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Enhancing the Identification of Brain Tumours Using the CNN Ensemble Model

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ABSTRACT

The early and accurate detection of brain tumors is a critical challenge in diagnostics and healthcare due to the severe consequences of delayed diagnosis. This paper addresses this issue by employing an ensemble of Convolutional Neural Network (CNN) models to enhance the identification of brain tumors using MRI images. The methodology integrates pre-processing techniques such as image augmentation, Gaussian blurring, and Sobel edge detection to improve image quality. Various CNN architectures, including Scratch CNN, InceptionV3, Xception, EfficientNetB0, ResNet50, and VGG19, were evaluated alongside machine learning classifiers such as AdaBoost, Random Forest, SVM, KNN, and SoftMax. Among these, EfficientNetB0, Xception, and InceptionV3 demonstrated superior performance, achieving the highest classification accuracy of 98.67% and an average accuracy of 96.90%. This research underscores the significance of selecting appropriate models and classifiers for medical image classification and highlights the potential for further advancements in clinical applications.

1. INTRODUCTION

In the field of diagnostics and healthcare, detecting brain tumors early and accurately has become a challenge. In diagnostics and healthcare, the early and precise detection of brain tumors has emerged as a formidable task. Brain tumors, regardless of their nature—benign or malignant, can have severe repercussions if not diagnosed and treated promptly [1]. The demand for efficient detection methods has never been more urgent, considering how quickly the disease can progress and affect patient's lives.Historically, the identification of brain tumors heavily rested on the expertise of radiologists who methodically analyzed medical pictures, such as those produced from magnetic resonance imaging (MRI) and computed tomography (CT) scans [2]. While these professionals possess knowledge and experience, the sheer volume of medical imaging data and the need for accuracy calls for an efficient and reliable approach. Deep learning techniques, which are a subset of artificial intelligence (AI), come into play in this context.Deep learning, which falls under the category of machine learning, has made advancements in recent times [3]. Its ability to autonomously learn patterns from datasets has paved the way for groundbreaking developments across various fields, including medical image analysis [4]. In brain tumour detection, deep learning is promising in improving accuracy, speed and consistency.

1.1 *Medical Images*

Medical imaging holds significant importance in assessing and managing diverse health conditions [5]. Specifically, when examining the complex structure of the human brain, several imaging techniques offer unique perspectives. Magnetic Resonance Imaging (MRI) stands out as a cornerstone in neuroimaging, delivering exceptional comprehensive images of the brain's interior architecture through the application of magnetic fields and radio waves. These high-resolution images permit clinicians to spot small abnormalities, such as brain tumours, with amazing precision [6]. Computed Tomography (CT) scans, utilizing X-rays to generate cross-sectional pictures, supplement MRI by providing crucial information regarding tissue density. Despite its slightly reduced resolution, CT serves a significant role in the overall evaluation of brain health.

Positron Emission Tomography (PET) imaging offers a metabolic component to the diagnosis of brain malignancies.

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By tracing the spread of a radiotracer, PET scans highlight areas of heightened metabolic activity, aiding in detecting and characterising malignancies. While not as common in brain imaging, Ultrasound remains a flexible modality. Though it is commonly linked with prenatal imaging, ultrasonography can be applied in specific neuroimaging circumstances, particularly in measuring blood flow and detecting anomalies [7]. The development of Functional MRI (fMRI) significantly advances our understanding of the brain's dynamic activities, allowing doctors to correlate structural abnormalities, such as tumours, with changes in neural activity. As technology progresses, so does our capacity to utilize imaging modalities like Diffusion Tensor Imaging (DTI), which studies water diffusion in tissues to determine white matter pathways. In the field of brain tumor detection, these different imaging tools collectively contribute to a comprehensive diagnostic strategy, establishing the framework for integrating cutting-edge technology, including deep learning approaches, to automate and refine this delicate process.

1.2 Motivation

Primary brain or spinal cord tumours arise in these tissues. Primary malignant brain and spinal cord tumours will affect 24,810 Americans (10,530 women and 14,280 men) in 2023. This kind of tumour is rare, less than 1%. Brain tumours account for 85%–90% of first CNS malignancies. Worldwide, 308,102 instances of primary brain or spinal cord tumours were expected in 2020. US CNS tumour diagnoses in children under 20 are expected to reach 5,230 in 2023. The rest of this manual cover's adult primary brain tumours. Brain and nerve system malignancies are incurable and the ninth leading cause of death for men and women. Primary malignant brain and central nervous system tumours will kill 18,990 Americans in 2023 (seven 970 women and 11,020 men). Primary malignant brain and central nervous system cancers killed 251,329 people worldwide in 2020. Under-15s had a 75% 5-year relative survival rate. The 5-year relative survival rate for 15-39-year-olds is 72%. The 5-year relative survival rate was 21% for those over 40. Doctors calculate brain tumour survival rates every five years [8].

About 120 types of brain tumours affect different brain tissues. Benign or noncancerous brain tumours might be dangerous owing to their size or location. Brain and nerve cancers affect 30 per 100,000 Americans. Brain tumours damage healthy brain tissue by pressing on or spreading into it. Certain brain tumours may become cancerous. If they obstruct cerebral fluid flow, skull pressure may increase. Certain cancers may spread via spinal fluid to distant spine or brain regions [9].

Global cancer observatory (2020) ranks 1,284 new cases 22nd with a cumulative risk of 0.82% and a rank of 0.09. The sickness caused 1,144 deaths, ranking 19th, with a cumulative risk of 1.0% and 0.08. These numbers show the prevalence of brain and CNS cancer. In all age categories, 2,898 cases occurred over five years, resulting in a 1.76 per 100,000 rate [10].

In Bangladesh, according to research by Sarkar et al. (2021), Treatment of brain tumours is in requirement of joint efforts by several professionals from neurosurgery, neuroradiology, neuropathology, oncology, and radiation. The result is poorer in underdeveloped nations compared to developed countries because of shortcomings in adequate registration, lake of awareness of patients, failure of prompt diagnosis, lack of availability and co-ordination of numerous professionals for complete care and high abandonment rates [11].

Brain tumours have decreased, although they remain a medical concern. Brain tumours may profoundly impact an individual's quality of life and well-being. Brain tumours must be detected early to optimize therapy and patient survival.

Early detection and therapy are crucial for the cure of brain tumours. Risky, untreated brain tumours raise healthcare expenses and suffering. However, early discovery and proper therapy may improve brain cancer. Early brain tumour detection improves treatment outcomes and lowers disease severity. So, the goal is to use image processing and machine learning techniques to identify brain cancers early, benefiting the medical business.

1.3 Objective

The methodology comprises three key sub-objectives aimed at achieving efficient and effective brain tumour detection. Firstly, a suitable dataset of brain tumour images is collected and enhanced for clarity and characteristics through various augmentation and filtering techniques. This step ensures optimized data for accurate analysis. Secondly, the gathered data is processed by training it with carefully chosen Convolutional Neural Network (CNN) models, which excel at extracting intricate features from images. These models are coupled with specific classifiers to categorize the extracted features with precision, enhancing overall efficacy. Finally, the focus shifts to developing a model specifically tailored for detecting brain tumours from imaging data, with particular emphasis on refining its precision. Through a meticulous development process, method selection is grounded in the functionality of each component, ensuring an iterative refinement approach towards achieving the desired outcome of accurate brain tumour detection.

2. BACKGROUND STUDY

In this paper, have developed methods for detecting and classifying brain tumours using learning models such as CNN, Xception, InceptionV3, ResNet50, EfficientNetB0, and VGG19. So many researchers and doctors work on it to improve brain tumour detection Using deep learning, artificial intelligence, image processing, and so many others. The paper uses Convolutional Neural Network (CNN), Xception, InceptionV3, ResNet50, EddicientNetB0, and VGG19. Researchers have found new ways and algorithms to improve accuracy of the detection of brain tumours.

Hafiz Muhammad Tayyab Khushi et al., deep learning models include InceptionV3, Resnet50, and VGG19. ResNet50 achieved the highest and best validation accuracy. That is 89.45%, with a validation loss of 0.28. The model InceptionV3 achieved a validated accuracy of 76.33%. The EfficientNetB7 model has a state-of-the-art model accuracy of 98.97%. That demonstrates excellent performance [12].

