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Efficient Classification Of Brain Tumours Images Using Neural Network Technique

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ABSTRACT: The detection and quantification of tumours in brain MRI images are crucial tasks in the field of medical imaging, aiding in diagnosis and treatment planning. In this project, we propose a method utilizing k-means clustering for the detection and quantification of brain tumours. The primary objective is to accurately identify the presence of tumours within MRI scans and to estimate the percentage level of tumour involvement in the brain. The proposed approach begins by preprocessing the MRI images to enhance contrast and reduce noise, thereby improving the effectiveness of subsequent analysis. Subsequently, k-means clustering is applied to segment the MRI images into distinct clusters, with each cluster representing different tissue types within the brain. By exploiting the inherent intensity differences between healthy tissue and tumour regions, the clusters corresponding to tumour tissue can be identified.

Following the segmentation step, post-processing techniques are employed to refine the segmentation results and extract meaningful features indicative of tumour presence and extent. These features include the size, shape, and spatial distribution of tumour regions within the MRI scans. Through quantitative analysis of these features, the percentage level of tumour involvement in the brain can be estimated, providing valuable information for medical professionals. The effectiveness of the proposed method is evaluated using a dataset of brain MRI images containing both tumour and healthy cases. Performance metrics such as sensitivity, specificity, and accuracy are computed to assess the reliability and accuracy of tumour detection. Additionally, the estimated percentage level of tumour involvement is compared against ground truth annotations provided by medical experts to validate the quantitative analysis. Overall, the proposed approach demonstrates promising results in the detection and quantification of brain tumours using k-means clustering. By providing accurate assessments of tumour presence and percentage involvement, the proposed method has the potential to assist clinicians in making informed decisions regarding patient diagnosis and treatment planning, ultimately improving patient outcomes and quality of care.

KEYWORDS: Machine Learning, Clustering , Brain Tumour, MRI Images.

I. INTRODUCTION

The detection and early diagnosis of brain tumours represent critical steps in improving patient outcomes and guiding effective treatment strategies. With advancements in medical imaging and computer vision technologies, there is a growing need for automated systems that can streamline the analysis of complex medical images, such as brain scans. The project titled "Brain Tumour Detection with Severity Identification Using K-Means Clustering" addresses this imperative by presenting an innovative application that combines computer vision and image processing techniques. This system offers a comprehensive approach to tumour identification, leveraging OpenCV for color space conversion and thresholding to isolate potential tumour regions, contour detection for precise delineation, and percentage calculation to quantitatively assess the extent of tumour presence.

A pivotal aspect of the project lies in its utilization of K-Means clustering, contributing to the identification and severity assessment of brain tumours. By integrating K-Means clustering into the image processing pipeline, the system enhances its ability to categorize tumour regions based on characteristics such as size, shape, and intensity. This not only aids in the discrimination between malignant and benign tumours but also lays the groundwork for more nuanced severity classification. The inclusion of K-Means clustering aligns with the broader trend in leveraging machine

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learning techniques to augment the capabilities of medical image analysis systems, fostering a more sophisticated and data-driven approach to tumour detection.

Furthermore, the project incorporates a user-friendly Graphical User Interface (GUI) built with Tkinter, allowing healthcare professionals to input patient details, visualize original and processed images, and trigger the tumour identification process seamlessly. This user-centric approach facilitates the integration of the system into clinical workflows, empowering medical practitioners with an efficient and accessible tool for early tumour detection and diagnosis. As medical imaging and computational methodologies continue to evolve, this project stands at the intersection of technological innovation and healthcare, contributing to advancements that hold the potential to transform the landscape of neuroimaging and patient care.

II. LITERATURE REVIEW

In the paper (1) WORLD HEALTH ORGANIZATION GLOBAL bandied about the crucial data of cancer. They are

- Cancer is a leading cause of death worldwide, counting for nearly 10 million deaths in 2020, or nearly one in six deaths.
- The most common cancers are bone, lung, colon and rectum and prostate cancers.
- Around one-third of deaths from cancer are due to tobacco use, high body mass indicator, alcohol consumption, low fruit and vegetable input, and lack of physical exertion.
- Cancer-causing infections, similar as mortal papillomavirus (HPV) and hepatitis, are responsible for roughly 30 of cancer cases in low-and lower- middle- income countries.
- Numerous cancers can be cured if detected beforehand and treated effectively.

