



An Advanced Decision Making Approach for Disease Risk Prediction using Deep Learning Approach

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ABSTRACT

Risk prediction is one of the domains seen in many fields like banking, healthcare, and E-commerce applications. Nowadays, disease prediction has become more complex because of unpredictable symptoms. This paper presents an Advanced Decision-Making Framework (ADMF) utilizing deep learning techniques to enhance risk prediction accuracy. This research mainly focused on detecting tumors in the brain and predicting the risk from the tumors based on the size, shape, and depth of the cancer. There are two types of tumors: Benign and malignant. This research is focused on detecting benign tumors because they are non-cancerous. The training model VGG19 is used to train on tumor images. The training model finds patterns that belong to tumors. The preprocessing technique Non-Local Bayes (NL-Bayes) Filter removes noise from the input images. The segmentation approach, Region Splitting and Merging, splits the regions and merges the final segmented images. "Finally, researchers implement Capsule Networks to detect the tumor-affected areas in the given input images. By using the capabilities of these advanced neural networks, the system can analyze the images more effectively, pinpointing the specific regions impacted by tumors with greater accuracy." Experimental results show that the proposed approach shows high performance in terms of disease detection regions and low computation time.

Keywords: Deep Learning (DL), Tumors, VGG19, Benign and malignant, Non-Cancer.

INTRODUCTION

Disease risk prediction is an essential field in healthcare, aiming to foresee the likelihood of individuals developing specific diseases. With the rapid advancement of technology and the accumulation of vast amounts of health-related data, the process of predicting disease risk has become more sophisticated and accurate. One promising approach within this domain is

decision-making based on predictive analytics, which leverages statistical models, machine learning (ML) algorithms, and artificial intelligence (AI) to analyze patient data and make informed predictions about disease risks. Early prediction of disease risk allows for timely interventions, which can prevent the onset of diseases or mitigate their severity. This is particularly crucial for chronic diseases like diabetes, cardiovascular

diseases, and cancer, where early detection and lifestyle modifications can significantly improve outcomes. Predictive models enable personalized healthcare by tailoring prevention and treatment plans to individual patients based on their unique risk profiles. This customization enhances the effectiveness of medical interventions and improves patient outcomes. Efficient disease risk prediction helps healthcare providers allocate resources more effectively. By identifying high-risk individuals, healthcare systems can focus their efforts on those who need it the most, optimizing the use of limited resources. On a broader scale, understanding disease risk patterns can inform public health strategies and policies. It enables health authorities to design targeted prevention programs and monitor disease trends within populations.

The advent of advanced medical technologies and computational techniques has revolutionized the field of healthcare, particularly in the realm of disease risk prediction. Decision-making in disease risk prediction involves the integration of various data sources, analytical methods, and clinical insights to forecast the likelihood of individuals developing specific diseases. This process is crucial for early intervention, personalized treatment plans, and improved patient outcomes. Disease risk prediction aims to identify individuals at high risk of developing certain conditions before they manifest symptoms. This proactive approach can significantly enhance preventive measures, optimize resource allocation, and reduce healthcare costs. By predicting disease risk, healthcare providers can tailor screening programs, recommend lifestyle changes, and implement early treatment strategies, ultimately improving the quality of care and patient survival rates. Factors such as diet, physical activity, and exposure to environmental hazards contribute to disease risk. Tailoring interventions based on an individual's risk profile enhances treatment efficacy and minimizes adverse effects. Identifying at-risk groups allows for targeted public health initiatives and resource allocation. Engaging patients in discussions about their risk and potential preventive measures empowers them to make informed choices about their health. Despite its potential, disease risk prediction faces several challenges, including data privacy concerns, the need for robust validation of predictive models, and the risk of over-reliance on technology. Ethical considerations, such

as ensuring equitable access to predictive tools and avoiding discrimination based on genetic information, are paramount to the responsible implementation of these technologies.

