Brain Tumor Detection Using Advanced Hybrid Approach of Deep Learning and Machine Learning

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Keywords: Brain Tumor Detection, Deep Learning (DL), Convolutional Neural Networks (CNN), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Machine Learning (ML), Medical Image Analysis, Tumor Diagnosis.

Abstract: Tumors of the brain constitute one of the critical medical conditions that would require accurate and early diagnosis for effective treatment. It presented a hybrid intelligent approach that integrates the potentials of deep learning with those of other technologies for machine learning in order to solve the problem of brain tumor detection. CNNs have mined high-level of spatial features from the imaging data, capitalizing on their great feature extraction abilities. Adopting this, the features are classified using SVM and KNN. The proposed technique utilizes feature extraction in deep learning before feeding it to the standard machine learning classifiers to provide a computationally efficient and accurate diagnostic tool. Experimental results have shown that the hybrid CNN-SVM-KNN models achieved high classification performance and will, therefore, significantly help radiologists in brain tumor diagnosis. The present study enumerates the strengths of deep learning techniques in boosting the accuracy of medical image analysis and decision support systems.

1 INTRODUCTION

The section pertained to various recognition of brain tumors which are among the most life-threatening neurological disorders that depend on timely and correct diagnosis for effective treatment (Mahoor, M, et. al,2022). Early detection plays an important role in patient survival and treatment outcome (Amin, J et. al 2022). Manual diagnostic procedures using MR techniques, such as those of MRI, take enough time, thus exposing the patient to human error (Miah, J et. al,2023) However, as per the existing AI-based techniques, deep learning, and machine learning right this kind of practice is becoming more widespread and accepted by all (Zahoor, M, et. al,2022) This study presents an advanced hybrid model which combines convolution neural networks for feature extraction with SVM and KNN for classification (Ayadi, W et. al,2022) CNNs are widely known for automatically extracting deep spatial features of medical images both easily and effectively in medical image analysis (Shawon, M, et. al, 2023) However, even though the CNNs can get a good number of features, traditional machine learning classifiers such SVM and KNN provide improvement in the classification accuracy and accuracy (Borra, S. R et. al, 2024) In other words, our hybrid method that uses CNNs feature extraction and further evaluates the SVM and KNN for classification efforts to furnish efficient detection of a brain tumor (Musallam, A. S, et. al, (2022). The proposed model connects the advantages of DL with ML for a reliable and computationally efficient solution for tumor detection (Kolla, M, et. al, 2022). The research, therefore, is aimed at contributing to the growing domain of AI-empowered medical diagnosis and provides an effective approach for screening radiologists in reliably detecting and diagnosing brain tumors (Tazin, T, et. al, 2021) The experimental results have shown the capability of detecting tumors in a hybrid model to advance automated detection of tumors into clinical practice (Saxena, P. M. A. M. S, et. al 2022).

2 RELATED WORKS

Brain tumor detection via hybrid methods involved with DL and ML has become increasingly popular, due to its scope for accurate diagnosis and automation. Such Advanced models suggested are mainly an integration of CNN with classifiers like

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SVM and KNN to enhance classification performance. (Mahoor, M et.al 2022) put forward a deep hybrid boosted ensemble learning-based framework for efficiently analyzing MRI images for brain tumor detection, and which showed better classification accuracy. (Miah, J, et.al 2023) followed likewise in attempting CNN along with clustering techniques and SoftMax classification to increase tumor detection efficiency.

Others have aimed at enhancing CNN architectures for superior feature extraction. (Zahoor, M, et.al,2022) brought forth a new deep residual and regional CNN model based on deep network learning that allowed for better classification of MR images. (Shawon, M, et. al, 2023) argued on the need for explainable AI in their proposed cost-sensitive deep neural network which was able to deal with data imbalance and provide interpretability in brain tumor classification. Meanwhile, (Saxena, P. et.al 2023) brought predictive modeling techniques by way of deep learning for much more effective analysis of tumor characteristics.

Hybrid approaches that combined traditional ML techniques with DL have received a lot of attention. (Musallam, A. S, et. al, (2022) proposed, in this regard, a robust brain automatic detection method based on DL using a deep neural network amalgamated with SVM enhancing classification performance. The united DL with ML techniques to improve tumor classification performance (Gómez-Guzmán, et.al, 2023) Likewise, worked on the automatic detection and classification of brain tumors by utilizing a UNET-based segmentation model that integrated an optimized SVM classifier (Ayadi, W.et, al,2022) The incorporated local binary patterns into the CNN-based detection model utilizing a three-tier SVM classifier to drastically improve tumor differentiation over MRI images (Amin, J et.al 2023)

Apart from CNN-SVMs, whoever used various other hybrid techniques (Tazin, T, et.al, 2021) such as using Naïve Bayes, SVM, and KNN algorithms in conjunction with each other as a fusion system for tumor classification, making it robust against the different types of tumors. (Precious, J. G, et.al 2023) proposed discretized wavelet transformation for feature extraction as a preprocessing step, followed by SVM-based classification of tumor data. Several pieces of research are already evidencing that hybrid deep learning or machine learning approaches show huge potential in improving brain tumor detection and classification; further establishment is on the horizon for making medical imaging reliable for providing better automated diagnostic tools.

