



A Review: Utilizing Machine Learning Algorithms for the Detection and Identification of Brain Tumors

¹Lajwanti Singh, ²Garima Singh, ³Harshita Jangir, ⁴Khushi Singh, ⁵Neha Kumari

¹Assistant professor, ²⁻⁵Student
¹⁻⁵Department of Physical Sciences,
¹⁻⁵Banasthali Vidyapith, Tonk, Rajasthan, India

Abstract : Brain tumors, abnormal growths within the brain, represent a critical healthcare concern due to their potential impact on cognitive function and overall, well-being. Cerebrum cancers are of two sorts: benign (non-cancerous) and malignant (cancerous). Early and exact discovery is vital for successful treatment. In the field of clinical science, X-ray pictures are broadly utilized in cancer identification. The applications of machine learning (ML) for the detection of brain tumors are thoroughly examined in this paper. Surveying a diverse range of research papers, we categorize and compare methodologies, dataset, and performance matrices. For the purpose of automating and increasing the accuracy of tumor detection, medical imaging data have been subjected to a variety of ML algorithms, including conventional algorithms and sophisticated deep learning models. This comparative study is used to identify various challenges, opportunities, and trends providing valuable insights for practitioners and researchers selecting productive ML techniques for brain tumor detection.

Index Terms - Convolutional Neural Network (CNN), Deep Learning, Machine Learning(ML), Magnetic Resonance Imaging (MRI), X-ray.

I. INTRODUCTION

The development of tumorous cells inside the skull is the indication of a cerebrum growth. Cerebrum growths can be characterized into two principal classes: dangerous (malignant) and harmless (benign). Primary and secondary brain tumors are the two types that can occur. Most primary brain tumors are not dangerous. Optional mind cancers are likewise alluded to as metastatic cerebrum growths [1].

Tumors can be identified using a variety of medical imaging techniques, including computed tomography (CT), positron emission tomography (PET), magnetic resonance imaging (MRI), and X-rays [2]. Attractive reverberation imaging (X-ray) is the most frequently involved strategy for finding and following the development of mind tumor growths because of its outstanding goal [3]. Figure 1 and 2 shows the healthy and infected brain MRI images respectively.

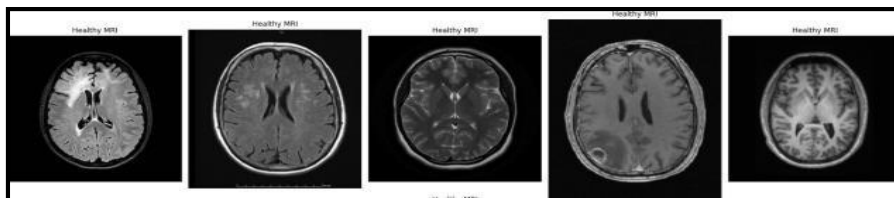


Figure 1. Healthy Brain MRI images

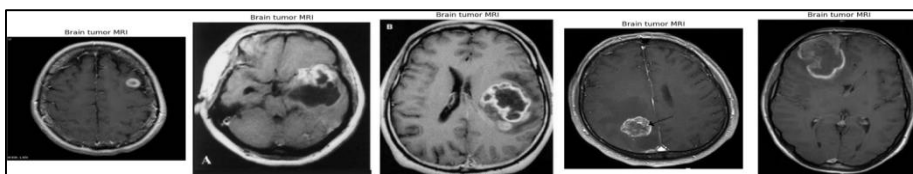


Figure 2. Brain Tumor MRI images

In the medical world, brain tumors from MRI images are still identified manually by radiologists and physicians. Because of this, even for medical specialists, interpreting MRI pictures can be difficult. Because brain tumors can mimic healthy brain tissues

in a patient, it is challenging to manually detect them because of the complicated layout of the human brain [4]. The rates of survival of patients are significantly impacted by early brain tumor identification and treatment initiation [5]. Cerebrum growth biopsy is more troublesome than a biopsy of some other segment of the body. Thus, the necessity for a different, non-surgical approach to obtain an accurate diagnosis is crucial [6].