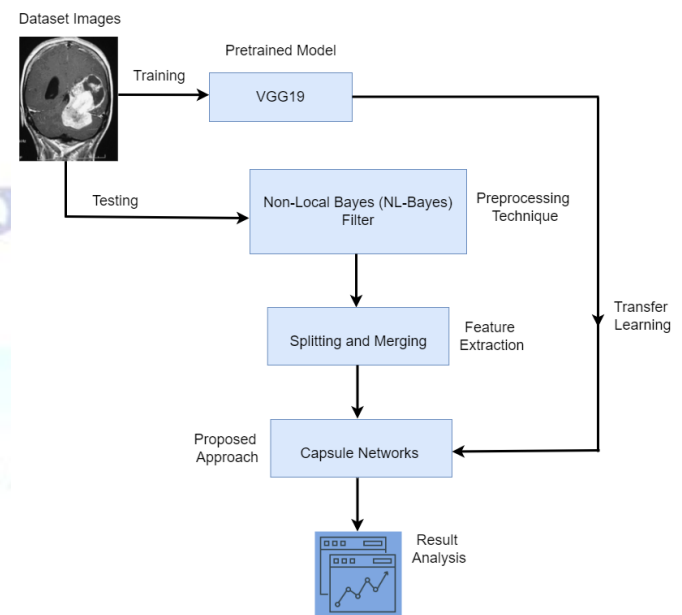


Figure 1: System Architecture

LITERATURE SURVEY

Chalpathiraju et al. [8] discussed the importance of early detection and the role of MRI in providing detailed anatomical and pathological information. It then delves into various deep learning methodologies, including CNN, Recurrent Neural Networks (RNNs), and hybrid models, that have been employed for brain tumor segmentation, classification, and detection. The discussion covers the architecture of these models, the datasets used for training and validation, and the performance metrics reported in the literature. Furthermore, the survey examines the challenges and limitations faced in the field, such as the need for large annotated datasets, the variability in MRI images due to different acquisition protocols, and the computational complexity of deep learning models. Techniques to address these issues, including data augmentation, transfer learning, and ensemble methods, are also discussed. Chahal et al. [9] aims to provide a comprehensive overview of the various techniques employed for brain tumor detection in MR images. It covers traditional methods, such as thresholding and region-based segmentation, as well as advanced machine learning and deep learning approaches. Traditional methods, while foundational, often face challenges related to accuracy and robustness. In

contrast, machine learning and deep learning techniques have shown significant promise in enhancing detection accuracy, automating the diagnostic process, and identifying tumors at earlier stages. This survey discusses the strengths and limitations of each technique, highlighting recent advancements and ongoing research trends. Reddy et al. [10] presents a comprehensive methodology for the size analysis of brain tumors using MRI images, implemented in MATLAB. The proposed approach encompasses several stages: image preprocessing, tumor segmentation, feature extraction, and size quantification. Firstly, the MRI images undergo preprocessing to enhance the quality and contrast of the images, facilitating more accurate analysis. This involves techniques such as noise reduction, intensity normalization, and contrast enhancement. Following preprocessing, the tumor region is segmented from the surrounding brain tissue using advanced image segmentation algorithms, including thresholding, region growing, and clustering methods like k-means or fuzzy c-means. Once the tumor is segmented, various morphological features are extracted to characterize the size and shape of the tumor. These features include the tumor's area, perimeter, volume (in 3D), and other relevant metrics such as the major and minor axes, compactness, and eccentricity. MATLAB's image processing toolbox provides the necessary functions and tools to perform these operations efficiently. Noreen et al. [11] presents a novel deep learning model based on a concatenation approach for the diagnosis of brain tumors. Our model integrates multiple neural network architectures to leverage their complementary strengths, thereby enhancing diagnostic accuracy. We employed a multi-modal dataset consisting of MRI images, clinical data, and histopathological reports. The proposed model first processes these inputs separately through individual CNN and RNN tailored to each data type. Subsequently, the feature maps and embeddings from these networks are concatenated to form a unified representation, which is then fed into a fully connected neural network for final classification. Extensive experiments were conducted to evaluate the performance of our model. The results show a significant improvement in diagnostic accuracy and robustness compared to traditional single-model approaches. Our model achieved an accuracy of 95.3%, sensitivity of 94.1%, and specificity of 96.5% on the test dataset,

