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Classification Of Pituitary Brain Tumours Using Machine Learning

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Abstract: Machine learning (ML) a type of Artificial Intelligence (AI) that allows systems to learn and improve from data without being explicitly programmed. It uses artificial neural networks and deep learning to analyse large amounts of data, identify patterns, and make predictions. ML is used in many areas of our lives, including banking, online shopping, social media, healthcare, and entertainment. A pituitary tumour is an abnormal growth of cells in the pituitary gland, a small gland located in the brain that produces hormones that regulate many bodily functions. A tumor is carried on by rapid and uncontrolled cell growth in the brain. If it is not treated in the initial phases, it could prove fatal. Despite numerous significant efforts and encouraging outcomes, accurate segmentation and classification continue to be a challenge. Detection of brain tumors is significantly complicated by the distinctions in tumor position, structure, and proportions. The main disinterest of this study stays to offer investigators, comprehensive literature on Magnetic Resonance (MR) imaging's ability to identify brain tumors. Using computational intelligence and statistical image processing techniques, this research paper proposed several ways to detect brain cancer and tumors. Classifying brain tumours accurately is crucial for treatment and prediction. In the proposed work, the ML models, including k-nearest neighbour (KNN), decision trees, logistic regression and Support Vector Machine (SVM algorithms, are used to classify pituitary brain tumours. MRI dataset of Brain Tumour Classification, available in Kaggle, is used. It contains 105 images of no tumour and 74 images of pituitary tumour. From the empirical analysis, it is found that the CNN Classifier has exhibited an accuracy of 88%. ML algorithms exhibit strong performance in classifying brain tumors, with near-maximum area under the curves, sensitivity, and specificity.

Keywords: Brain Tumour, machine learning, Convolutional Neural Networks, Decision Tree Algorithms, KNN, SVM

I. Introduction

An unchecked expansion of brain tissues is known as a brain tumor. It produces pressure in the skull and interferes with the brain's natural functioning. Brain tumor comes in two different types: Benign (non-cancerous) and Malignant (cancerous). Among them, malignant tumors grow quickly in the brain, damage the normal tissues, and may replicate themselves in other parts of the body. Brain tumors are an abnormal mass of tissue that forms within the brain. Brain tumors can be classified as either primary or metastatic. Primary brain tumors originate within the brain itself, while metastatic tumors form in other parts of the body and then spread to the brain. There are several types of primary brain tumors, including pituitary tumors, which form in the pituitary gland. Pituitary tumors are a type of primary brain tumor that develop in the pituitary gland, which is a small gland located at the base of the brain. The pituitary gland produces hormones that regulate various bodily functions, including growth, reproduction, and metabolism. Pituitary tumors can be benign (non-cancerous) or malignant (cancerous), and they can cause a variety of symptoms depending on their location and size. In this project, we will focus on the classification of pituitary tumors using machine learning techniques. We will use a dataset of brain MRI images to train a machine learning model that can classify pituitary tumors based on their characteristics.

II. The estimated number of incident cases of cancer in India for the year 2022 was found to be 14,61,427 (crude rate:100.4 per 100,000). In India, one in nine people are likely to develop cancer in his/her lifetime. Lung and breast cancers were the leading sites of cancer in males and females, respectively. Among the childhood (0-14 yr) cancers, lymphoid leukaemia (boys: 29.2% and girls: 24.2%) was the leading site. The incidence of cancer cases is estimated to increase by 12.8 per cent in 2025 as compared to 2020. After the age of 70 years, 16% people having pituitary tumour were observed. The volume of fossa was statistically greater in elderly patients.

III. [1] presents, Convolutional Neural Networks are designed for the classification of Multiple Sclerosis Brain Lesions and Pituitary Tumour. The T1-weighted Contrast-enhanced MRI images are preprocessed. Reported a classification accuracy of 99.7% for pituitary Tumor, and 99.2% for Multiple Sclerosis brain Lesions.

IV. [2] presents a comprehensive study on the classification of brain tumor images, using five pre-trained vision transformer (ViT) models, namely R50-ViT-l16, ViT-l16, ViT-l32, ViT-b16, and ViT-b32, employing a fine-tuning approach. ViT-b32 model demonstrated a high accuracy of 98.24% in accurately classifying brain tumor images.

V. [3] uses Convolutional Neural Network (CNN) for classifying MRI images for grading (classifying) the brain tumors into three classes (Glioma, Meningioma, and Pituitary Tumor). Reported an accuracy of 98.93% and sensitivity of 98.18% for the cropped lesions.

VI. [4] develop a machine learning model that can accurately detect the presence of tumour in the MRI image. It trains a machine learning model on a dataset of brain tumour images using supervised learning.