Muhammed Celik el al., explained brain tumour classification using MRI imaging and deep learning. Using CNN models and the proposed model hybrid, they achieved classification with 97.15% accuracy and a recall of 97%. The pre-trained models were EfficientNetB0, VGG19, ResNet50, InceptionV3, and Xception. Most of the ResNet accuracy was

96% and the accuracy of the CNN model proposed by Generic was 81.05 % accuracy [13].

Ahmeed Suliman Farhan el al., introduced brain tumour detection in MRI images. The models assessed the two datasets, which are state-of-the-art models, achieving 94.77% and 97.1% inception vacancies, respectively. Comparative models are used: VGG19, EfficientNetB0, InceptionV3, ResNet50, and Xception. VGG19 accuracy is 97%, 98%, and 99% for the modalities. In the second scenario, the Inceptionv3 model is used to extract different features from different Inception modules, which are fed into a softmax for brain tumor diagnosis. Total accuracy was 94.77% for a fast table. And the second table's accuracy was 97.1%. [14]

Ranit Sen et al., proposed a novel approach for datasets and categories of brain tumours and also employed state-of-the-art CNN-like architectures, like EfficientNetB0, Xception, ResNet50, MobileNetV2, and VGG16, using transfer learning then classified the three types of brain tumour. The MRI images across 4 classes and image enhancement methods. The EfficientNetB0 gave the best performance, with an accuracy of 97.61%. And ResNet50, Xception, MobileNetV2, and VGG16 accuracy are 96.26%, 96.64%, 96.90%, and 72.45%, respectively. The classification of abnormal brain pixels is crucial for finding distinct tumour types. [15]

R. Tamilarasi proposed delves into brain tumour highlight and detection to improve patients' quality of life. There are two models used to achieve high accuracy in brain tumor classification. One identifying tumour accuracy of 98.6% and another pituitary tumour accuracy of 98%. The proposed CNN models are ResNet-50, and Inceptionv3. Overall Multi-Classification accuracy was 98%. [16]

Yuting Xie et al., CNN to classify medical images, using distinct models tailored to specific classification challenges. The research implements CNN for medical image classification. It achieved impressive accuracies of 97.6% in tumour detection and 98% in tumour classification. This includes custom CNN models, VGG, ResNet, and EfficientNet. Deep learning techniques CNN-based were published on Scopus and PubMed from 2015 to June 2022. At last, it reaches a remarkable accuracy of 98% [17].

Saif Ahamad et al., seven transfer learning methods, such as VGG-19, InceptionV3, ResNet50, Inception, Xception, and ResNetV2. For instance, VGG19-SVM achieved a height accuracy of 99.39%. That is the accuracy of the height classification. On the other hand, the InceptionV3-Decision has an accuracy score of 75.67%, which is the lowest among the models. The section covers dataset data augmentation, description, CNN, and image pre-processing models [18].

Naeem Ullah proposed the critical need for the timely detection of brain tumours. To identify and classify three major brain tumour types: glioma, meningioma, and pituitary. These classifications are evaluated, including Inceptionv3, Xception, and Resnet50. The accuracy of Inceptionv3, Resnet50, Xception is 94.48%, 67.03%, and 98.37%, respectively. The time limit is too high. And resnet50 accuracy was not good [19].

Md Ishtyaq Mahmud et al., application of AI, specifically deep learning algorithms. This thesis paper used a dataset of 3264 MR images, with 80% of the data used and 20% for testing. Identify brain tumours using CNN architectures, also against established models like CNN, Inception V3, and ResNet-50. The CNN model brain tumor accuracy of 93.3%, on the other hand, an AUC of 98.43%, a recall of 91.19%, and less than 0.25. Using the assessment of deep learning models for brain tumour detection performance modes, ResNet-50, CNN, and Inception V3 are 93.30% accuracy, 81.10%, and 80.00%, respectively [20].

Ahmad Osman's proposal highlights the importance of early and easy brain tumour detection and its impact on mortality rates. VGG-19 is the top performer with 97% accuracy, while EfficientNetB7 has the lowest accuracy at 93%. On the other hand, ResNet-50's accuracy is 94%. The analysis of the implications of CNN used in stress and healthcare reveals both their potential benefits [21].

Muhammad Naeem Tahir extensively explores various classifications for MRI brain tumour photo analysis using classifications such as SOM, KNN SVM, and others. Focusing on brain tumour MRI images for tumour diagnosis, the study aims to extract and select features (texture, colour, tumour region, location, and edge) from images. Pre-processing includes the segmentation and image filtering, and post-processing includes resizing, classification, and tumour area calculation using DNN. Achieving 90% classification accuracy using DNN is possible and has revealed the efficiency of the algorithm [22].

Anjaneya Teja Sarma Kalvakolanu et al. focus on non-invasive brain tumours and classification using deep learning methods. They used registration and segmentation techniques to separate skull images from MRI images using grab-cut methods that validated tumour features in the processed images. Here, 3064 MRI images were used, especially with a dataset consisting of T1 flare MRI photos. The model achieved a high classification accuracy of 98.83% for training, 96.26% for validation, and 95.18% for the test set. ResNet50 was used as the base model for accurate classification of multiple tumor types. This method gave promising results compared to other studies, which showed that the method works well for brain tumour classification [23].

Gokila Brindha et al. introduce brain tumours using MRI scans of diagnosis. It emphasizes artificial neural network (ANN) and Convolutional neural network (CNN) machine learning for accurate detection and acceleration. The focus is comparing the performance of artificial neural networks and convolutional neural network models on brain tumour MRI datasets. The main objective of doing this is to demonstrate the efficiency and effectiveness of this learning method in differentiating tumour-affected and normal brains, aiding in the rapid treatment and diagnosis of brain tumours in patients. The ANN model, trained over 50 times, exhibits a training accuracy of 97.13%, 71.51% validation accuracy, and 80.77% testing accuracy. Suggests optimization techniques for determining ideal layers and filters for this advanced model [24].

Sidra Sajid et al., introduce a deep learning-based method for segmentation using different MRI modalities. By observing the hybrid CNN architecture and contextual information, the data imbalance and overfitting problems were solved. Validation indicated improved segmentation performance compared to existing techniques on the BRATS 2013 dataset, emphasizing the efficacy of the method to accurately detect and segment brain tumours. The role of the hybrid CNN model for brain tumour segmentation is many. It achieved superior performance compared to state-of-the-art technology [25].

Abdullah A. Asiri et al., An advanced model combining CNN U-Net and ResNet50 for improved brain tumour detection segmentation and classification. Using public datasets for validation and training, the U-Net model performed best in accurately segmenting tumour regions compared to other models, in which the U-Net with Resnet 50 coefficient value came in at 95%. Besides, the proposal and validation for a hybrid model - CNN, U-Net, and ResNet50- for robust brain tumour detection, classification, and differentiation from MRI images. ResNet50 performed well in correctly detecting the presence of tumours. Contributed significantly to advances in medical analysis and patient treatment planning [26].

Aryan Verma et al., focused on early detection of brain tumours using deep learning techniques by MRI slices. Here, VGG 16, ResNet 50, and EfficientNet architectures were analyzed. ResNet 50 provides performance: determined accuracy of 99.37%. It surpasses many of the detection mechanisms that exist in the brain. The model performed very well in triaging patients and assisting clinicians in decision-making. A newly introduced dataset, JMCD (Jabalpur Medical College Dataset), including annotated MR sequences in 140 patients, supports research in targeted brain tumour detection. Its main objective was to improve brain tumour detection methods [27].

Abdullah A. Asiri et al., aimed to enhance brain tumour diagnosis using a computer-aided system and the challenge of manual segmentation from many magnetic resonance images for cancer analysis. They refine VGG19 with CNN architecture through a block-wise mechanism for precision, which proposes the BW-VGG19 architecture. Various Chinese hospitals used a contrast-enhanced MRI dataset between 2005-2020, achieving 98% accuracy using their method. Here, using CNN, VGG16, and VGG19 performed better against the method. Here, the BW-VGG19 model showed an exceptional accuracy of 0.98%, which outperformed other models like CNN and VGG19. This method played a significant role in the detection of brain tumours [28].