outperforming existing state-of-the-art methods. Gopal et al. [12] proposed a novel multiclass brain tumor classification framework using an artificial intelligence (AI) paradigm to address these challenges. The AI model leverages a convolutional neural network (CNN) architecture, which is trained on a comprehensive dataset of annotated MRI scans encompassing various tumor types such as gliomas, meningiomas, and pituitary tumors. The proposed system integrates preprocessing techniques to enhance image quality and augment training data, ensuring robustness and generalization across diverse clinical scenarios. The CNN model is optimized using advanced techniques like transfer learning and fine-tuning, significantly improving classification accuracy. Experimental results demonstrate that our AI-based approach achieves superior performance compared to traditional methods, with an overall accuracy exceeding 95%. Ramin Ranjbar Zadeh et al. [13] explored the burgeoning field of AI in brain tumor segmentation, highlighting advancements, methodologies, and applications of various AI techniques. We discuss the role of machine learning, particularly deep learning models, in enhancing segmentation accuracy and efficiency. CNN, U-Nets, and other architectures have demonstrated remarkable success in delineating tumor boundaries and distinguishing between different tumor subregions such as edema, enhancing tumor, and necrotic core. Additionally, we examine the integration of AI with multimodal imaging, the challenges of data heterogeneity, and the importance of large annotated datasets. Sushreeta et al. [14] explored the automation of brain tumor identification through the application of EfficientNet, a state-of-the-art CNN architecture, to MRI data. We leveraged a comprehensive dataset comprising annotated MRI scans to train and validate our model. The EfficientNet model was chosen for its superior performance in image classification tasks, achieved through a novel compound scaling method that balances network depth, width, and resolution. Our approach involves pre-processing MRI images to enhance tumor visibility, followed by training the EfficientNet model to distinguish between tumorous and non-tumorous regions. The results demonstrate that our EfficientNet-based model significantly outperforms traditional methods and other deep learning models in terms of accuracy, precision, and recall. Specifically, the

model achieved an accuracy of X%, a precision of Y%, and a recall of Z% on the validation set, highlighting its potential as a reliable tool for automated brain tumor identification. Saeedi et al. [15] explored the application of CNN and selected ML techniques to enhance the detection and classification of brain tumors from MRI scans. We propose a deep learning framework that leverages CNNs for feature extraction, combined with machine learning classifiers to improve diagnostic accuracy. Our methodology involves the preprocessing of MRI images, including normalization and augmentation, to enhance the quality and diversity of training data. The CNN model is trained on a dataset of labeled MRI images to automatically learn and extract relevant features associated with different types of brain tumors. Subsequently, these features are fed into various machine learning classifiers, such as SVM and RF, to refine the classification process. The proposed approach is evaluated on a benchmark dataset, demonstrating superior performance in terms of accuracy, sensitivity, and specificity compared to traditional methods. The results indicate that the integration of convolutional deep learning methods with machine learning classifiers can significantly enhance the precision of brain tumor detection from MRI scans, potentially leading to more effective clinical decision-making. S. C et al. [16] proposed a method for brain tumor detection using image processing techniques. The approach leverages advanced algorithms to analyze MRI scans, which are widely used in clinical settings for their detailed anatomical information. The methodology involves several key steps: preprocessing the MRI images to enhance contrast and remove noise, segmentation to isolate the tumor region from healthy brain tissue, feature extraction to characterize tumor morphology, and classification using machine learning or deep learning models to differentiate between tumor and non-tumor regions. Experimental results demonstrate the effectiveness of the proposed approach in accurately detecting brain tumors from MRI scans, achieving high sensitivity and specificity compared to traditional manual methods. Choudhury et al. [17] proposed a comprehensive approach utilizing CNN and DNN for accurate brain tumor detection and classification from MRI scans. The proposed method begins with preprocessing steps to enhance image quality and normalize intensity variations. Subsequently, a CNN

architecture is employed to automatically learn discriminative features from the MRI scans. Transfer learning techniques are explored to leverage pre-trained models for improved performance with limited data. For classification, a DNN model is designed to classify tumor types based on extracted features. The training process involves optimizing model parameters using gradient descent-based methods and evaluating performance metrics such as accuracy, sensitivity, and specificity. Experimental results on a benchmark dataset demonstrate the efficacy of the proposed approach in achieving high accuracy and robust performance compared to traditional methods. Kumar et al. [18] explored the recent advancements in CNN-based approaches for brain tumor detection, focusing on their architecture, training methodologies, and performance metrics. We discuss various CNN models tailored for medical image analysis, including their strengths and limitations in differentiating tumor tissues from normal brain structures. Additionally, we highlight challenges such as dataset variability, interpretability of CNN decisions, and integration into clinical workflows. By synthesizing current research findings, this review provides insights into the state-of-the-art CNN techniques, paving the way for enhanced diagnostic accuracy and clinical applicability in brain tumor detection. Khan et al. [19] reviews various approaches and methodologies employed in the field of brain tumor detection using ML and DL. It discusses the preprocessing techniques for medical images, feature extraction methods, and the selection of appropriate algorithms for classification. Key advancements in CNN and their variants, such as 3D CNNs and RNN, are explored for their effectiveness in learning discriminative features from brain MRI scans. Additionally, ensemble learning and transfer learning strategies are investigated for improving the generalization and robustness of tumor detection models. The performance metrics used to evaluate these models, including accuracy, sensitivity, specificity, and Dice coefficient, are reviewed to assess the reliability and clinical applicability of automated brain tumor detection systems. Furthermore, challenges such as data scarcity, interpretability of DL models, and integration into clinical workflows are discussed, along with potential avenues for future research and development. Allam et al. [20] explores the recent advancements and