A crucial initial step in the detection of brain cancer is image segmentation. Division serves in adjusting a picture appearance. To help locate tumor locations, it basically modifies the image to detect boundaries and divides it into multiple parts [7]. Thus, the development of an image segmentation system with quick computation speed and precise outputs is crucial [8].

Medical imaging patterns may now be recognized and categorized as a result of recent developments in machine learning [9, 10, 11]. Images of cancer, particularly brain tumors, can be examined, segmented, and categorized using machine learning methods, especially deep learning [12].

The purpose of this research is to provide a summary of the numerous approaches or procedures that are available for detecting brain cancers in MRI scans because medical imaging methods and images are so crucial in the medical world of today.

Figure 3 illustrates the typical process for identifying brain tumors using machine learning. The block's specifics will be included in the paper's subsequent section [13].

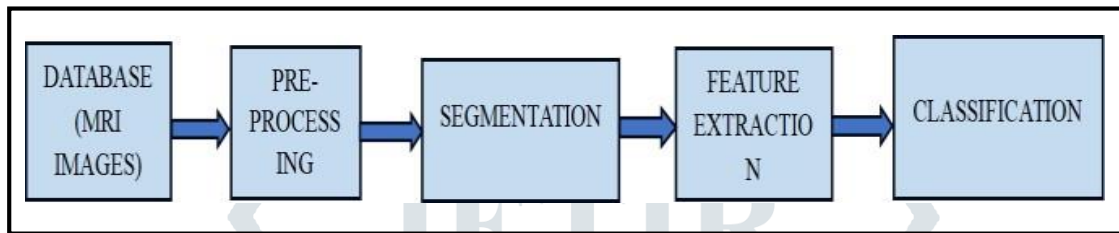


Figure 3. Block diagram of brain tumor detection

II. DATABASE

A lot of images are needed for the machine learning and deep learning algorithms to work [14]. Therefore, the following datasets are listed for research purposes: The Whole Brain ATLAS, ISLAS, BRATS from 2012 to 2019, TCIA, and Kaggle.

III. PRE-PROCESSING

The two stages of pre-processing are image registration and image smoothing. To obtain a standard image, the input image is pre-processed using a variety of image processing filters. A clear, noise-free image with excellent contrast and quality is produced through pre-processing [15, 16]. Figure 4. presents the review analysis of several filters.

| Reference | Database | Pre-processing techniques | Model employed | Accuracy |
|-----------|----------|---------------------------|----------------|----------------------------|
| [29] | Private | Median filter | SVM | 95% |
| [30] | Kaggle | Gaussian blur | CNN | 97% |
| [31] | Private | Average filter | PNN+LVQ | 100% (when spread value=1) |

Figure 4. Pre-processing techniques of machine learning and deep learning.

IV. SEGMENTATION

The process of dividing a digital image into groups of pixels is known as image segmentation [17]. Image segmentation aids in accurately detecting the tumor boundary region when it comes to brain tumor identification. Similar pixels are grouped together in the segmented image to make them easier to distinguish from other areas of the image. Methods for segmenting images include threshold-based, region-based, clustering, edge-based, and more [18, 28, 20]. Figure 5 provides a thorough analysis of several segmentation strategies.

| Reference | Segmentation techniques | Advantages | Disadvantages |
|-----------|-------------------------|--|---|
| [33] | Threshold based | Its features are intuitive, and its implementation is easy. | The dataset requires a lot of time to train and difficulty in identifying an object against a background. |
| [32] | Region-based | Global segmentation, border closure, and high accuracy. | Its sensitivity to local minima is very strong. |
| [34] | Edge based | It is employed to remove marginal edges that arise from noise and insufficient lighting. | Because there are broken, stray, or noisy edges in the outputs of the edge-based approach, they cannot be used as a partially segmented output. |
| [35] | Cluster based | It produces segmentation masks immediately and efficiently. | For noisy images, it does not produce segmentation markings, which results in significant error. |

Figure 5. Segmentation techniques

V. Feature extraction

The elements, like shape, size, region, direction, and so forth. are separated from the pre-processed pictures utilizing highlight extraction methods. By taking into account the description of the relevant picture features into feature vectors, the chosen feature should give the classifier the characteristics of the input type [21]. The three forms of feature extraction types are:

- Intensity- Mean, Standard Deviation
- Texture- contrast, correlation
- Shape – Area, perimeter, shape [22].