VII. [5] evaluates the current applications of AI and ML in the management of Pilocytic Astrocytoma (PA)s and proposes areas for improvement. AI and ML have demonstrated utility in early diagnosis, treatment planning, and predicting responses to surgery, medication, and radiotherapy, as well as patient outcomes. Advanced imaging techniques such as MRI-based radiomics, facial imaging, and pathological image analysis further enable predictive modeling.

VIII. [6] EXPLORES THE USE OF DEEP LEARNING (DL) MODELS, SPECIFICALLY MULTILAYER PERCEPTRON (MLP) AND CONVOLUTIONAL NEURAL NETWORK (CNN), FOR PREDICTING PROGRESSION/RECURRENCE (P/R) IN NONFUNCTIONING PITUITARY MACROADENOMAS (NFMAS) BY INTEGRATING CLINICAL DATA AND PREOPERATIVE MRI FEATURES. THE MULTIMODAL CNN-MLP MODEL, WHICH COMBINED CLINICAL AND MRI FEATURES, ACHIEVED THE BEST PREDICTIVE PERFORMANCE WITH AN ACCURACY OF 83%, PRECISION OF 90%, AND AN AREA UNDER THE CURVE (AUC) OF 0.85.

IX. [7] addresses brain tumor detection in MRI scans using a large collection of brain tumor images. The authors demonstrate that fine tuning a state-of-the-art YOLOv7 model through transfer learning significantly improved its performance in detecting gliomas, meningioma, and pituitary brain tumors. It uses the deep learning model to accurately identify the presence and precise location of brain tumors in MRI images.

X. [8] suggests a novel MRI brain tumour detection method based on DL and ML. Initially the MRI images are collected and pre-processed using Adaptive Contrast Enhancement Algorithm (ACEA) and median filter. Fuzzy c-means based segmentation is done to segment the preprocessed images. The features like energy, mean, entropy and contrast are extracted using Gray-level co-occurrence matrix (GLCM). The abnormal tissues are classified using the proposed Ensemble Deep Neural Support Vector Machine (EDN-SVM) classifier. The numerical findings reveal a better accuracy (97.93 %), sensitivity (92 %), and specificity (98 %) in recognizing aberrant and normal tissue from brain MRI images.

XI. From the literature survey it is evident that, less work is reported for the detection of pituitary brain tumors. Most of the reported works focus on classifying the tumors at a broader level. Even though the reported accuracies are high, clinical correlation with expert physicians is required, since the issue is critical. Hence, this work focuses only on Pitutary tumour detection. Once detected, it can be subjected to classification and prediction.

XII. Brain tumors are graded into four different categories:

XIII. **Grade I**: These tumors do not spread quickly and develop slowly. These are connected to a higher chance of enhanced order and may be surgically eliminated nearly entirely. One such tumor is a pilocytic astrocytoma.

XIV. **Grade II:** Although they may migrate to surrounding tis sues and advance to higher grades, these tumors also grow The associate editor coordinating the review of this manuscript and approving it for publication was Wei Wei . over time. These tumors may detect even though treatment is taken by the patient. An oligodendroglioma tumor is an example of an overtime growth tumor.

XV. **Grade III:** The growth of these tumors has been quicker than grade II malignancies and could spread to adjoining tissues. Such tumors require post-operative chemo or radio therapy because surgery alone would be insufficient to treat them. Aden squamous astrocytoma is an indication of such a tumor.

XVI. **Grade IV:** The most dangerous and likely to spread malignant tumors are in this category. They might even use blood vessels to speed up their growth. An illustration of one of these tumors is glioblastoma multiforme.

XVII. Brain tumors must be identified in time and appropriately be classified in order to get proper treatment and endure for patients. Because of the several vulnerabilities including different shapes, sizes of tumors, appearance, positions, scanning parameters, and modalities detection of brain tumors is a very challenging job to perform. To attain this task a number of traditional and intelligence techniques are being used. Typically, traditional approaches like Leksell Gamma Knife, Gamma Knife (GK), and Radioactive beams are helpful in diagnosing the lesions, but this process includes human involvement and is often a time-consuming task to perform. For brain tumor identification, many medical imaging modalities like Computer Tomography (CT), Magnetic resonance imaging (MRI) scans, and Poisson Emission Tomography (PET) are employed. Also, A unique MR technique called chemical exchange saturation transfer (CEST) makes it possible in imaging some substances at concentrations that are too low to affect the contrast of conventional MR imaging and too low to be directly identified in MRS at usual water imaging resolution. Among them, MRI scan is a non-invasive method that shows the internal body structure with the help of magnetization and microwave pulses. For brain tumor diagnosis, three categories of magnetic resonance image patterns are used:

XVIII. Fluid Attenuated Inversion Recovery (FLAIR), T1 weighted, and T2 weighted. The problem of identifying and detecting tumor-infected areas using brain MRI is crucial.