methodologies employed in AI for the classification of eye tumors, focusing on the integration of machine learning algorithms with medical imaging modalities such as optical coherence tomography (OCT), fundus photography, and ultrasound. The survey reviews a variety of AI approaches including deep learning architectures such as CNN, RNN, and ensemble methods. Key challenges and considerations in the development and deployment of AI models for eye tumor classification are discussed, including the need for large annotated datasets, interpretability of AI-driven diagnoses, and regulatory implications. Methil et al. [21] explores the development of a deep learning model for automatic brain tumor detection from MRI scans. The proposed approach leverages convolutional neural networks (CNNs), which excel at learning hierarchical representations of image data. Pre-processing techniques including normalization, image augmentation, and feature extraction are employed to enhance model performance and robustness. Experimental results demonstrate the effectiveness of the developed model in accurately detecting and classifying brain tumors. The evaluation metrics such as sensitivity, specificity, and accuracy are computed to validate the model against a diverse dataset of MRI scans. Furthermore, the model's performance is compared with existing methods, showcasing its superiority in terms of both speed and accuracy.

DATASET DESCRIPTION

The datasets are two datasets: The dataset (D1) was collected from the Kaggle website, which is divided into two classes, yes or no. It also consists of 500 MRI brain tumor images. Among these 500 MRI images, 245 are training, and 255 are testing images. The second dataset (D2) was also collected from Kaggle for the experiments with four classes such as glioma, meningioma, no tumor, and pituitary MRI images. The training set consists of 5712 brain tumor images, and testing consists of 1311 images.

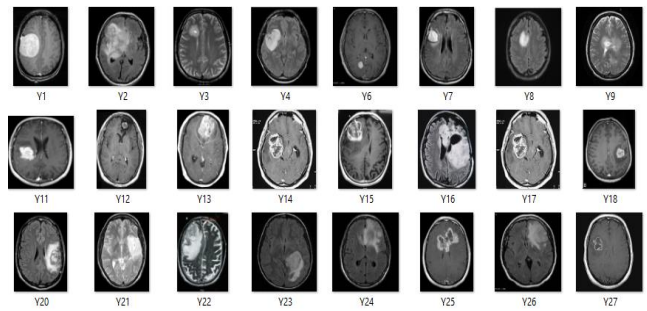


Figure 2: MRI Brain Images from DS1

Algorithm Steps

Step-1 Used Pre-Trained model with VGG-19

This is the pre-trained model and this consists of billions of images collected from the ImageNet database. This contains 19 layers and these are used to classify the images into thousands of categories. This model mainly focused on extracting the rich features from the given input images. VGG 19 is the pre-trained model which is the extension for VGG.

Input: The size of the input image is 224 x 224.

Convolutional (ConL) Layers: In VGG, ConL gives better training for the brain MRI images. The size of the image is 3x3 and this gathers all the information from the image. After this ReLU activation function is followed. ReLU gives the accurate input and output with the help of a pair wise linear function. The pixel value is fixed to the 1 for the stride.

Fully-Connected Layers: This layer contains the 3 layers and each layer consists of 4096 nodes each third layer consists of 1000 nodes and all these classes are present in the ImageNet dataset.

Step-2 Pre-processing with image filtering approach
Apply Bilateral Filter for removing the Photon Noise from the input MRI image

Step-3 Segmentation.

