BRAIN TUMOUR DETECTION AND CLASSIFICATION

Aryan Galande[1], Suraj Mohite[2], Pavan Thorat[3], Prof. Rajani Jadhav[4]

[1]Aryan Galande: Student, Dept. of Computer Engineering, PICT Pune.
[2]Suraj Mohite: Student, Dept. of Computer Engineering, PICT Pune.
[3]Pavan Thorat: Student, Dept. of Computer Engineering, PICT Pune.
[4]Prof. Rajani Jadhav: Professor, Dept. of Computer Engineering, PICT Pune.

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Abstract - *Cancer is one of the largest health problems the world faces today, and early detection is key to better patient outcomes. Traditional tumour detection methods sometimes involve intrusive procedures and have disadvantages. The integration of Artificial Intelligence (AI) and Machine Learning (ML) has led to breakthrough developments in the field of medical diagnostics in recent years, particularly in the identification of malignant tumours. This research provides a thorough analysis of the application of AI and ML techniques in the early diagnosis and detection of cancer. Keywords—Cancer Detection, Tumor Detection, Artificial Intelligence, Machine Learning, Medical Imaging, Radiology, Healthcare, Early Diagnosis.*

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1.INTRODUCTION

A crucial area of medical research and clinical practice is the detection of cancer in the brain. This field focuses on the identification and diagnosis of tumours that originate inside the central nervous system, which includes the brain and spinal cord. Brain tumours, commonly referred to as brain cancer, can be malignant (cancerous) or benign (noncancerous). Early brain cancer detection is essential for successful treatment and better patient outcomes. The following are some important details about brain cancer detection: Different Brain Tumour Types: Brain tumours are categorized according to their origin, location, and level of malignancy. Whereas secondary brain tumours originate from cancer that has progressed to the brain from other parts of the body, primary brain tumours originate in the brain or spinal cord. Brain cancer symptoms can vary greatly and include weakness, eyesight issues, altered behaviour or cognitive function, chronic headaches, and seizures. Due to the mild and non-specific nature of these symptoms, early identification is frequently difficult. Diagnostic Tools: A mix of diagnostic tools and medical imaging techniques, such as magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET) scans, are commonly used to detect brain cancer. The presence, location, and size of brain tumours can be seen with the aid of these imaging investigations. Biopsy: To obtain a conclusive diagnosis, a biopsy often entails taking a tiny sample of the tumour tissue to be examined under a microscope. This aids in identifying the exact type of tumour and whether it is malignant. Blood Tests: New studies are investigating the possibilities of liquid biopsies, which entail testing blood samples for the presence of DNA mutations linked to brain cancer or tumor-specific markers. Developments in Imaging: The capacity to accurately map brain tumours and evaluate their effects on surrounding brain structures has been enhanced by developments in medical imaging technology, including diffusion tensor imaging and functional magnetic resonance imaging. Options for Treatment: Surgery, radiation therapy, chemotherapy, immunotherapy, targeted therapy, or a mix of these may be used to treat brain cancer. Options for less invasive treatment are frequently made possible by early detection. Research and Innovation: Developing novel treatments for brain tumours and enhancing the precision and noninvasiveness of diagnostic methods are the two main objectives of continuous efforts in the field of brain cancer detection. Early Diagnosis and Prognosis: Early detection of brain cancer is critical to improving patient quality of life and raising the chance of a successful treatment plan. Moreover, accurate prognosis is necessary to tailor treatment plans to individual patients.

1.1 Literature Survey

In a 2021 study by Q.D. Buchlak et al., the applications of machine learning in neuroimaging for glioma detection and classification were explored. This research offers valuable insights into the use of AI specifically for glioma diagnosis, a common and aggressive type of brain tumor. Understanding the specific methods and algorithms employed for glioma diagnosis is essential for comprehending the broader landscape of brain tumor detection. M.K. Abd-Ellah et al.'s 2019 review provides a comprehensive overview of brain tumor diagnosis from MRI images, with a focus on the practical implications. This study offers a holistic perspective on the challenges and opportunities associated with using MRI for brain tumor diagnosis, shedding light on the real-world applications of this technology. The same work by M.K. Abd-Ellah et al. emphasizes lessons learned from the application of MRI in brain tumor diagnosis. The lessons derived from this research are crucial for understanding the evolving landscape of brain tumor diagnosis and serve as valuable guidance for future studies. V.P. Grover et al.'s 2015 publication on magnetic resonance imaging principles and techniques is instrumental in providing a fundamental understanding of MRI, which forms the basis for brain tumor imaging. Understanding the underlying principles of MRI is essential for interpreting the results of machine learning models applied to MRI data. In a 2000 study by H. Tang et al., MRI brain image segmentation using multi-resolution edge detection and region selection techniques was discussed. This study provides insights into the image processing approaches used in the context of brain tumor detection and their integration with machine learning for more accurate tumor delineation. In a 2010 study by K. Somasundaram et al., a fully automatic brain extraction algorithm for axial T2-weighted MRI images was presented. This addresses a crucial preprocessing step for brain tumor diagnosis. The automatic extraction of the brain region is an essential component of the pipeline, and this study contributes to the technical aspects of the process.