XIX. Rest of the paper is organized into 4 sections. Section II presents the methodology of the work. Dataset details are discussed in Section III. Section IV discusses results. Finally, Section V concludes the work and presents the future applications.

II. Methodology

In recent years, a lot of research has been directed toward the adaptation of machine learning models in diagnosing brain tumors. Academicians have put in their efforts and with the help of high-end computing devices, higher accuracy has been achieved. Convolutional neural networks (CNN), which include input, output, hidden layers, and hyperparameters, are often called Deep Learning (DL). It uses supervised classification and generates feature maps by having the kernel convolve all around the input image. Automatic-based feature extraction is both possible with DL models. Apart from its usefulness for medical condition detection, it has some shortcomings, including the requirements to design complex models, fine-tuning of hyper-parameters, the requirement of large data set, and time and effort to training/testing. As per recent research, significant data augmentation methods like resizing, rotation, scaling, and transformation are enforced to tackle the big data availability problem. A trained NN is used in transfer learning techniques to extract similar properties from an application-specific dataset. Pre-processing, segmentation, extraction of features, and categorization are the four key phases of ML techniques used to diagnose brain tumors.

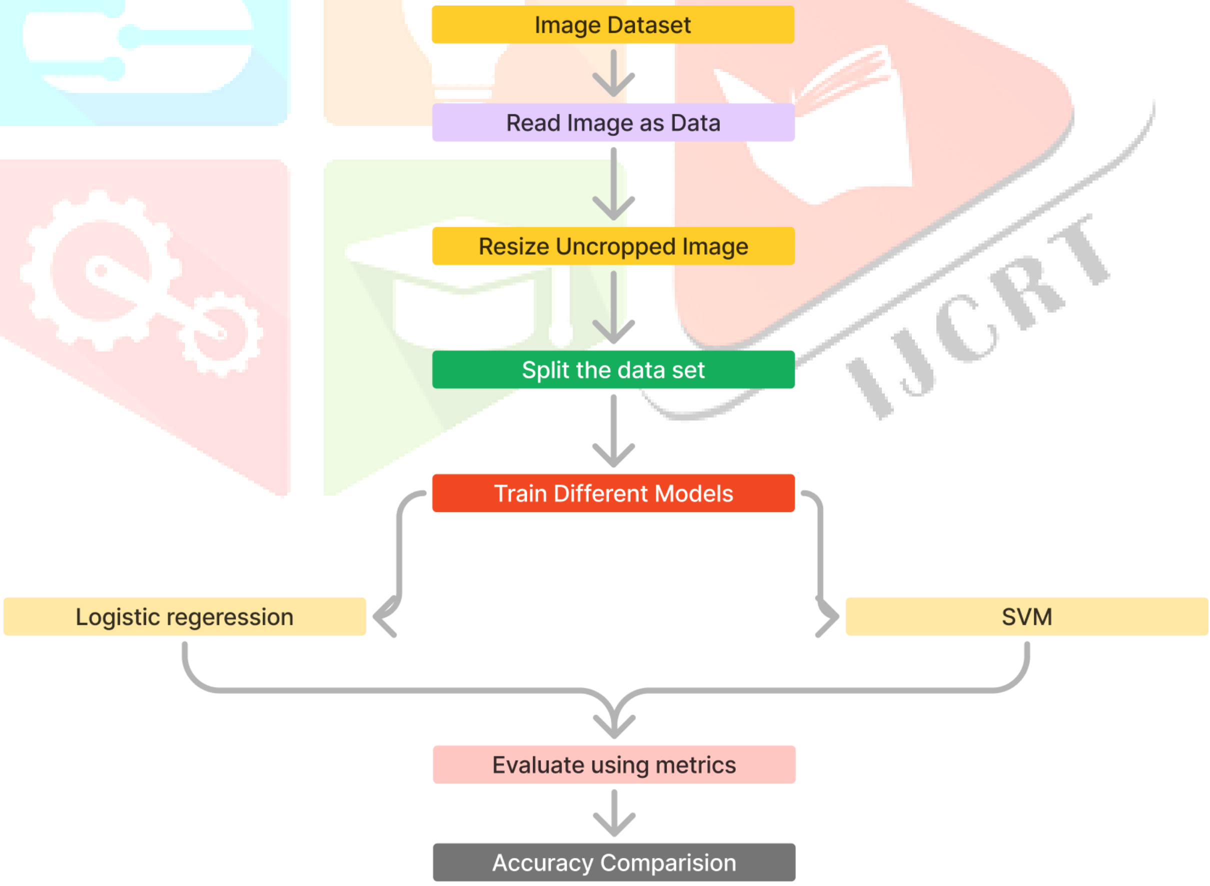
1) PREPARATION - To produce accurate diagnoses in the clinical field, precise imaging is essential. The efficiency of clinical images is influenced by the artifact acquisition methods, like magnetic resonance scans, CT, and PET. A Magnetic resonance scan's real images could contain a lot of unwanted and pointless details. Magnetic resonance imaging is impacted by Rician noise. It is challenging to remove Rician distortion since it is signal-sensitive. Pre-processing techniques including filtration, intensity correction, and skull stripping is being used to maintain the original visual characteristics.