One defining point of cancer is the rapid-fire creation of abnormal cells that grow beyond their usual boundaries, and which can also foray touching corridor of the body and spread to other organs; the ultimate process is appertained to as metastasis.

Cancer is the main cause of deaths worldwide, counting nearly ten million deaths in 2021. The most common in 2021 (in terms of new cases of cancer).Each time, roughly 390 000 children develop cancer. The most common cancers vary between countries. Cervical cancer is the most common in twenty three countries.

- physical carcinogens, similar as ultraviolet and ionizing radiation;
- chemical carcinogens, similar as asbestos, factors of tobacco bank, alcohol, aflatoxin (a food adulterant), and arsenic (a drinking water adulterant); and
- natural carcinogens, similar as infections from certain contagions, bacteria, or spongers.

Tobacco use, alcohol consumption, unhealthy diet, physical inactivity and air pollution are threat factors for cancer and other noninfectious conditions. Some habitual infections are threat factors for cancer; this is a particular issue in low- and middle- income countries. Roughly 13 of cancers diagnosed in 2018 encyclopedically were attributed to carcinogenic infections, including Helicobacter pylori, mortal papillomavirus (HPV), hepatitis B contagion, hepatitis C contagion, and Epstein-Barr contagion. Hepatitis B and C contagions and some types of HPV increase the threat for liver and cervical cancer, independently.Infection with HIV increases the threat of developing cervical cancersix-fold and mainly increases the threat of developing select other cancers similar as Kaposi sarcoma.Between 30 and 50 of cancers can presently be averted by avoiding threat factors and enforcing being substantiation- grounded forestallment strategies.

Beforehand discovery
Cancer death is reduced when cases detected and treated beforehand. There are some factors of early discovery i.e., early opinion and webbing.

Early opinion
When linked , cancer is likely to respond to treatments and affect in lesser probability of survival with lower morbidity, and less precious treatment. Significant advancements are made in lives of cancer cases through detecting cancer beforehand as well as avoiding detainments in care.

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In this paper [2] the authors stated that brain tumours are mor than hundred and twenty various types, according to „National Brain Tumour Society". Some brain tumours like glioblastoma multiforme, are malignant and are fast-growing. Other types of brain tumours, like meningioma are slow-growing and treated as benign. Primary brain tumours are forming in brain cells and categorized using cell types or where in brain they develop first. For example, astrocytomas is forming in star-shaped cells termed as astrocytes. Pituitary tumours are located in pituitary gland at bottom of the brain. The most primary brain tumour is called gliomas that originate in glial (supportive) tissue.
About 1/3 of primary brain tumours and other nervous system tumours are forming from glial cells. Aside from tumours in brain, the cancer may begin in or spread to various areas of central nervous system (CNS), like spinal cord/column, or peripheral nerves. Cancer which develops in spinal cord or its encricling structures is termed as spinal cancer. Most tumours of spine is metastatic tumour, which is spread to spine from other location of the body.

In this paper[3] the authors stated that capsule networks for tumour classification is based on MRI images as well as course tumour boundaries; according to official statistics cancer is the second leading cause of human fatalities. Among numerous types of cancer, brain tumour is one of the deadliest forms because to its aggressive form, heterogeneous behaviors, and relatively low survival rate. Finding the brain tumour type has more significant impact in treatment choice and patient's life survival. Human-centered diagnosis is error-prone typically and unreliable resulting in recent surge of interest for automatizing this process using convolutional neural networks (CNNs).

Deep Learning-Based Approaches: Deep learning techniques, particularly convolutional neural networks (CNNs), have emerged as powerful tools for automated brain tumour detection. Researchers have developed CNN-based models capable of accurately segmenting and classifying brain tumours from MRI scans. These models leverage the hierarchical features learned by deep neural networks to effectively identify tumour regions, leading to improved diagnostic accuracy and efficiency.