1.2 Methodology

A. Detecting brain tumors using a Support Vector Machine (SVM) algorithm involves several steps, from data collection and preprocessing to model training and evaluation. Here's a step-by-step algorithm on how to detect brain tumor using SVM:

2. ALGORITHM

1. Start
2. Data Collection
3. Data Preprocessing: Process the MRI images to prepare them for training and testing.
4. Feature Extraction: Depending on your dataset and the nature of the images, you may want to extract relevant features from the images. Some common feature extraction methods include Histogram of Oriented Gradients (HOG) or Local Binary Patterns (LBP). 5. Feature Vector Generation: Convert the processed or extracted features into feature vectors that can be fed into the SVM. Each image should be represented as a set of numerical features.
6. Labeling: Assign labels to your feature vectors, such as 0 for non-tumor and 1 for tumor. Ensure that your labels match the images in the training set.
7. SVM Model Selection: Choose the appropriate type of SVM (linear, polynomial, radial basis function, etc.) based on your dataset and problem. You can experiment with different kernel functions to see which one works best for your problem.
8. Model Training: Train the SVM model on the labeled training data. The SVM algorithm will learn the decision boundary that best separates the tumor and non-tumor classes. You can use libraries like scikit-learn in Python for SVM implementation.
9. Model Evaluation: Assess the performance of your SVM model using appropriate evaluation metrics. Common evaluation metrics for binary classification tasks include accuracy, precision, recall, F1-score, and ROC curve analysis.
10. Hyperparameter Tuning: Fine-tune the hyperparameters of the SVM model, such as the regularization parameter (C) or the kernel parameters, to optimize the model's performance. You can use techniques like cross-validation for this.
11. Testing: Use the trained SVM model to predict tumor vs. non-tumor labels on your test dataset.
12. Post-processing: You can apply post-processing techniques to improve the model's output, such as thresholding to reduce false positives or false negatives.
13. Visualization: Visualize the SVM's decision boundary or important features, which can help understand the model's decision-making process.
14. Deployment
15. If the model performs well, we can deploy it for real world brain tumor detection, possibly in a medical setting.
16. End

Using the above algorithm, we can detect samples containing brain tumour.

2. EXPERIMENTS AND RESULTS

For this experiment, we utilized a diverse dataset comprising MRI images of the brain, including both cancerous and non-cancerous cases. The dataset was carefully curated to encompass a wide range of tumor types, sizes, and locations, ensuring the diversity necessary for training and evaluating the SVM model effectively.

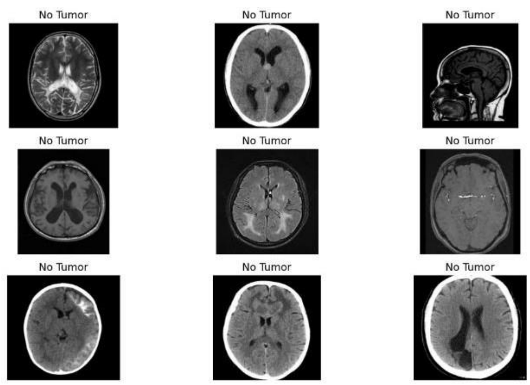

Fig. 2. Samples tested for no tumor.

The chosen dataset includes two types of data:-

1)Training Data

2)Testing Data

Each of these divisions of datasets includes MRI Scansof Human Brain having no tumor and MRI Scans of Human Brain having Pituitary Tumor.

The SVM Model is trained on the training data of chosen dataset, Fig 2 shows results of testing of SVM model on the testing data of chosen dataset for no tumor.

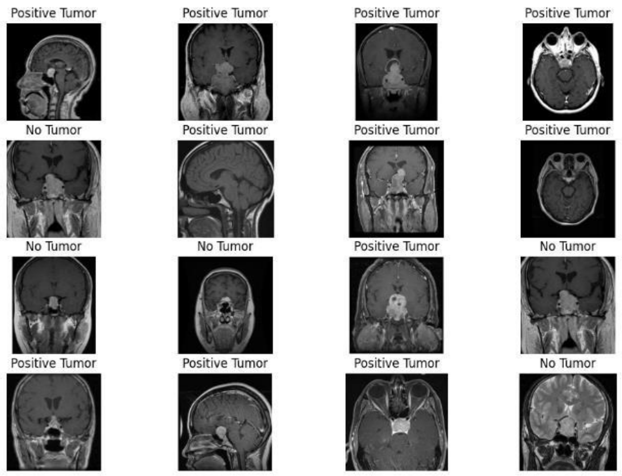

Fig. 3. Samples tested for pituitary tumor.

Fig 3 shows results of testing of SVM model on the testingdata of chosen dataset for pituitary tumor.

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Training Score: 0.9887410440122825
Testing Score: 0.9591836734693877
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Fig. 4. Testing Results.

After testing the model, we got the training score of 0.9887 andtesting score of 0.9592.

3. CONCLUSIONS

In conclusion, a promising direction in the field of medical diagnostics is the application of Support Vector Machines (SVM) for brain tumour detection. SVMs are a useful tool for accurate classification, but there are issues that need to be resolved, including issues with generalization, data limitations, and ethics.

Investigating deep learning methods, multimodal data fusion, and real-time detection systems, among other possibilities, can significantly improve the efficiency and accuracy of tumour detection. Moreover, collaboration between AI and medical experts is necessary for the successful integration of SVM-based tumour detection in clinical settings. These developments herald a bright future for improving brain tumour identification, which will eventually lead to better patient outcomes and care.

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