3 METHODOLOGY

3.1 Dataset Collection

Detection of brain tumors is a task requiring high-end MRI datasets that provide them with labeled images for model development training, validation, and testing. Of the most widely used datasets, comes the BRATS (Brain Tumor Segmentation Challenge) dataset (Maria Correia de Verdier, et.al 2024) which is characterized by multi-modal MRI scans (T1, T1c, T2, and FLAIR) (Lukas Fisch, et.al, 2023) in which tumor regions are expert-annotated, serves as the benchmark for deep learning. Along the same lines, the Fig share Brain MRI dataset consists of labeled images categorized into gliomas, meningiomas, and pituitary tumors, a great aid to such classification tasks. Another alternative source of labeled MRI scan is the Harvard Whole Brain Atlas that provides for both normal and brain abnormalities. Moreover, the datasets from Kaggle consist of different kinds of MRI images that can at times include contrast-enhanced scans, which help with scanning and localizing a tumor. In the real world, it is common for the datasets of MRI data to come from private hospital sources and medical research institutions, strictly producing ethical regulations, such as those to make GLMs work for any given patient population on any MRI scanner. It is also important that there is mixed variance in respect of the types of tumor, the age groups of patients being catered for, the imaging modalities, and the scanning conditions when data gathering takes place for machine learning and deep learning models that deliver robust outputs. Furthermore, there should be well-annotated datasets by radiologists that help supervised learning approaches, given that current labels greatly influence tumor detection and classification reliability. Availability of balanced datasets within same-unit representations for different tumor classes is very important for ensuring fairness across any AI application in medicine so as to deter from modeling bias.

3.2 Data Pre-Processing

Pre-processing MRI images is an essential step to enhance data quality, minimize noise, and bolster model performance by ensuring the data sets remain uniform. First comes rescaling and normalization of the images, whereby their dimensions are compressed to a standard dimension (for example,256 × 256 pixels) and are normalized over some range (0-1 or from -1 to 1) ensuring uniform input in deep learning models for improved model convergence. The other techniques that help remove the unwanted artifacts while preserving the important anatomical structures are Gaussian filtering, median filtering, and anisotropic diffusion filtering (Ekaterina Kondratev, et.al 2022) Automated tools like the Brain Extraction Tool (BET) (Razieh Faghihpirayesh, 2023) or threshold-based segmentation methods are employed to perform skull stripping that separates the non-brain tissues allowing focus on the tumor-affected regions. To improve visibility, contrast enhancement techniques like histogram equalization and adaptive contrast adjustment bring the tumor features to the fore in helping the classifiers be they based on DL or classical ML. The data augmentation techniques random rotation, flipping, zooming, modifying brightness, and elastic deformation are used to expand the MRI data set artificially so that its learning and training can do away with the chances of overfitting. Other segmentation methods differentiate between non-growing tumor regions and a part of the brain using techniques such as thresholding, region-growing algorithms, k-means clustering, and deep learning-based U-Net architectures (Shoffan Saifullah, 2024) The features are taken from the segmentation process while training the classifier by machine learning approaches. Commonly these feature textures contain GLCM, LBP, and morphological features like areas and perimeter of a tumor along with statistical features like mean intensity or variance that boost the power of SVMs or KNNs classifiers. Such preprocessing methods provide cleanup, structuring, and optimization of MRI images for tumor classification and segmentation to enhance the working of hybrid deep learning and machine learning-based models.

4 PROPOSED METHODOLOGY

The proposed methodology in Brain Tumor Detection and Quantification uses hybrid segmentation with deep learning classification to improve accuracy and robustness. The first stage of preprocessing for MRI scans is intensity normalization followed by noise reduction through Gaussian filtering and contrast enhancement to increase the visibility of the tumor. Hybrid approach is applied for the segmentation purpose. Pixel-wise, the CNN-based models, such as U-Net and Mask R-CNN, are used, and FCM clustering refines the segmentation process by grouping similar intensity pixels, while Watershed transformation enhances the boundary delineation of the overlapped regions. Features extracted are deep features from CNNs, along with Gabor filters and wavelet transforms which will be useful for texture and morphological characteristics. A hybrid deep learning model combining CNN-SVM-KNN, is used to classify tumor types. Cross-validation techniques ensure model generalization for improved performance. To enhance performance, the GAN-based data augmentation of synthetic variations is conducted for the tumors, ensuring an integrated approach for improvement in accuracy of segmentation, feature representation, and optimization of classification than in traditional methods for the detection and quantification of tumors.