Krisna Nuresa Qodri et al. explore the classification of brain tumours in MRI images using Deep learning and transfer learning. Based on brain tumours in the United States and Indonesia, the research was done and found its flaws. In this study, 23,890 adults (10,300 females and 13,590 males) and 3,540 children under 15 years of age collected brain tumour photos. Within this, a public dataset consisting of 253 images (98 tumour-free and 155 tumour images) was used. The study employed residual networks (ResNet), NASNet, Xception, DenseNet, and VGG methods. Among them, ResNet50 and VGG16 achieved 96% accuracy. Despite the best accuracy of ResNet50 and VGG16, the Xception model achieves better accuracy in terms of specificity and sensitivity. These results were able to accurately detect MRI images for brain tumours, particularly highlighting the transfer learning performance demonstrated by ResNet50 and VGG16 [29].

Md. Tanvir Rouf Shawon et al. explore brain tumour detection for deep neural networks from MRI images. CNN, ResNet50, InceptionV3, EfficientNetB0, and NASNet-Mobile were used here. A pipeline was developed to combine these five models and apply them to a dataset. Using cost-sensitive InceptionV3 and CNN models demonstrates an accuracy of 92.31%. Using the proposed InceptionV3 model achieved 99.33% accuracy. However, this introduces artificial intelligence (AI) to clarify decision-making. The results suggest the effectiveness of InceptionV3 and CNN for brain tumour detection, potentially providing diagnostic applications [30].

Abhishek Anil et al. explore the application of modern technology in brain tumour detection using deep learning from MRI images. This study, using deep learning methods, specifically developed a classification network that can distinguish between brain images with and without tumours, trained by migration. Demonstrates the potential to improve brain tumour detection accuracy and medical imaging efficiency. Here is a dataset created from multiple sources. Then split it into test and training sets. evaluated three networks—AlexNet, VGG16, and VGG19—for performance in tumour detection. VGG19 demonstrated the highest accuracy of 95.78%. Which also outperformed other models. The data used here was able to demonstrate larger MRI image sizes without data loss. [31]

Feature extraction from MRI images means picking out important information, such as unique patterns that indicate brain tumours. Classification is the process of sorting patterns into categories – identifying whether this is a tumour or not. Tried various ways to prove it. One way was to use custom-designed CNNs, which are specialized programs for rendering patterns. Another way would be to use models like Xception and EfficientNetB0 that already know something about the pattern. Taking these factors together, we found that some tumours were better at being identified accurately and with fewer errors. The way these subjects are selected and combined works very well for finding brain tumours from MRI images.

The datasets are used to teach computers about brain tumours and represent sets of MRI images. Think of this as a huge collection of images, each image showing a different aspect of the tumor, which works like a report card. They measure things like accuracy, which indicates how often the computer correctly detects the tumour, and confidence in the predictions. Here, various classifiers have been tested—AdaBoost, KNN, RF, SVM, and Softmax–using these metrics to see which methods would perform better on images for tumour detection. By examining different types of datasets and metrics, we can understand which classifiers performed better in correctly classifying brain tumours. These methods evaluate how well they learn from image sets and how confident they are in their judgments.

Challenges in this field include accurately distinguishing between tumours for which otherwise complex MRI data can be interpreted. Future directions involve different models to handle different tumours and sizes. Another challenge is to ensure that these models perform well across different MRI uses and settings. Advances in deep techniques can advance model sensitivity to subtle tumor characteristics, improving overall detection accuracy. Also ensures credibility. Interpretability will be very important in understanding how decisions are made using these models. The inclusion of more diverse datasets may strengthen the ability of these models to detect atypical tumours. Collaborative efforts between medical experts and AI researchers can address this situation and advance the accuracy and reliability of brain tumour detection using MRI.

The literature review summarised has explored the six CNN models, Xception, InceptionV3, ResNet50, EfficientNetB0, and VGG19, in brain tumour classification using images. Softmax, SVM, RF, KNN, and AdaBoost are used in all these models. Using this classification, all models are given better results. The research paper explores CNN 92.07%, Xception 95.47%, InceptionV3 96.26%, ResNet50 87.03%, EfficientNetB0 97.86%, and lastly, VGG19 82.6%. Among these models, InceptionV3, EfficientNetB0, and Xception Accuracy have performed well. The three models incorporate a combination of features. After doing the combined feature, the result is that InceptionV3 and EfficientNetB0 have an accuracy of 95.86%; on the other hand, EfficientNetB0 and Xception have an average accuracy of 95.9%; and the last two, InceptionV3 and Xception, have an average accuracy of 96.87%, after doing these InceptionV3, EfficientNetB0, and Xception combined features. The top two accuracies were identical, that is, InceptionV3 and Xception, as well as EfficientNetB0 and Xception. Here found the correctness by combining these two methods. That is an ensemble classifier accuracy of 96.9%. Overall, all CNN models show promise in medical imaging. Their efficiency depends on computational resources.

3. METHODOLOGY

Brain MRI input is followed by data preparation, including image scaling, augmentation, and filtering. Feature extraction is done using VGG19, a scratched CNN, Xception, InceptionV3, ResNet50, and EfficientNetB0. AdaBoost, k-Nearest Neighbors (kNN), Random Forest (RF), Support Vector Machine (SVM), and Softmax are used with each CNN.

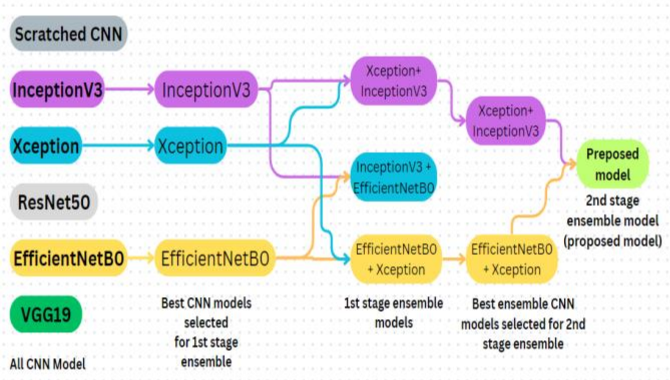


Fig. 1. Selection Process of CNN Architectures for a Two-Stage Ensemble Model in Image Processing

3.1 Dataset

The dataset, Br35H (2020), is specifically designed for brain tumour localization. Accurate identification and categorization of brain tumours, which are severe conditions that impact individuals of all ages, are essential for appropriate medical therapies. Brain tumours account for a vast majority, around 85 to 90 per cent, of primary Central Nervous System (CNS) tumours [1]. They affect over 11,700 persons each year. The dataset has three folders: "yes," "no," and "pred," which together include 3060 Brain MRI Images. In addition, the situation emphasizes the difficulties presented by the intricacies of brain tumours, particularly in areas where there is a shortage of highly trained neurosurgeons. The suggestion is to introduce a cloud-based automated solution to address these difficulties [32].

3.2 Data Pre-processing

Analysis and machine learning need data preparation, which cleans, transforms, and organizes raw data. Missing values, outliers, and category variables to numerical format are among its duties. This technique provides data consistency and relevance for analysis or model training. Noise, inconsistencies, and missing data are addressed to increase analysis and machine learning model accuracy and dependability [33]. Standardization, feature engineering, and dimensionality reduction improve data quality during pre-processing [34].

3.3 Filtering

In signal processing, image processing, and data analysis, filtering modifies or extracts certain data or signal while attenuating others. Filter type and settings rely on analysis or processing goals [35]. For the purpose of applying a filter, an input picture is processed by first applying Gaussian Blur, and then utilizing the OpenCV library to perform Sobel Edge Detection after that.

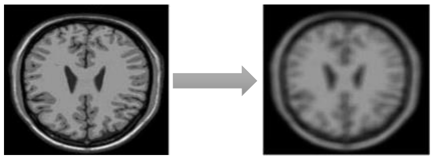


Fig. 2. Image comparison for Gaussian filter.

The picture is first smoothed down by the Gaussian Blur function, and then Sobel edge detection is carried out in both the horizontal and vertical axes. Utilizing the Sobel outputs, one may arrive at the ultimate conclusion by performing a calculation to determine the magnitude of the gradients. In order to improve the appearance of edge characteristics in photographs, this function is helpful.

