, using the retrieved features from the ResNet50 model as input. SVMs are used because they work well in problems involving binary and multiclass classification, especially in the interpretation of medical images.

In MRI imaging, the algorithms ResNet50 and SVM are crucial for classifying various forms of brain cancers [25]. Together, they are able to distinguish between distinct tumor kinds and extract complex data from images. For example, ResNet50 is able to capture distinct features such texture, shape, and location of meningioma, pituitary, and glioma tumors. Based on patterns they have learnt from training data, SVM classifiers use these features to accurately classify tumors in the interim [19]. This combination makes it possible to precisely identify and characterize tumors, which helps patients with brain tumors receive better diagnoses and treatment plans.

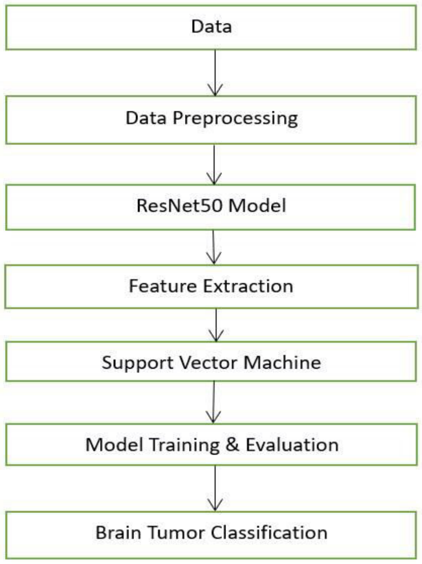


Fig 2. Block Diagram of the Proposed System

*3. 3. Model Training and Evaluation*

The curated MRI dataset [11] is used to train the combined ResNet50-SVM classification model; a subset of the dataset [3] is kept aside for testing and validation [15]. Using the attributes that were retrieved, the model is trained to categorize photos of brain tumors into the appropriate groups. Known criteria like accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve

(AUC-ROC) are used to assess the model's performance [1]. It is also possible to use crossvalidation techniques to make sure the model is resilient and generalises to a variety of tumor kinds and imaging settings. By using deep learning techniques, ResNet50 feature extraction, and SVM classification, the study hopes to create an accurate and effective brain tumor classification model. The suggested classification system for diagnosing brain cancers from MRI scans is reliable and successful because of the carefully chosen dataset and rigorous methodology [27].

*4. 4. ResNet50 (Residual Neural Network)*

A convolutional neural network architecture called ResNet50 was created expressly to meet the difficulties associated with deep network training. Remaining blocks are used, each of which has several convolutional layers, batch normalization, and ReLU activation algorithms [20]. ResNet50's main innovation is the addition of skip connections, which let the network pick up residual functions. A residual block's mathematical output is expressed as follows:

Output=ReLU(Conv(BatchNorm(Input)))+Input

This formula shows how residual information is captured by adding the convolutional layer's output to the original input following batch normalization and ReLU activation [31].

5. *Support Vector Machine (SVM)*

For classification problems, supervised learning algorithms like SVM are employed. When it comes to classifying brain tumors, SVM uses the decision function to learn how to divide the data that ResNet50 extracted into distinct tumor cate-gories. A linear SVM's decision function can be shown as follows:

Let $f(x) = \operatorname{sign}\left(\sum_{i=1}^{N} \alpha_i y_i K(x, x_i) + b\right)$

Sigmoid, polynomial, linear, and radial basis function (RBF)

kernels are often employed functions that de-fine how the input space is converted into a higherdimensional space for classification [30]. The decision function is represented by the for-mula f(x).

Input feature vector is denoted by x.

N represents the quantity of support vectors. yi and αi stand for class labels and Lagrange multipliers, respectively.

The kernel function that calculates the similarity between x and xi is called K(x,xi). The bais term is b.

## IV. INTEGRATION IN BRAIN TUMOR CLASSIFICATION

ResNet50 and SVM work together to create a potent pipeline for precise brain tumor categorization. Complex features are extracted from MRI images by ResNet50, and SVM learns to classify these features into different tumor kinds. The integrated strategy improves treatment plans and patient outcomes in neuro-oncology by precisely diagnosing brain cancers by fusing ResNet50's feature extraction skills with SVM's classification expertise.

## V. CONCLUSION

A strong method for classifying brain tumors [1] is the combination of ResNet50 with SVM, which provides a complementary set of features for classification and feature extraction[26]. The deep learning architecture of ResNet50 is em-ployed to collect complex patterns and features from brain MRI images, yielding an extensive representation of tumor characteristics. Consequently, accurate tumor typeand grade classification is made possible by SVM's capacity to classify these ex-tracted features, which helps with accurate diag-nosis and treatment planning [7].

This work emphasizes how important it is to use cuttingedge machine learning methods in medi-cal imaging, especially when it comes to neuro-oncology [21]. The suggested approach shows encouraging outcomes in terms of improving diagnostic precision and expediting the brain tumor classification procedure. Subsequent investigations could concentrate on refining the incorporation of deep learning models such as ResNet50 with SVM classifiers and confirming the methodology through comprehensive clini-cal validation trials. In the end, these develop-ments could greatly enhance clinical results and patient care in the treatment of brain cancers.

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