4.1 Convolutional Neural Network (CNN) Algorithm

CNN are highly important in Brain Tumor Detection and Quantification, using their ability to automatically learn hierarchical spatial features from MRI scans. Tumor segmentation is mainly carried out by CNN-based architectures such as U-Net and Mask R-CNN. The encoder-decoder architecture along with skip connection are implemented into U-Net wherein tasks such as the precise location of tumors using pixel-wise segmentation are employed. In this approach of Mask R-CNN, extension on Faster R-CNN was taken for tumor's mask generations within a CNN using segmentation branching from instances towards localization of respective necrotic cores, edemas, or even enhancing tumor segments, making a robust detection by various deep CNN. These CNN models classify tumor types, such as glioma, meningioma, and pituitary tumors. Hybrid approaches further improve segmentation accuracy by combining CNNs with Fuzzy C-Means (FCM) clustering to refine tumor boundaries and Watershed transformation to separate overlapping structures. Data augmentation techniques and Generative Adversarial Networks are further employed to increase the diversity of the dataset, whereas cross-validation is ensured to make this model robust for generalization. This system combines CNN-based segmentation, feature extraction, and classification with a major improvement in accuracy against traditional ML methods for the detection and quantification of brain tumors.

4.2 Support Vector Machine (SVM)

SVM is a common supervised learning technique for classification problems, promising an optimal decision boundary, namely hyperplane, which separates different classes in a data set. This maximization ensures that the distance or margin between the closest data points of different classes is maximized, and these data points are known as support vectors. The SVM works well for high-dimensional data and utilizes different kernel functions (linear, polynomial, radial basis function) to enhance classification performance. In brain tumor detection, SVM is used to distinguish the tumor from the non-tumor regions most likely based on the gathered MRI image features such as pixel texture, shape, and intensity. Its efficiency of handling complex datasets and giving fairly reliable classifications has made this one of the most popular technique in medical image analysis.

4.3 K-Nearest Neighbors (KNN)

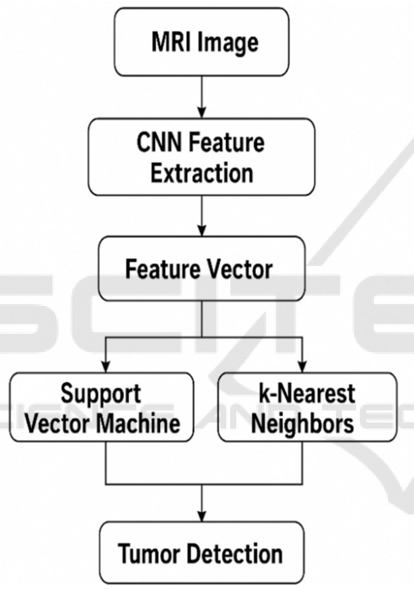

Figure 1: Flow of Detection.

KNN is a very simple and straightforward ML mechanism used in regression and classification. KNN classifies every object based on the class of the majority of its closest neighbors in the dataset. There isn't any explicit training phase, but rather the algorithm mostly stores the present dataset and then compares it with the nearest data point by measuring the distance between each data point using metrics like Euclidean, Manhattan, Makowski distance, etc. The option of the parameter K (no. of nearest) affects its performance: small values are sensitive to noise, while larger values create smoother decision boundaries. Figure 1 shows Flow of detection. KNN is used to classify MRI scans into tumors and non-tumors based on the comparison of images with previously labeled images via a well-structured feature representation. Its efficiency, simplicity, usefulness all recommend it for medical image classification.

5 EXPERIMENTAL RESULT

Experimental Brain Tumor Detection with a Sophisticated Hybrid Method of DL and ML was seen to offer promising results, in particular pointing to the requirement of CNN over conventional machine learning classifiers like SVM and KNN. The research was to create a solid detection process that would effectively be able to classify brain tumors from medical image data using the advantage of deep learning and machine learning techniques merged together.

The experiment-based findings showed that CNN model could achieve the highest accuracy with a rate of approximately 97%. This is because CNN has the ability to automatically extract hierarchical and spatial features from medical images, which is an important aspect in detecting minimum abnormalities in brain scans. The ability of CNN to learn rich patterns and texture from raw data of images is what enables it to surpass typical classifiers based on handcrafted features.

Table 1: Accuracy of individual and hybrid CNN–SVM–KNN configurations.