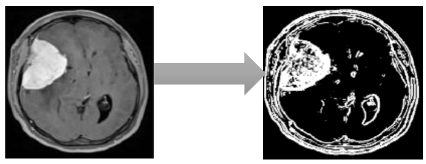


Fig. 3. Comparison of Sobel Edge Filter

3.4 Data Augmentation

The datasets undergo just a minimal amount of preparation, which consists of picture augmentation and scaling. The act of scaling an image is a frequent pre-processing procedure, particularly when dealing with convolutional neural networks (CNNs) or other deep learning models [36]. For the purpose of applying scaling to each picture in the list, it makes use of the OpenCV library. The 'image_size' argument is responsible for determining the particular dimensions that are associated with the resized pictures. This resizing process is frequently utilized for the purpose of standardizing or changing the size of photographs contained inside a dataset. All of the photographs have been scaled to a resolution of 128*128. Finally, the dataset is subjected to the application of six distinct forms of augmentation procedures, which include horizontal flipping, rotation, height shift, width shift, and fill mode.

It guarantees that all of the photos that are entered have the same height and width. When the batch size is set to 32, it indicates that each training cycle will include the processing of 32 photos simultaneously. Choosing the appropriate batch size may have an effect on the amount of memory that is required for training. The usage of smaller batch sizes is common in the context of online or stochastic training, whilst the use of larger batch sizes allows for the utilization of parallelism and may result in more stable convergence [37].

Data normalization is a technique that is frequently utilized in machine learning applications, particularly when working with image data. The purpose of this technique is to guarantee that neural networks and other models have input ranges that are consistent and controllable. It does this by dividing each member in the array by 255.0, with the goal of bringing the values closer to the range of 0 to 1.

The dataset was loaded as input, and the data and label lists were set to empty. Following that, it goes through each folder in the given path and tries to load every image file in those folders using OpenCV [38]. If the picture loads properly, it is added to the "data" list, and the label (folder name) that goes with it is added to the "labels" list. An error message is shown if there is a problem loading the picture. This method is meant to load pictures from a dataset location and link each image to the label that goes with it.

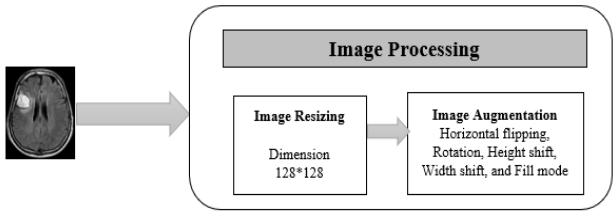


Fig. 4. Data Pre-processing Stages

3.5 *Feature extractors*

In the field of machine learning and data analysis, one of the most essential processes is called feature extraction. This process entails translating raw data into a condensed and comprehensible representation that is referred to as features [40]. This crucial stage is of the utmost importance for a variety of applications, including as pattern recognition, natural language processing, and image and signal processing [41]. The key goals of feature extraction are improving the representation of data and lowering the dimensionality of the data in order to promote efficient analysis [42].

During the process of feature extraction, five pre-trained models and a CNN model that was created from scratch were taken into consideration. On account of the fact that it has previously been trained with an issue that is comparable, it has the benefit of requiring less time to train. Scratch CNN [43], Xception [44], InceptionV3 [45], ResNet50 [46], EfficientNetB0 [47], and VGG19 [48] are the five pre-trained CNN models that have been modified and used for feature extraction in this study. These models that had been pre-trained were used on the dataset that was described, and later tweaks were made to the models via the use of random search in order to at least partially offset the effects of overfitting [43].

3.6 *Proposed Scratch CNN*

An approach that is considered to be a pioneer in the area of deep learning for the purpose of medical image analysis is known as Scratch Convolutional Neural Networks (CNNs). The CNNs in question are constructed from the ground up, without relying on models that have been pre-trained [49]. Within the realm of brain magnetic resonance imaging (MRI), these networks have shown remarkable potential by making it feasible to automatically extract precise properties directly from raw pixel data [50]. Because the model is initialized from scratch in Scratch CNNs, it is feasible to design task-specific architectures that are able to recognize tiny patterns within brain MRI data. This is made possible by the fact that Scratch CNNs are available. This not only adds to a better knowledge of neurological illnesses but also increases the accuracy of diagnostic procedures [51].

There is a total of sixteen layers in this design, which includes three convolutional layers, three max pooling layers, one flattens layer, and a dropout layer. A default value of 128 x 128 is assigned to the first input size. One of the goals was to build a Convolutional Neural Network (CNN) For the objective of extracting features from two-dimensional pictures. By using the Keras Application Programming Interface (API), the function generates a sequential model that represents a linear stack of layers. The model is made up of three convolutional layers that are successively stacked, with each layer being followed by a max of pooling. The rectified linear unit (ReLU) activation function is used by the convolutional layers, which are initialized with 32, 64, and 128 filters of size (3, 3), respectively. This activation function enhances the non-linearity in the feature maps. By contributing to spatial down sampling and so lowering the dimensionality of the feature maps, the max-pooling layers, which have a pool size of (2, 2), are also crucial. Importantly, a flatten layer is introduced in order to convert the two-dimensional feature maps into a one-dimensional vector. This helps to get the data ready for the future layers that are completely linked. This function provides a fundamental framework for a CNN-based feature extractor, which is often used in image processing jobs. It is also capable of being expanded or customized to meet the needs of a particular application.

3.7 *Modified Xception*

Xception convolutional neural network (CNN) architecture dominates deep learning for brain MRI processing (Chollet et al., 2017). A 2017 extension to Inception, Xception, uses depth-wise separable convolutions to separate cross-channel and spatial correlations [52]. This unique approach reduces parameter count and enhances feature extraction, boosting computation efficiency without reducing predictive performance.

The Xception deep learning model and conventional machine learning classifiers classify brain MRI images. MRI brain pictures are pre-processed and improved. The Xception model trains and evaluates many classifiers utilising high-level picture attributes, including AdaBoost, K-Nearest Neighbours (KNN), Random Forest (RF), Support Vector Machine (SVM), and Softmax Regression.

The advanced pre-trained neural network Xception categorises images. Complex MRI patterns and representations are recorded. Brain tumour classifiers are trained using the collected data. The method assesses classifiers by accuracy and log loss, which measure prediction uncertainty. Using extracted features, AdaBoost, KNN, RF, and SVM classifiers classify brain MRI images. Logistic regression for multiclass classification, Softmax Regression, accurately classifies brain tumours.

This complete method classifies brain tumours using deep learning and standard machine learning, showing how sophisticated neural networks and classical classifiers work together. Average accuracy and log loss measures help evaluate and compare the models' medical picture categorization effectiveness. Researchers and practitioners benefit from the architecture's adaptability and feature extraction in medical imaging's ever-changing sector.

Xception excels at brain MRI image analysis. Bai et al. [53] employed Xception in a semi-supervised learning framework for network-based cardiac MR image segmentation, proving its adaptability and dependability in challenging medical imaging applications. Xception was used to locate cancer metastases on gigapixel pathology images by Liu et al. [54]. Prasoon et al. [55] segmented knee cartilage using Xception, demonstrating its deep feature learning in numerous anatomical circumstances. Brain MRI interpretation is difficult; thus, adaptation is crucial.

3.8 Modified EfficientNetB0

The goal of EfficientNet is to solve the problem of striking a balance between computing efficiency and model correctness. Traditionally, while developing Convolutional Neural Networks (CNNs), researchers have mostly concentrated on expanding the network structure in order to enhance accuracy. Nevertheless, this often results in escalated computational expenses, posing a difficulty in implementing these models on devices with limited resources.

EfficientNet presents a new approach called compound scaling, which consistently adjusts the depth, breadth, and resolution of the network. This novel methodology distinguishes itself via its efficacy, attaining exceptional results in tasks such as picture classification, object identification, and segmentation, while showcasing better utilization of resources in comparison to previous methods. The architecture of EfficientNetB0 consists of recurring building blocks that use depth-wise separable convolutions, batch normalization, and non-linear activation functions such as Swish. The distinguishing feature of EfficientNet is its compound scaling mechanism, which consistently adjusts the depth, breadth, and resolution of the model. The use of specified coefficients in this balanced scaling guarantees a systematic method for getting the best possible performance of the model [47].

The brain MRI dataset is loaded and undergoes preprocessing, which involves shrinking and using EfficientNetB0's preprocessing algorithm. The EfficientNetB0 model, which has been pre-trained on ImageNet, is then used to extract features from both the training and testing datasets, yielding feature vectors. Afterwards, a varied range of classifiers, including AdaBoost, K-Nearest Neighbors (KNN), Random Forest (RF), Support Vector Machine (SVM), and Softmax Regression, are initialized and trained using the retrieved features.