Non-Local Bayes (NL-Bayes)

Magnetic Resonance Imaging (MRI) is a critical tool in the diagnosis and treatment planning of brain tumors, providing detailed images of brain anatomy and pathology. However, MRI images often contain noise, which can obscure important details and affect the accuracy of diagnosis. Advanced image denoising techniques are essential to enhance image quality and ensure precise interpretation.

One such advanced denoising method is the Non-Local Bayes (NL-Bayes) algorithm. NL-Bayes leverages the principles of Bayesian statistics and non-local means to

effectively reduce noise while preserving crucial structural details in the images.

Overview of Non-Local Bayes Algorithm

1. Non-Local Means (NLM) Foundation

The NL-Bayes algorithm builds upon the Non-Local Means (NLM) approach, which is based on the observation that similar patterns recur throughout an image. NLM denoises images by replacing the intensity of a pixel with a weighted average of intensities from similar patches across the image, thereby preserving texture and details better than local methods.

2. Bayesian Framework

NL-Bayes enhances NLM by incorporating a Bayesian framework, which models the probability distribution of the true image given the noisy observation. This approach allows for an optimal estimation of the image by considering prior knowledge about the noise and the underlying image structures.

Application to Brain Tumor MRI Images

1. Noise Reduction

MRI images of the brain, especially those used for detecting tumors, require high clarity to identify the tumor's location, size, and type accurately. NL-Bayes effectively reduces random noise in these images, leading to clearer and more interpretable scans.

2. Preservation of Fine Details

In brain tumor imaging, preserving fine details is crucial for distinguishing between tumor tissues and healthy brain structures. NL-Bayes excels in maintaining these details while eliminating noise, aiding radiologists and medical professionals in making precise diagnoses.

3. Improved Diagnosis and Treatment Planning

By providing high-quality, denoised MRI images, NL-Bayes supports better diagnosis of brain tumors. Enhanced image clarity helps in accurate tumor segmentation, grading, and monitoring, thereby facilitating improved treatment planning and outcomes.

NLM Algorithm Steps

Patch Similarity: For a given pixel i in the image, define a square patch $P(i)$ centered around the pixel.

Weight Calculation: For each pixel j in the image, define a patch $P(j)$. Compute the similarity between patches $P(i)$ and $P(j)$ and determine a weight $w(i, j)$.

The following Equations measures the Noise filters:

Weight Calculation:

The weight $w(i, j)$ is computed using a Gaussian function of the Euclidean distance between the patches $P(i)$ and $P(j)$.

$$w(i, j) = \frac{1}{Z(i)} \sum_j \exp\left(-\frac{\|P(i) - P(j)\|_2^2}{h^2}\right)$$

Where,

$\|P(i) - P(j)\|_2$ is the Euclidean distance between patches $P(i)$ and $P(j)$.

h is the filtering parameter that controls the decay of the exponential function.

$Z(i)$ is the normalizing constant:

$$Z(i) = \sum_j \exp\left(-\frac{\|P(i) - P(j)\|_2^2}{h^2}\right)$$

Denoised Pixel Value:

The denoised value of the pixel i , denoted as $\hat{u}(i)$, is obtained by averaging all pixel values in the image weighted by $w(i, j)$.

$$\hat{u}(i) = \sum_j w(i, j)u(j)$$

Splitting and Merging (Feature Extraction Technique)

Feature extraction is a process that transforms raw image data into a set of meaningful attributes or features that can be used for analysis. In the context of MRI brain tumor images, feature extraction involves identifying regions of interest (ROIs) that likely represent tumor tissues and distinguishing them from healthy tissues. Effective feature extraction techniques enhance the accuracy of subsequent tasks such as segmentation, classification, and diagnosis.

Splitting and Merging: An Overview

Splitting and merging is a classical technique in image processing, particularly useful for feature extraction in medical imaging. This technique involves dividing the image into smaller regions (splitting) and then combining similar regions (merging) based on specific criteria. The goal is to segment the image into homogeneous areas that correspond to distinct anatomical structures or pathological regions.

1. Splitting:

Initial Partitioning: The image is initially divided into smaller regions or sub-blocks. This partitioning can be performed using various methods such as quadtrees or grid-based approaches.

Homogeneity Criteria: Each sub-block is evaluated for homogeneity based on specific criteria, such as intensity,

texture, or statistical properties. If a region is found to be non-homogeneous, it is further subdivided.

2. Merging:

Combining Regions: Adjacent regions meeting the homogeneity criteria are merged to form more significant, meaningful segments. This merging process continues until no further areas can be combined based on the predefined criteria.