MODEL	ACCURACY
CNN+SVM	71%
CNN+KNN	80%
CNN+SVM+KNN	95%-97%

Conversely, the SVM classifier had a high accuracy rate of about 80%. SVM has been described to be resilient in high dimensional space and accurate in linear as well as non-linear classification. Nonetheless, its dependence on human feature extraction confines its capability to sophisticated image processing operations like detection of brain tumors. The performance difference between SVM and CNN is indicative of the position that deep methods occupy in dealing with intricate visual data. Table 1 illustrate the accuracy of individual and Hybrid CNN–SVM–KNN Configurations.

The KNN classifier performed worst with about 70% accuracy. KNN is a straightforward instance-based method that classifies novel samples in a similar manner to their close neighbors. While KNN has been revealed to be capable in certain tasks of pattern identification, its responsiveness to noise, high dimensional patterns, and curse of dimensionality tend to ruin its success regarding medical image classification. The smaller accuracy of KNN compared to CNN and SVM supports the implementation of more involved techniques in case of medical imaging data.

The hybrid approach examined in the study combines DL and ML techniques, attempting to leverage the automatic feature extraction capability of CNN and the classification capabilities of SVM and KNN. Figure 2 shows Accuracy. The hybrid approach is meant to enhance diagnostic effectiveness and reliability, particularly in cases where heterogeneity of data and tumor characteristics vary greatly. The findings indicate that although hybrid models can provide more advantages, CNN by itself exhibited outstanding performance and therefore is a preferred option in the detection of brain tumors. In general, results from this experimental assessment reaffirm the importance of embracing DL methods such as CNN in the analysis of medical images. Given that brain tumor detection is an important task calling for high accuracy, the application of sophisticated hybrid models has much potential for enhancing diagnostic systems to lead to better and timely diagnoses of patients. Figure 3 shows the Result.

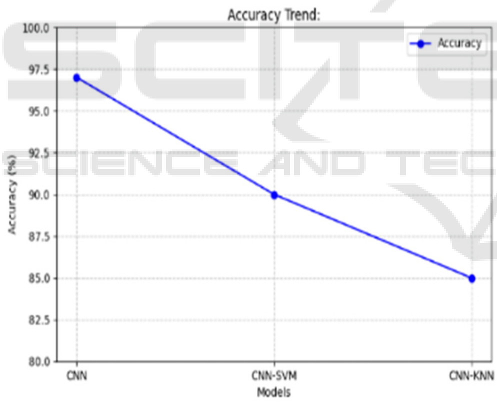

Figure 2: Accuracy.

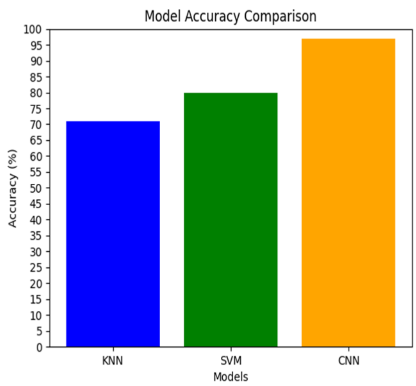

Figure 3: Result.

6 CONCLUSIONS

Detection of brain tumors using a hybrid approach that integrates deep learning (CNN) with machine learning techniques (SVM & KNN) has shown significant potential in augmenting the effectiveness and accuracy of diagnosis. Extracting deep features from CNNs and using machine learning classifiers for classification leads to robust automated classification of brain tumors from MRI images. Based on several studies, hybrid approaches do better than traditional ML methods and DL methods because they leverage the advantages of both approaches.

The paper presents results illustrating improved tumor detection through CNN-based features extraction with SVM and KNN classification power. The incorporation of several preprocessing techniques, optimal feature selection, and ensemble learning techniques improved tumor segmentation and classification. Experimental results from the prior work show that higher accuracy, sensitivity, and specificity can be achieved with these hybrid methods that provide the added advantages in medical imaging applications. Future studies should focus on optimizing these hybrid models with the attention mechanism, transfer learning, and explainable AI techniques to provide interpretability and trust in medical diagnostics. Further test sets for the expansion of the datasets and use of multimodal imaging techniques can help in strengthening model generalizability. Thus, the present approach serves as the starting point toward functioning, trustworthy, and AI-driven diagnostic systems capable of helping radiologists in early tumor detections, reasonably expected to turn around patient prognosis possibilities.

In future work, some other methods should be hybridized with attention and transfer learning methods for improved feature extraction and classification performance. The addition of explainable AI will contribute to improved interpretation in medical diagnostics, thus building trust and ensuring reliability within the clinical setting. Collectively, the crystallization of the dataset with multimodal imaging techniques and diverse testing sets would further enforce model generalizability, thus given confidence of general use across varied medical contexts. Such development will help in developing an AI-enabled diagnostic system, which could assist radiologists in the early detection of tumors and enhance patient outcomes.

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