The `apply_filters` function in image processing is crucial for improving the distinguishing characteristics in input pictures for brain MRI classification. To reduce noise and provide a cleaner visual representation, a Gaussian blur is applied using a kernel size of (5, 5). The procedure highlights the edges and important elements in the picture, which helps to extract relevant information for further processing and analysis. The function is executed using the OpenCV library, and its use as a first step is crucial in enhancing the input pictures for reliable brain MRI categorization.

Considering accuracy scores and log loss values, the assessment step evaluates each classifier's performance on the test set. The Softmax Regression classifier notably uses probability estimations to calculate log loss. The calculation of average accuracy and average log loss provides a comprehensive evaluation of the feature extraction using EfficientNetB0 across several classifiers. This technique highlights the potential of EfficientNetB0 in analyzing brain MRI and provides valuable insights for accurate classification in medical imaging applications.

The model's high level of efficiency and adaptability contribute to its widespread use in diverse applications, such as medical picture categorization and object recognition in autonomous cars. Pre-existing weights for EfficientNetB0 learned on large datasets, such as ImageNet, enhance the process of transfer learning for specific tasks, particularly when there is a scarcity of labelled data [57].

3.9 Modified InceptionV3

InceptionV3 is a significant convolutional neural network (CNN) structure specifically created for the purposes of image categorization and feature extraction [58]. The InceptionV3 architecture relies on the inception module, which combines filters of various sizes in a single layer. This allows the network to effectively capture hierarchical characteristics at different scales. The use of 1x1 convolutions helps to decrease computational complexity while maintaining crucial information. The entire design consists of many inception modules, resulting in an efficient and robust feature extraction process.

The InceptionV3 model will be used for extracting features in the specific setting of brain MRI classification, followed by an assessment of several classifiers. The InceptionV3 model is used as a feature extractor to extract distinctive characteristics from the dataset. Afterwards, a number of classifiers, such as AdaBoost, K-Nearest Neighbors (KNN), Random Forest (RF), Support Vector Machine (SVM), and Softmax Regression, are initialized. Every classifier is trained separately using the characteristics retrieved by InceptionV3 and then assessed for accuracy. Log loss is computed for classifiers that provide probability estimates. The script closes by calculating the mean accuracy and mean log loss for all classifiers, offering a thorough summary of their performance.

Within the field of medical imaging, InceptionV3 has shown significant achievements, namely in tasks pertaining to MRI analysis. The capacity to record complex patterns and hierarchical structures is especially advantageous for identifying minor nuances in medical pictures, such as those seen in the identification of brain tumours [59]. InceptionV3 is a useful tool for medical image analysis applications, where labelled datasets are often scarce, because of its pre-trained weights on large-scale datasets and transfer learning capabilities.

3.10 Modified VGG19

The University of Oxford Visual Geometry Group created the VGG19 convolutional neural network (CNN) for image categorization. Noteworthy features include 3x3 convolutional filters with stride 1 and padding 1 to preserve spatial information across the network. The model's ability to learn hierarchical visual data representations makes it versatile in computer vision applications. Fine-tuning VGG19 for MRI brain tumor diagnosis requires adjusting the model to brain image datasets and using transfer learning from pre-trained weights, such as ImageNet. Sequential convolutional layers and max-pooling layers with a 2x2 filter and stride of 2 improve feature extraction [60].

Starting with brain MRI dataset loading and preprocessing, it follows a methodical methodology. Shuffled, scaled, and normalized images ensure processing-ready input. As a feature extractor, the InceptionV3 model extracts discriminative characteristics from the dataset. After that, AdaBoost, K-Nearest Neighbors (KNN), Random Forest (RF), Support Vector Machine (SVM), and Softmax Regression are initialized. Individual classifiers are trained using InceptionV3 features and tested for accuracy. Additionally, the input layer is resized to 128 × 128 to align with the picture size. VGG19 is deep and uniform with 19 layers, 16 convolutional and 3 completely linked [43]. Additional sources supporting VGG19's effectiveness and use in various circumstances include [61].

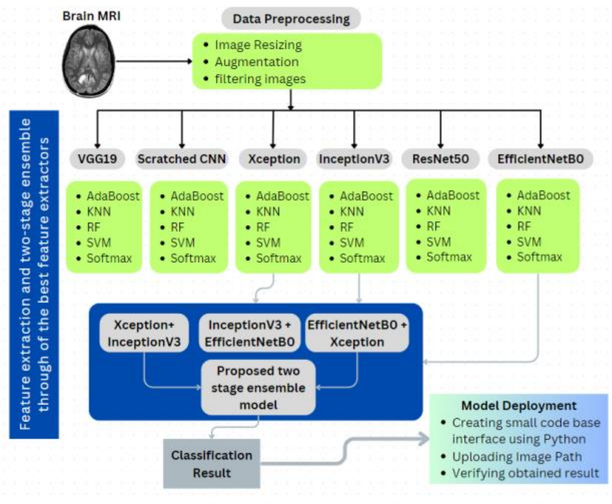


Fig. 5. Flowchart of Ensemble Machine Learning Pipeline for Brain MRI Analysis with Two-Stage Model Deployment

3.11 Classifier

A classifier is a computer model or programmed that classifies incoming data. It predicts new occurrences by learning patterns and characteristics from labelled training data. Machine learning uses classifiers for image identification, sentiment analysis, and spam detection. They map input characteristics to output classes using learnt patterns. Support vector machines, decision trees, and neural networks are classifiers [62].

3.12 Adaboost

Adaptive Boosting (AdaBoost) is a classification and regression ensemble learning technique. The predictions of numerous weak learners (usually basic models, called "weak classifiers") are combined to generate a strong classifier. The approach weights training examples and corrects weak learners' faults in subsequent rounds. Each cycle of boosting trains and evaluates a new weak learner. Misclassified cases gain weight, making them more impactful next iteration. This cycle continues until a certain number of poor learners or a perfect model is attained. AdaBoost is frequently utilized in machine learning applications because it improves weak model accuracy simply and effectively [63]. The sign function (1) and weighted error rate for weak classifier (3) and misclassified samples (2) for Adaboost classifier.

$$H(X) = sign\left(\sum_{t=1}^{T} \alpha_t \,.\, h_t(X)\right) \tag{1}$$

$$D_i^{(t+1)} = \frac{D_i^{(t)}.\exp\left(-\alpha_t.y_i.h_t(X_i)\right)}{Z_t} \tag{2}$$

$$\epsilon_t = \sum_{i=1}^{N} D_i^{(t)}.I\left(y_i \neq h_t(X_i)\right) \tag{3}$$

3.13 Random Forest

Random Forest is an ensemble learning technique that trains several decision trees and outputs the mode (classification) or mean prediction (regression) of the individual trees. Each tree in Random Forest is trained on a random portion of the training data, and each split considers a random sample of characteristics. By majority voting for classification tasks or average for regression tasks, all tree forecasts are combined to make the final prediction [64]. The approach uses randomization in sample selection (bagging) and feature selection during tree construction, improving robustness and generalization. Random Forest is accurate, overfit-resistant, and adaptable to varied datasets [65]. In random forest the most frequently predicted class is voting on (4) and the equation for margin function on (5).

$$f(x) = \arg\max_{y \in \mathcal{Y}} \sum_{j=1}^{J} I\left(y = h_j(x)\right) \tag{4}$$

$$\begin{aligned} mg(X,Y) = {} & av_k I\left(h_k(X) = Y\right) \\ & - \max_{j \neq Y} av_k I\left(h_k(X) = j\right) \end{aligned} \tag{5}$$

3.14 KNN

Machine learning method k-Nearest Neighbors (KNN) is simple and intuitive for classification and regression. KNN labels data points based on the feature space majority class of their k-nearest neighbors [100]. Distance metrics like Euclidean distance are used to measure closeness. KNN is instance-based and non-parametric, therefore it doesn't assume data distribution. It works in many fields, especially when the decision boundary is complicated and non-linear [101]. Five classifier technique - AdaBoost, K-Nearest Neighbors (KNN), Random Forest (RF), Support Vector Machine (SVM), and Softmax Regression were used[102]. The distance between two data points in a feature space, typically using Euclidean distance (6), then majority voting (7) and weighted voting (8) is represented below.

$$Distance\left(X_i, X_j\right) = \sqrt{\sum_{l=1}^{n} \left(X_i^{(l)} - X_j^{(l)}\right)^2} \tag{6}$$

$$y = \arg max_c \sum_{i=1}^{k} \omega_i.I\left(y_i = c\right) \tag{7}$$

$$\omega_i = \frac{1}{Distance(X, X_i)} \tag{8}$$

3.15SVM

SVM is a sophisticated supervised machine learning technique for classification and regression. SVM seeks a feature space hyperplane that maximally separates two classes. SVM maximizes the margin, the distance between the hyperplane and the nearest data point from either class. The equation of the hyperplane is given by f(x)=⟨w,x⟩+b, where w is the weight vector, x is the input vector, and b is the bias term. The optimization problem for SVM involves minimizing 1/2 * ∥w∥^2 subject to the constraint that each data point is on the correct side of the margin. The kernel technique maps input data into a higher-dimensional space for SVM to handle non-linearly separable data. The ultimate forecast is based on tree majority [66].