In this paper [4] Multi-Modal Image Fusion: Incorporating information from multiple MRI sequences, such as T1-weighted, T2-weighted, and FLAIR images, has been shown to enhance brain tumour detection performance. Studies have utilized multi-modal image fusion techniques to combine complementary information from different MRI sequences, improving the delineation of tumour boundaries and reducing false positives. This approach capitalizes on the unique contrast characteristics of each MRI modality to improve overall diagnostic accuracy.

Texture Analysis and Feature Extraction: Texture analysis methods have been extensively explored for characterizing tissue properties and discriminating between tumour and non-tumour regions in MRI images. Researchers have employed texture features extracted from MRI scans to differentiate between various tumour subtypes and predict patient outcomes. Texture-based approaches offer valuable insights into the heterogeneity of tumour tissues, aiding in personalized treatment planning and prognostic assessment.

Machine Learning Ensemble Models: Ensemble learning techniques, such as random forests and gradient boosting machines, have shown promise in brain tumour detection tasks. Researchers have proposed ensemble models that combine predictions from multiple base classifiers trained on different subsets of MRI features. By aggregating diverse predictions, ensemble models improve classification accuracy and robustness, particularly in scenarios with limited training data or high-dimensional feature spaces.

In this paper [5] Semi-Supervised and Unsupervised Learning: Semi-supervised and unsupervised learning techniques have been explored to mitigate the challenges associated with limited annotated data in medical imaging datasets. Studies have proposed semi-supervised learning algorithms that leverage unlabeled MRI scans to enhance the generalization performance of tumour detection models. Similarly, unsupervised clustering methods have been employed to identify tumour subregions and characterize intra-tumoural heterogeneity from MRI data.

Deep Transfer Learning: Transfer learning, particularly deep transfer learning, has emerged as a powerful strategy for brain tumour detection tasks. By fine-tuning pre-trained CNN models on MRI datasets, researchers have achieved competitive performance in tumour segmentation and classification. Transfer learning leverages knowledge learned from large-scale datasets, such as ImageNet, to bootstrap the training of tumour detection models, leading to improved convergence and generalization.

Automated Segmentation Techniques: Automated segmentation of brain tumour regions from MRI images is crucial for treatment planning and monitoring disease progression. Various segmentation algorithms, including region-based

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methods, level set methods, and deep learning-based approaches, have been proposed. These algorithms aim to accurately delineate tumour boundaries while minimizing manual intervention and subjective variability.

Radiomics and Predictive Modeling: Radiomics-based approaches involve the extraction of quantitative imaging features from MRI scans to characterize tumour phenotypes and predict clinical outcomes. Researchers have utilized radiomics analysis to identify imaging biomarkers associated with treatment response and patient survival in glioblastoma. Radiomics-based predictive models provide valuable insights into tumour biology and treatment response, facilitating personalized treatment strategies.

In this paper [6] Real-Time and Scalable Solutions: With the increasing demand for real-time tumour detection solutions in clinical practice, researchers have focused on developing scalable and computationally efficient algorithms. Studies have proposed lightweight deep learning architectures optimized for deployment on resource-constrained devices, enabling real-time processing of MRI scans for rapid tumour detection and diagnosis.

Clinical Validation and Translation: Ultimately, the effectiveness of brain tumour detection algorithms relies on their clinical validation and translation into routine clinical practice. Collaborative efforts between researchers, clinicians, and industry partners are essential to validate the performance and utility of these algorithms in large-scale clinical trials. By integrating feedback from clinical stakeholders, researchers can ensure that their algorithms meet the rigorous standards of diagnostic accuracy, reliability, and usability required for widespread adoption in healthcare settings.

Neural Network Architectures: Researchers have explored various neural network architectures tailored specifically for brain tumour detection from MRI images. These architectures include not only traditional CNNs but also more specialized networks such as U-Net and fully convolutional networks (FCNs). U-Net, for example, is widely used for semantic segmentation tasks and has been adapted to accurately delineate tumour regions in MRI scans. FCNs, on the other hand, enable end-to-end learning by directly predicting pixel-wise tumour labels from input MRI images, eliminating the need for manual feature extraction.