The review analysis of feature extraction methods is given in fig.6.

| Reference | Algorithm for classification | Feature extraction | Accuracy |
|-----------|------------------------------|--|----------|
| [30] | CNN | To increase and decrease the size of image | 97% |
| [29] | SVM | Auto correlation, contrast , energy, entropy | 95% |
| [32] | Naive bayes | Texture | 98.6% |
| [36] | SVM+CNN | Intensity | 99.7% |

Figure 6. Methods of feature extraction

VI. Classification

Numerous sophisticated image classification approaches, such as ANN, SVM, fuzzy logic, etc., are used for classification. The study contributes to the conclusion that the Neural Network technique to classification will yield more accurate information from each class [23, 24, 25].

Artificial Neural Network (ANN)

When there is high-quality labeled data, ANN performs better than other models and does well with larger datasets. But because these models need more data to function well than other conventional algorithms, they are more computationally expensive [26].

Convolutional Neural Network (CNN)

CNN is capable of classifying images well. Once trained, they use the same information in all image locations and have very quick prediction times. Any quantity of layers and inputs can be used with it. In addition, it uses less compute than a standard neural network. On the other hand, a highly deep network will operate a little more slowly and require a large quantity of dataset to function well [27].

Support Vector Machine (SVM)

SVM is better in large-dimensional spaces and can be used for both classification and regression problems. In comparison to the Naïve Bayes algorithm, it predicts with a high degree of accuracy and proceeds more quickly. Nevertheless, it requires more

time to train and is not appropriate for huge datasets. Furthermore, it is ineffective when there are overlapping classes [19]. Figure 7 provides a comparative analysis of several classification algorithms.

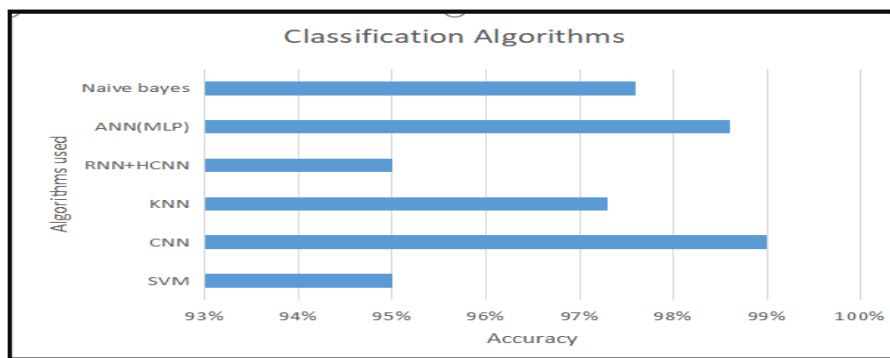


Figure 7. Study of classification algorithm.

VII. Conclusion

Brain tumors are still a hot topic of study in medical image processing. The most recent method for diagnosing brain tumors was thoroughly reviewed in this paper. Tumor detection, segmentation, and classification procedures make up brain tumor diagnosis. The main role of cerebrum cancer identification methods is the acknowledgment of growths from X-ray pictures put away in a data set, which is believed to be fundamental and direct methodology. In any case, different growth tissues inside X-ray pictures can be found and detached utilizing mind growth division methods. Additionally, abnormal images are classified as benign or malignant tumors using methodologies for classifying brain cancers. These three hybrid approaches and strategies help radiologists comprehend the MRI data needed for diagnosis and provide them with relevant information.

VIII. REFERENCES

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