3.16 Softmax

The Softmax function is essential to machine learning, especially multiclass classification. It converts raw scores or logits into probabilities to help comprehend model predictions. The Softmax function converts input vector z to output vector σ(z), where each element reflects class probability.

$$\sigma(\mathrm{z})_i = \frac{e^{zi}}{\sum_{j=1}^{k} e^{zj}} \quad (9)$$

Here, z is the input vector of raw scores or logits for each class, σ(z)i is the i-th element of the output vector, representing the probability of class i. K is the total number of classes. Softmax gives a probability distribution over several classes for a given input in neural network output layers [67]. It improves model interpretability and utility in multiclass settings.

Regarding learning-based brain MRI analysis, Matplotlib becomes indispensable. Its flexibility empowers researchers to create visually appealing graphics that simplify the communication of neuroimaging data. Medical image analysis researchers can enhance readability and impact by leveraging the capabilities offered by Matplotlib.

4. RESULT

This paper aimed to improve the precision of brain tumor detection using MRI images. Several deep learning models such, as CNN, InceptionV3, Xception, EfficientNetB0, ResNet50 and VGG19 were analyzed. To ensure feature extraction and classification the dataset underwent pre-processing techniques, like Augmentation, Gaussian Blurring and Sobel Edge Detection to optimize the quality of the images. Confusion Matrix:

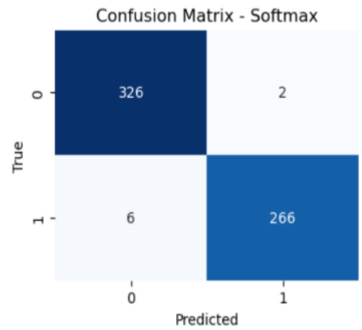


Fig. 1. Confusion Matrix (Softmax)

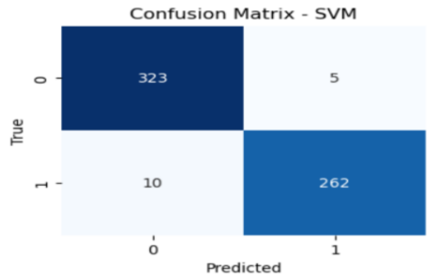


Fig. 7. Confusion Matrix (SVM)

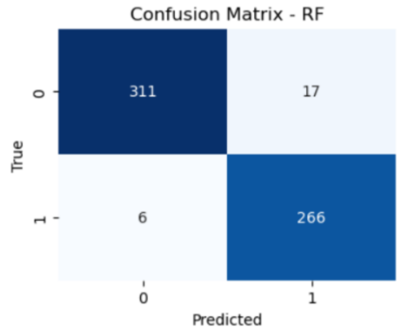


Fig. 8. Confusion Matrix (RF)

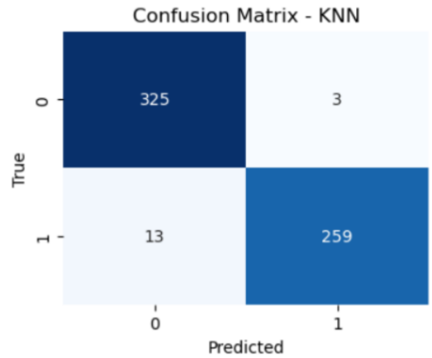


Fig. 9. Confusion Matrix (KNN)

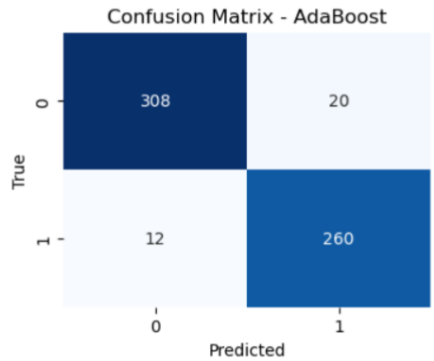


Fig. 10. Confusion Matrix (AdaBoost)