2) SEGMENTATION - It is a technique used to obtain areas of interest from digital images. The tumor's position must be distinguished from the MRI brain scans, which is crucial. For segmentation, numerous supervised methods are available, including thresholding, soft computing technique, atlas-based, Neural Networks (NNs), clustering, etc. Thresholding methods include global, adaptable, Otsu's, and histogram-dependent techniques. There are two unsupervised clustering methods namely K-means clustering and fuzzy C-means clustering. It successfully separates brain MRI scans into Gray Matter (GM), Cerebrospinal Fluid (CSF) as well as White Mat ter (WM). Segmentation techniques that draw inspiration from nature include Particle Swarm Optimization (PSO) and Genetic Algorithm. Recent studies show that DL frameworks like Convolutional Neural Networks (CNN), Mask- Recur rent Neural Networks, and UNET outperform conventional methods in segmentation.

3) FEATURE EXTRACTION - While extracting features, properties of brain MR scans such as shape, structure, wavelet, and Gabor are retrieved. The Gray-Level Co-occurrence Matrix (GLCM) is commonly studied. A second-order statistical method is used to evaluate textural features like energy, correlation, and intensity. Wavelet data is derived using the Discrete Wavelet Transform (DWT). The approximation coefficients are obtained, and it is applied to an original image, and then the feature vector is selected. Both automatic features produced by DL techniques like Convolutional Neural Networks, ResNet, Cap sule Networks, and handwritten features have shown success. To decrease the number of features, PCA and Genetic Algorithms are utilized.

4) CLASSIFICATION - Benign and malignant tumors are the most prevalent forms of brain tumors. The three types of malignant tumors include hypothalamic, gliomas, and malignant tumors.

The proposed methodology uses Brain Tumour Dataset of Kaggle. The dataset used for this project is the Brain Tumor Classification dataset available on Kaggle. The dataset consists of 1401 brain tumor images, which are divided into two categories, i.e., Pituitary_tumor and no_tumor. The dataset is imbalanced, with 901 Pituitory_tumor and 469 no_tumor images. The images are in the form of JPG files with varying sizes, and each image has a corresponding label indicating whether it is puitary_tumor or no_tumor. Images are re-sized to 200 X 200 pixels. The resulting images are reshaped. The dataset is split into training and testing, in the proportion: 80:20. Feature reduction is done using Principal Component Analysis. The model is trained using different models, logistic regression and SVM



In the model selection phase, I have chosen the Support Vector Machine (SVM) classifier because it demonstrated the highest accuracy compared to the other two models. The SVM classifier is a powerful and widely used algorithm in machine learning, particularly for classification tasks. It works by finding the optimal hyperplane that maximally separates the data points of different classes. During the evaluation process, I compared the performance of multiple models, including the SVM classifier, and assessed their accuracy metrics. After analyzing the results, it became apparent that the SVM classifier outperformed the other models in terms of accuracy. This indicates that the SVM algorithm was able to correctly classify the majority of the data instances, making it the most suitable choice for the task at hand. It is worth noting that accuracy alone may not always be the sole factor for model selection. Other considerations such as interpretability, computational efficiency, and the specific requirements of the problem should also be taken into account. Nonetheless, in this particular case, the SVM classifier's superior accuracy justified its selection as the preferred model.

III. Results and Discussion

The models are evaluated using different metrics: training score and test score. Training score of 1.0000 and test score of 0.9592 are resulted with logistic regression. SVM classifier yielded training score of 0.9939 and test score 0.9633

IV. Conclusion

CAD systems for the detection of brain tumors are developed using brain MRI scans and digital image processing methods like pre-processing, separation, and classification. The classic deep and machine-learning techniques for brain tumor identification are discussed in this work. Various research publications from reputable journals and conferences have been examined, with a full analysis of each work offered. This section provides a summary of commonly used MRI datasets. Although several ML and deep learning methods are used for classification, CNN has shown to be quite accurate. CNN is often used to categorize brain tumors into two types: normal and pathological. The development of an autonomous brain tumor detection system must consider reliability, accuracy, and calculation time. This review examines current method ologies and can be utilized in the future to build effective diagnostic tools for additional brain illnesses that as Alzheimer's disease, Parkinson's disease, dementia, and stroke using various MRI imaging modalities. Implementing this system in collaboration with multiple deep learning algorithms as deep hybrid learning for brain tumor detection and classification will be future work for this study.

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