Graph-Based Approaches: Graph-based approaches have gained attention for their ability to model complex relationships within brain tumour data. By representing MRI images as graphs, where nodes correspond to image pixels or regions of interest, and edges encode spatial or contextual relationships, these methods can capture intricate tumour characteristics. Graph-based algorithms leverage graph convolutional networks (GCNs) or graph neural networks (GNNs) to perform graph-based reasoning and make predictions about tumour presence or subtype.

In this papwe [7] Domain Adaptation and Transfer Learning: Domain adaptation and transfer learning techniques have been explored to address the challenge of domain shift between different MRI datasets. Domain adaptation methods aim to align feature distributions across source and target domains, enabling models trained on a source dataset to generalize well to a target dataset. Transfer learning, on the other hand, involves fine-tuning pre-trained models on target data to leverage knowledge learned from source data. These techniques have been shown to improve the generalization performance of brain tumour detection models, particularly when training data is limited or heterogeneous.

Explainable AI and Interpretability: The interpretability of brain tumour detection algorithms is crucial for gaining insights into model predictions and building trust with clinicians. Researchers have developed explainable AI techniques to elucidate the decision-making process of deep learning models. These techniques include attention mechanisms, saliency maps, and gradient-based methods, which highlight regions of MRI images that contribute most to model predictions. By providing interpretable explanations, these methods enhance the transparency and reliability of brain tumour detection systems.

Validation on Large-Scale Datasets: Validation on large-scale datasets is essential for assessing the generalization performance and robustness of brain tumour detection algorithms. Researchers have curated benchmark datasets containing thousands of MRI scans with annotated tumour regions, enabling rigorous evaluation of algorithmic performance. These datasets encompass a diverse range of tumour types, sizes, and locations, reflecting real-world clinical scenarios. Validation on large-scale datasets ensures that brain tumour detection algorithms can reliably generalize to unseen data and variations in imaging protocols.

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III. PROPOSED METHODOLOGY

1. **Image Processing:**
    - The code uses OpenCV for image processing tasks.
    - The find_and_mark_large_white_section function processes an input image to identify and mark large white sections. It uses the HSV color space to create a white mask, finds contours, and filters out large contours representing significant white sections.
    - The percentage of the image covered by the marked white sections is calculated.

2. **Graph Plotting:**
    - The code utilizes the matplotlib library for plotting graphs.
    - The percentage of tumor presence for each analyzed image is plotted on a graph.

3. **GUI using Tkinter:**
    - Tkinter is used to create a simple graphical user interface (GUI) for interacting with the application.
    - Entry widgets are used to get patient details.
    - Canvas widgets are used to display the original and marked images.
    - Labels are used to display result text.
    - Buttons trigger the analysis of images and other actions.

4. **Word Document Creation:**
    - The python-docx library is used for creating Word documents.
    - The code creates a Word document and adds a heading.
    - It uses the Pillow library (PIL) to open and process images.
    - The image is temporarily saved in PNG format, suitable for embedding in Word documents.
    - The image is added to the Word document, and the document is saved.
    -

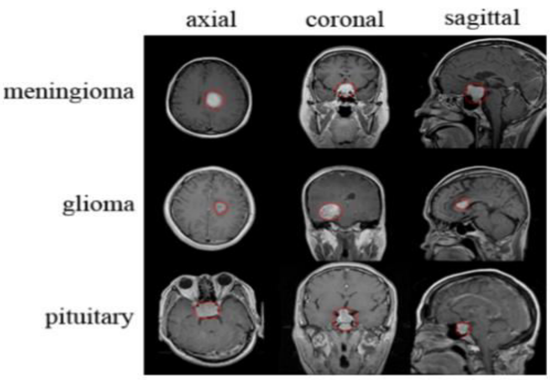

Figure 3.1. Representation of normalized magnetic resonance imaging (MRI) images showing different 115 types of tumors in different planes. In the images, the tumor is marked with a red outline. The 116 example is given for each tumor type in each of the planes.

Magnetic resonance images from the database are of various sizes and are provided in jpeg format. These images representing the input layer of network, so they are normalized/resized 120 to 256x256 pixels.