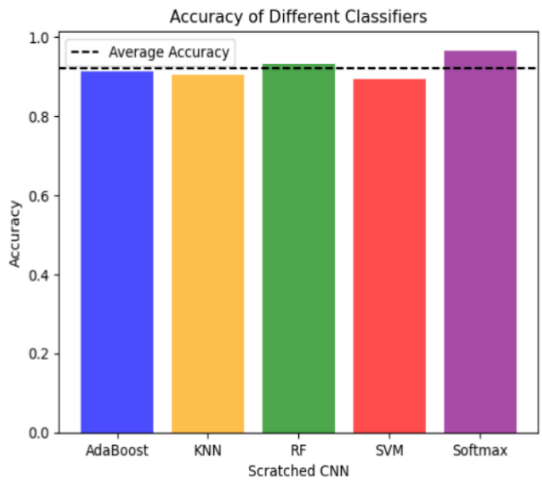


Fig. 11. Scratched CNN

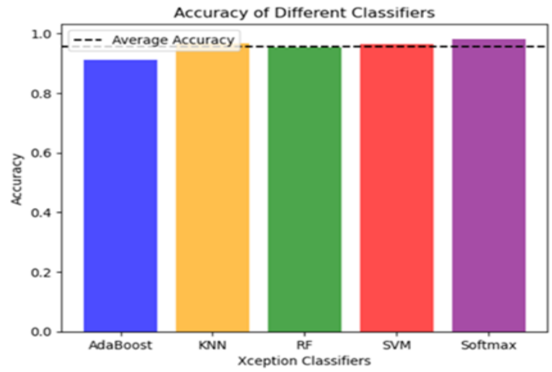


Fig. 12. Xception

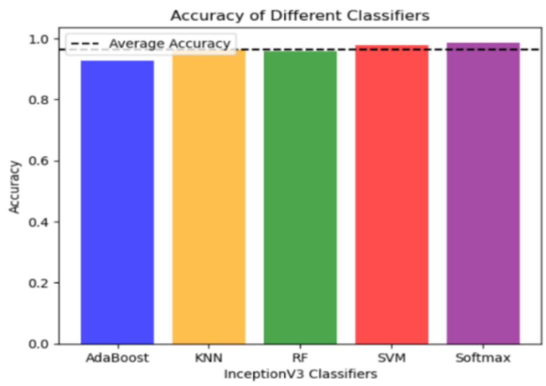


Fig. 13. InceptionV3

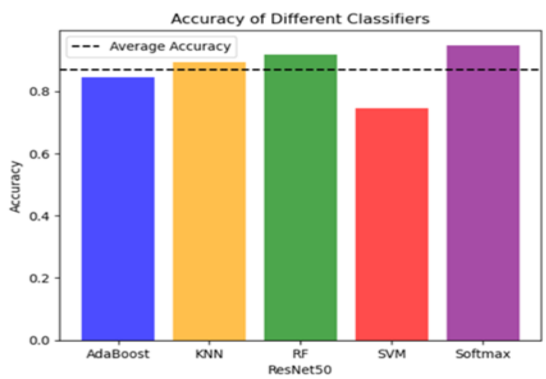


Fig. 14. RestNet50

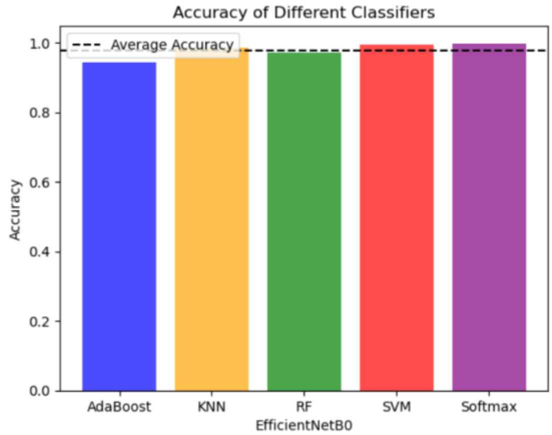


Fig. 15. EfficientNetB0

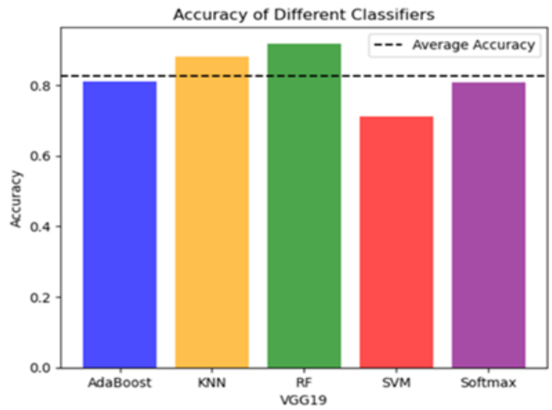


Fig. 16. VGG19

Various machine learning classifiers were used to evaluate the performance of six neural network (CNN) architectures. These architectures included Scratched CNN, Xception, InceptionV3, ResNet50 EfficientNetB0 and VGG19. Among them EfficientNetB0 showcased classification capability with the average accuracy of 97.87% and the lowest average log loss of 0.2571. On the hand ResNet50 demonstrated suboptimal classification performance, with the average accuracy of 87.03% and the highest average log loss of 0.4786. Xception and InceptionV3 performed competitively with accuracies of 95.47% and 96.27% respectively highlighting their effectiveness.

AdaBoost and Random Forest classifiers consistently achieved performance across all CNN architectures analyzed in this study. Support Vector Machines (SVM) and k Nearest Neighbors (KNN), however, showed outcomes in terms of their performance. Regarding log loss, Softmax consistently exhibited performance across all CNN architectures evaluated.

These findings underscore the importance of selecting a CNN architecture and classifier when performing image classification tasks. EfficientNetB0 stood out as the performing model among the models evaluated in this study.

Combining 3 best-performing models with each other: EfficientNetB0 & Xception, InceptionV3 & EfficientNetB0, InceptionV3 & Xception.

Table 1. EfficientNetB0 & Xception

	Accuracy	Loss
AdaBoost	92.33%	62.84%
KNN	97.00%	13.72%
RF	96.33%	18.01%
SVM	95.00%	13.55%
Softmax	98.83%	3.63%
Average	95.90%	22.35%

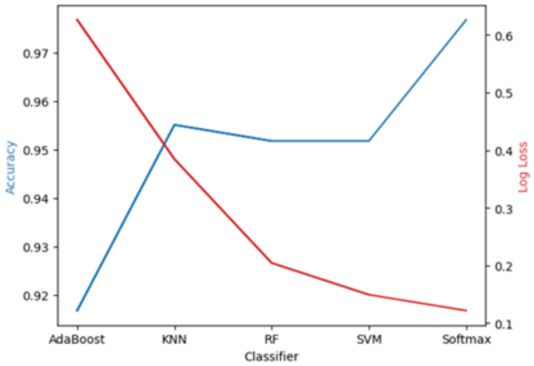


Fig. 17. Average Accuracy and Loss

EfficientNetB0 and Xception were combined for analysis. AdaBoost achieved an accuracy of 92.33% and a log loss of 62.84%. KNN performed better with 97.00% accuracy and a lower log loss of 13.72%. Random Forest and SVM displayed performance reaching, over 95% accuracy with log loss values. Notably Softmax stood out with the accuracy at 98.83% and the lowest log loss of 3.63%. On average the models achieved an accuracy of 95.90% with a log loss of 22.35% indicating high performance and reliable predictions, across different methodologies.

Table 2. EfficientNetB0 & InceptionV3

	Accuracy	Loss
AdaBoost	93.83%	62.51%
KNN	96.33%	30.90%
RF	94.50%	20.84%
SVM	96.00%	9.05%
Softmax	98.67%	5.91%
Average	95.87%	25.84%

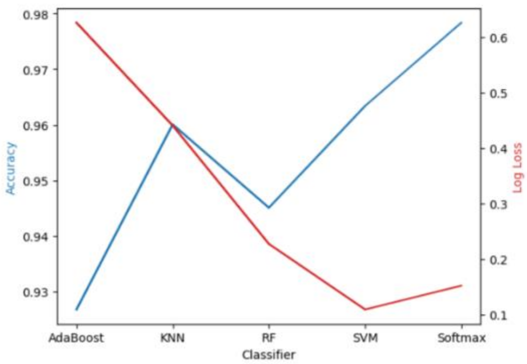


Fig. 18. Average Accuracy and Loss

In combined EfficientNetB0 and InceptionV3 architectures, AdaBoost model achieved an accuracy of 93.83% with a log loss of 62.51%. The KNN, Random Forest, SVM and Softmax models all showed accuracies ranging from 94.50%, to 98.67% with the Softmax model leading the pack. On average across all models achieved an accuracy of 95.87% and a log loss of 25.84%. These results demonstrate that our models performed overall with some models showing exceptional performance that makes them well suited for tasks requiring high predictive accuracy.

Table 3. InceptionV3 & Xception

	Accuracy	Loss
AdaBoost	94.67%	62.18%
KNN	97.33%	17.41%
RF	96.00%	20.49%
SVM	97.50%	5.14%
Softmax	98.83%	4.46%
Average	96.87%	21.94%

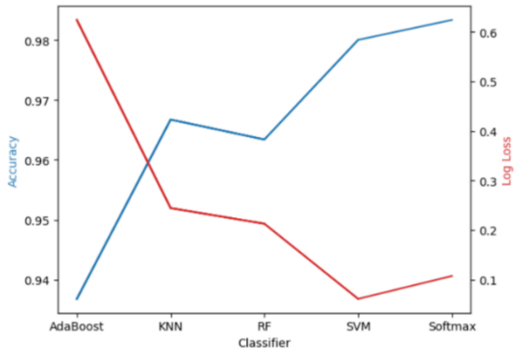


Fig. 19. Average Accuracy and Loss

The combination of InceptionV3 and Xception, in machine learning models produced outcomes. AdaBoost demonstrated accuracy at 94.67% closely followed by KNN and SVM which achieved accuracies above 97%. Softmax performed well with an accuracy of 98.83%. The overall average accuracy of 96.87% and a low average log loss of 21.94% highlight the effectiveness of this architecture, in achieving accuracy and minimizing errors across different tasks.

From these 3 models picking best 2 for final model EfficientNetB0 & Xception and InceptionV3 & EfficientNetB0.

The combination of EfficientNetB0, Xception and InceptionV3, in machine learning models is a blend of deep learning architectures. This group of models has shown performance across classification tasks highlighting its effectiveness in achieving high predictive accuracy and minimizing errors.

AdaBoost, which is one of the methods achieved an accuracy rate of 94.67%. This demonstrates its capability to enhance the performance of learners. Additionally, the low log loss score of 61.89% indicates that it can provide accurate probability estimates with consistency.

Table 4. EfficientNetB0, Xception & InceptionV3

	Accuracy	Loss
AdaBoost	94.67%	61.89%
KNN	97.33%	17.41%
RF	96.33%	17.78%
SVM	97.50%	6.13%
Softmax	98.67%	4.46%
Average	96.90%	21.53%

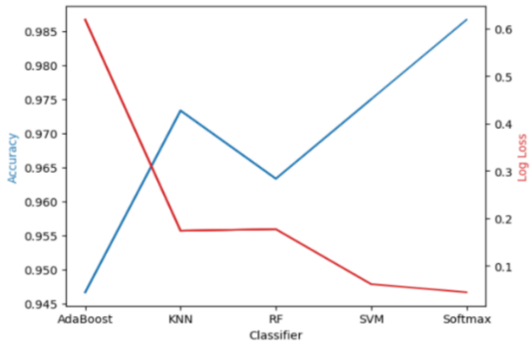


Fig. 20. Average Accuracy and Loss

K Nearest Neighbors (KNN) displayed an accuracy rate of 97.33% indicating its proficiency in classifying data points based on their proximity in feature space. The corresponding log loss score of 17.41% suggests that KNN provides calibrated probability estimates.