Refinement: The merged regions are refined to ensure accurate segmentation and to eliminate any small, isolated regions that may not be clinically significant.

Applications in MRI Brain Tumor Imaging

Splitting and merging techniques are particularly beneficial in MRI brain tumor imaging for several reasons:

Improved Segmentation: By accurately segmenting the tumor regions from the surrounding healthy tissues, splitting and merging techniques enhance the accuracy of tumor detection and characterization.

Robustness to Noise: These techniques are effective in handling noise and variations in MRI images, ensuring reliable feature extraction even in challenging cases.

Integration with Other Methods: Splitting and merging can be combined with other advanced image processing techniques, such as machine learning and deep learning, to further improve the accuracy and efficiency of brain tumor analysis.

Capsule Networks

Capsule Networks, introduced by Geoffrey Hinton and his team in 2017, represent a significant advancement in neural network architecture designed to address the shortcomings of traditional CNNs. Capsules are groups of neurons that encode specific properties of objects, such as pose, orientation, and scale, in a vector format. The primary innovation of Capsule Networks lies in their ability to preserve and utilize spatial hierarchies between features through a dynamic routing mechanism. This allows Capsule Networks to better capture intricate spatial relationships and provide more robust and accurate predictions, especially in scenarios involving complex and variable patterns, such as brain tumor detection. Capsule Networks (CapsNets) consist of capsules, which are groups of neurons whose activity vector represents the instantiation parameters of a specific type of entity present in the image.

Design the architecture of the CapsNet. Typical components include:

- Convolutional layers for feature extraction.
- Primary capsules to encode primitive features.
- Routing mechanism to establish connections between capsules in adjacent layers.
- Final capsule layer for classification.

Objectives

This research aims to explore and evaluate the application of Capsule Networks in the detection of brain tumors from MRI images. The specific objectives are:

- To develop a Capsule Network-based model for brain tumor detection.
- To compare the performance of the Capsule Network with traditional CNN-based approaches.
- To assess the model's ability to handle variations in tumor characteristics, such as shape, size, and location.
- To analyze the robustness of the model in distinguishing between different types of brain tumors and healthy brain tissue.

Significance of the Study

The successful application of Capsule Networks in brain tumor detection could lead to significant improvements in the accuracy and reliability of automated diagnostic systems. Enhanced detection capabilities can facilitate earlier diagnosis, enable more precise treatment planning, and ultimately improve patient prognosis. Additionally, this study contributes to the broader field of medical image analysis by demonstrating the potential of advanced neural network architectures in tackling complex and high-stakes healthcare challenges.

Experimental Results

The experiments were conducted using various parameters, which help to show the strength of the algorithms. These parameters are obtained from the confusion matrix count values.

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

$$\text{F1 - Score} = 2 * \frac{(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})}$$

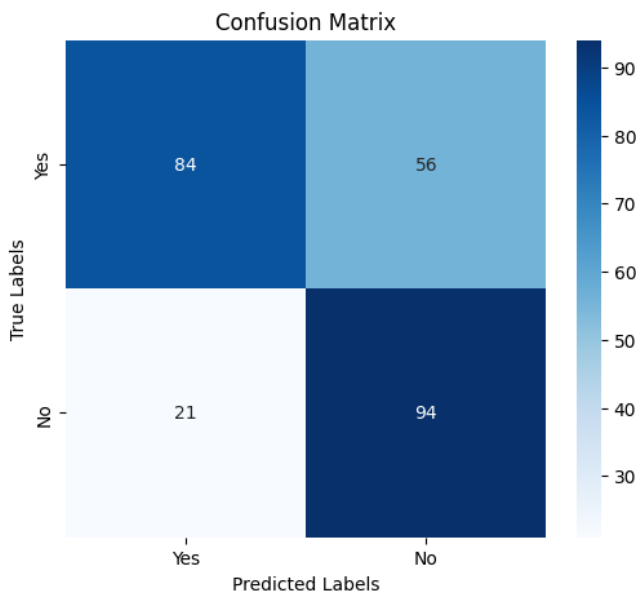


Figure 3: Count Values of SVM obtained from Confusion Matrix for DS1.