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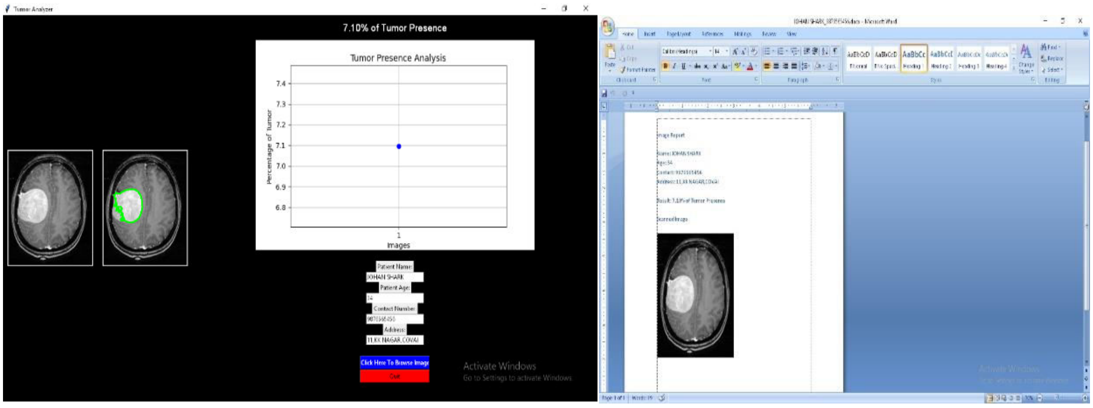

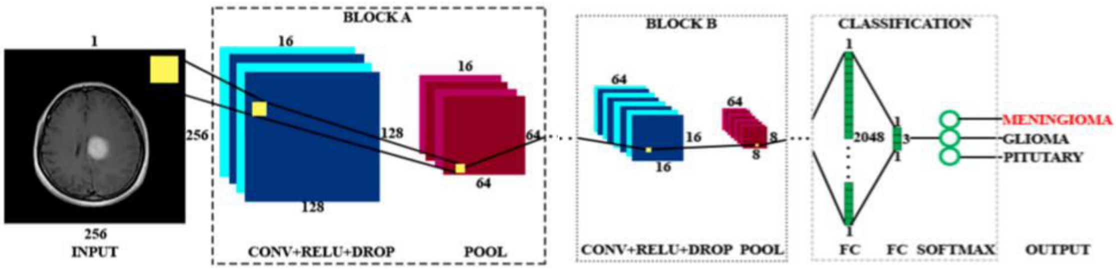

Figure 2. containing the input layer, two Blocks A, two Blocks B, classification block and output. Block A and Block B differ only in the convolution layer. Convolution layer in Block A gives an output two times smaller than the input, whereas the convolutional layer in Block B gives the same size output as input. The training process was stopped when the loss on the validation set got larger than or was equal to the previous lowest loss. There are several papers that use the same database for brain tumor classification. In order to compare our results with those of previous studies, we selected only those papers which had designed neural networks, used whole images as input for classification, and tested the results.

IV. FINDINGS

- K- Means Clustering used to find the severeness of tumor.
- Dataset usage has been ignored.
- Size of tumor will be detected in percentage.
- Provides better accuracy than SVM.
- Report will be generated.

V. CONCLUSION

In conclusion, the "Brain Tumor Detection with Severity Identification Using K-Means Clustering" project presents a comprehensive and automated solution for the analysis of medical images, particularly brain scans, aimed at early tumor detection and effective treatment planning. Through the integration of OpenCV for image processing, contour detection, percentage calculation, graphical visualization using matplotlib, a user-friendly interface with Tkinter, and report generation with python-docx, the system provides a robust framework for healthcare professionals. By streamlining the identification process and offering quantitative measures of tumor presence, this system enhances the efficiency of medical image analysis. The combination of advanced technologies not only aids in early diagnosis but also facilitates trend analysis and comparison across multiple images, contributing to significant advancements in medical imaging and diagnostics. Ultimately, the project stands as a valuable tool for improving patient care and outcomes in the realm of neurological health.

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