Random Forest (RF) a method achieved a strong accuracy rate of 96.33%. Its log loss score of 17.78% indicates reliable probability estimation abilities making it a dependable choice for classification tasks.

Support Vector Machine (SVM) exhibited an accuracy rate of 97.50%. With a log loss score, as 6.13% SVM not only demonstrates accurate classification but also provides calibrated probability scores effectively.

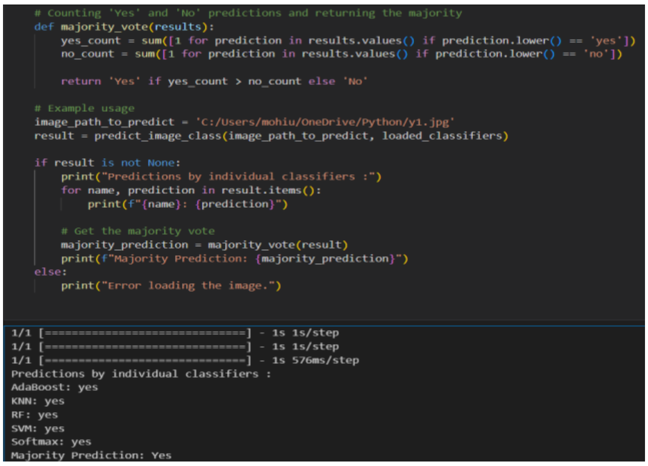
Softmax, a learning technique achieved an impressive accuracy rate of 98.67% and demonstrated a remarkably low log loss of 4.44%. This clearly emphasizes the capability of networks to capture intricate patterns, within data.

Ensemble methods have been utilized to combine the abilities of EfficientNetB0, Xception and InceptionV3 models. This combination has resulted in a performance that accurately reflects the capabilities of classifiers. The final accuracy metric, for this approach stands impressively at 96.90% highlighting the effectiveness of merging models to enhance accuracy.

Create a code base interface where the path to an MRI image was provided. The ensemble model effectively made predictions for image classifications by utilizing three pretrained neural networks; InceptionV3, EfficientNetB0 and Xception. The final prediction, for an image was determined by taking a majority vote from these classifiers ensuring a dependable method of classification.

It is worth noting that there can be conflicting outputs among classifiers when analyzing an MRI image, which can pose challenges to achieving predictive accuracy.

Despite these obstacles the ensemble model offers an approach towards achieving accuracy in identifying brain tumours in MRI images.



```
# Counting 'Yes' and 'No' predictions and returning the majority
def majority_vote(results):
    yes_count = sum([1 for prediction in results.values() if prediction.lower() == 'yes'])
    no_count = sum([1 for prediction in results.values() if prediction.lower() == 'no'])

    return 'Yes' if yes_count > no_count else 'No'

# Example usage
image_path_to_predict = 'C:/Users/mohiu/OneDrive/Python/y1.jpg'
result = predict_image_class(image_path_to_predict, loaded_classifiers)

if result is not None:
    print("Predictions by individual classifiers :")
    for name, prediction in result.items():
        print(f"{name}: {prediction}")

    # Get the majority vote
    majority_prediction = majority_vote(result)
    print(f"Majority Prediction: {majority_prediction}")
else:
    print("Error loading the image.")
```

```
1/1 [==============================] - 1s 1s/step
1/1 [==============================] - 1s 1s/step
1/1 [==============================] - 1s 576ms/step
Predictions by individual classifiers :
AdaBoost: yes
KNN: yes
RF: yes
SVM: yes
Softmax: yes
Majority Prediction: Yes
```

Fig. 21. Code base Interface

These results affirm that deep learning techniques advanced CNN architectures and ensemble methods play a role in improving healthcare outcomes for individuals suspected of having brain tumours.

This outcome demonstrates the effectiveness of learning models in detecting brain tumours. The high rates of accuracy attained by these models suggest their potential for applications. Further validation and refinement are necessary to ensure performance in real-world scenarios. This research contributes insights into the application of AI, in diagnostics specifically within the critical field of brain tumour detection.

5. DISCUSSIONS

This study used image processing techniques with MRI images, which are a unique method for detecting brain tumours. Here, the filtering identifies the brain tumour part after removing the noise from the image. Here, the Softmax, SVM, RF, KNN, and AdaBoost classifiers were used. Here are six types of models such as: CNN, InceptionV3, Xception, EfficientNetB0, ResNet50, and VGG19. Among these models, EfficientNetB0, Xception, and InceptionV3 have good accuracy, which has better performance and accuracy compared to other models. The combined accuracy is 96.9%. Also, good results were obtained by using an image.

5.1 Limitations

Considering the work done here and the good results, some limitations should be mentioned and acknowledged.

5.2 Limited Dataset Size

A small data set can be used for the study. For which it is possible to bring better results. Using larger data sets can sometimes lead to errors. For which saturated results are not available. If the use of a small dataset has courage, it can bring accurate results

5.3 Tumour-type Scope

Studies may focus on a specific subset of brain tumour types, which may contribute to and limit the results. Moreover, the brain tumour image size can be better and clearer, so it is possible to get better results. In addition, some other techniques may improve utility by including different tumour types.

5.4 Limited Clinical Validity

This procedure requires examining patients to see if they have a brain tumor. It is never possible to say exactly without testing. It would involve doctors and patients, and it would have to be used by people in hospitals to look for brain tumors. It must be checked whether it is safe. It's not enough for it to work well in the lab, it has to work properly when the doctor and patient use it. This new method is good enough for doctors to use in hospitals to help people with brain tumors.

5.5 Limited Comparison with Existing Method

Despite significant reliance on this approach, the use here may not directly correspond to other modern approaches. By comparing it with other previously proven techniques, a corresponding idea can be obtained, and efficiency can be measured.

5.6 Limited Clinical Validation

The issues that are mentioned in this paper and the computational and hardware requirements may not be included in the study. The deployment and real-time implementation of such systems here may be hampered by resource or computational limitations.

6. CONCLUSION

Brain tumours can be very scary and deadly, and it can lead to cancer in the long run. In this research, convolutional neural network (CNN) models accurately classify brain tumor detection using MRI images. There are six types of models. Such as CNN, InceptionV3, Xception, EfficientNetB0, ResNet50, and VGG19—in detecting brain tumours through MRI analysis. EfficientNetB0, Xception, and InceptionV3 have had better accuracy after combining them. Support Vector Machines (SVM), K-Nearest Neighbours (KNN), Softmax, Random Forest (RF), and AdaBoost, all of which create a new model using classification. Their final accuracy came to 96.9%. and reflected the accuracy of an ensemble classifier. Tried to get as much accuracy as possible.

However, this is highlighted by the conflicting output between classifiers for a single MRI image. Despite the predictive challenges, this model makes it easy to detect the presence of brain tumors in images. The models used here demonstrate promising accuracy rates and warrant further validation and refinement to ensure reliable performance. These machine-learning techniques are critical to improving healthcare outcomes for brain tumour diagnosis and patient care.

6.1 Future Works

In the future, Here will increase the accuracy of our models and aim to enhance them by using more advanced methods. The dataset is used from this source. Also, can also increase our dataset and add more images from here. Which identifies the better results. This research uses the models to ensure user-friendliness and ease in obtaining accuracy metrics. The use of these models can significantly benefit healthcare practitioners for brain tumors from MRI scans. Future developments will improve the user interface to make model deployment and clinicians easy access to precise predictions. In the future also work on Alexnet, Vgg-16, MobileNet, DenseNet121, EfficientNetB7, etc. If these models are well used, then it can get good results in the future. Also, work on more classifiers in this paper. Like Gradient Boosting Machines (GBM), Naive Bayes Classifiers, Decision Trees, Neural Networks, Logistic Regression, and Ensemble Techniques. Future work may focus on improving the algorithms for greater accuracy and performance, to improve results. Doctors should be able to easily detect brain tumours. Moreover, also can also work on the issue that patients do not have any kind of problems or dilemmas. Also, various parameters will be used, such as accuracy, specificity, time, efficiency, and many more. An automated system needs to be introduced that can detect the tumour at an early stage so that a better treatment plan can be made.

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