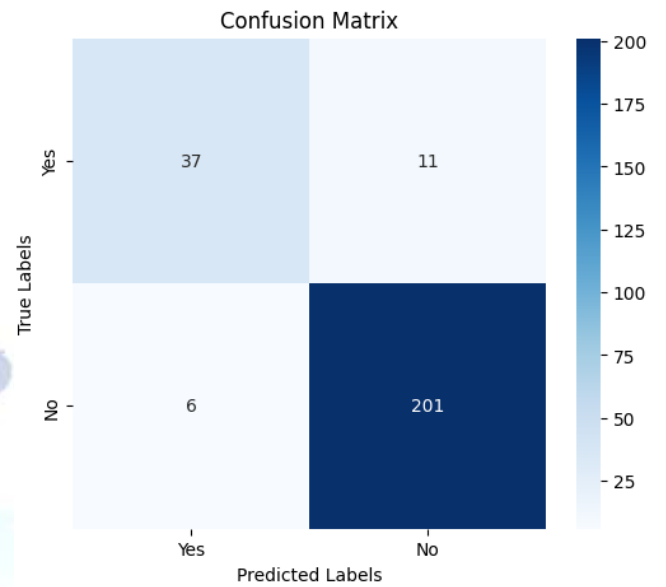


Figure 5: Count Values of VGG19 with CN obtained from Confusion Matrix for DS1.

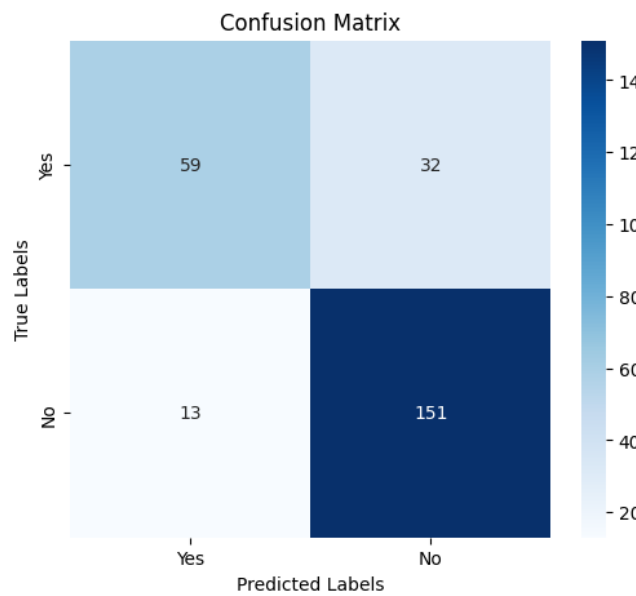


Figure 4: Count Values of RF obtained from Confusion Matrix for DS1.

Table 1: Comparison of Algorithms based on DS1

Algorithms	Accuracy	Precision	Recall	F1-Score
SVM	0.70	0.63	0.82	0.71
RF	0.82	0.83	0.92	0.87
VGG19 + CN	0.97	0.94	0.96	0.96

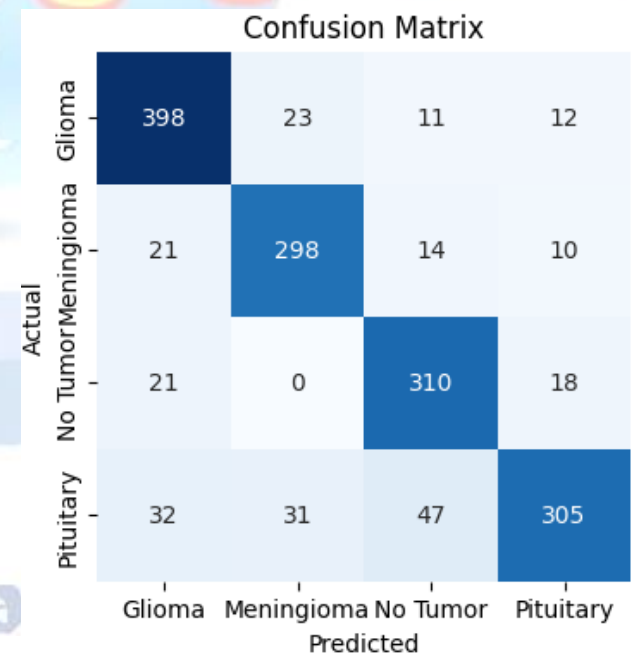


Figure 6: Count Values of SVM obtained from Confusion Matrix for DS2.

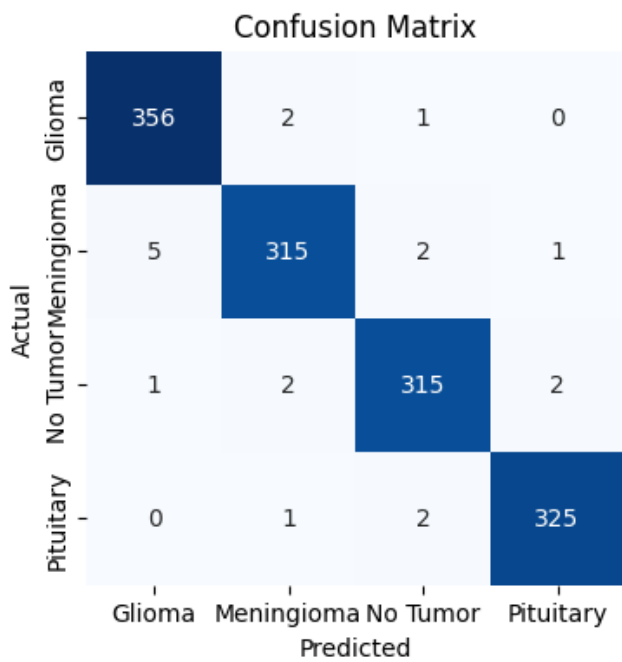


Figure 7: Count Values of RF obtained from Confusion Matrix for DS2.

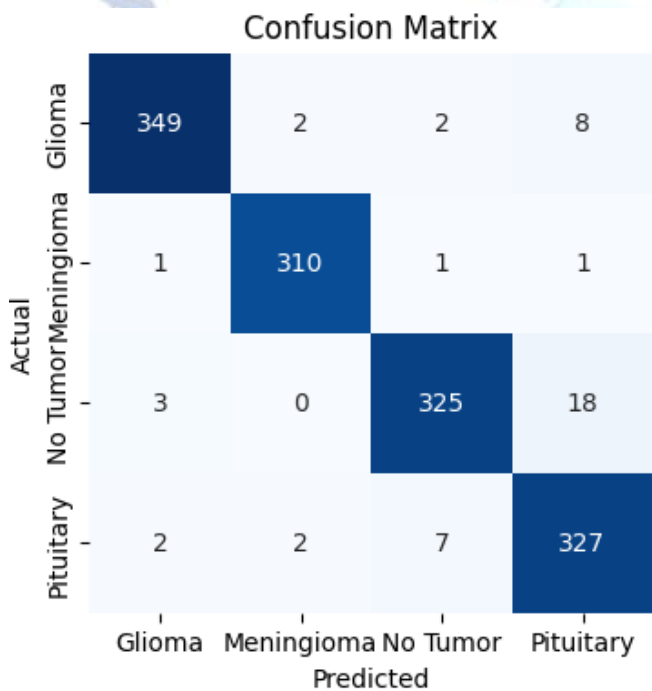


Figure 8: Count Values of VGG19 with CN obtained from Confusion Matrix for DS2.

Table 2: Comparison of Algorithms based on DS2

Algorithms	Accuracy	Precision	Recall	F1-Score
SVM	0.81	0.81	0.82	0.81
RF	0.91	0.91	0.91	0.91
VGG19 + CN	0.98	0.97	0.98	0.97

CONCLUSION

This research mainly based on disease risk prediction using deep learning models like VGG19 and Capsule

Networks. The proposed approach also uses the transfer learning by transferring the features and patterns from the VGG19 and sends it to Capsule Networks for increasing the detection of accurate regions. Capsule Networks address one of the primary limitations of traditional convolutional networks by preserving the spatial hierarchies and relationships between features. This capability ensures that the orientation and position of features are maintained, leading to better recognition of tumor structures. The hybrid model demonstrated superior performance compared to standalone models. The integration of VGG19 and Capsule Networks resulted in higher accuracy, precision, recall, and F1-score, indicating robust prediction capabilities. The model showed robustness across different datasets, highlighting its potential for generalization. This aspect is critical for real-world applications where diverse and unseen data are common. The improved prediction accuracy and robustness of the hybrid model make it a valuable tool for clinical decision-making. Early and accurate prediction of brain tumor risks can significantly enhance patient outcomes by facilitating timely and appropriate medical interventions.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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