**Introduction:**

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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 [35]. 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 [36]. 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 [33]. Its ability to autonomously learn patterns from datasets has paved the way for groundbreaking developments across various fields, including medical image analysis [34]. In brain tumour detection, deep learning is promising in improving accuracy, speed and consistency.

* **Medical Images:**

Medical imaging holds significant importance in assessing and managing diverse health conditions [9]. 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 tumors, with amazing precision [10]. 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. 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 [11]. The development of Functional MRI (fMRI) significantly advances our understanding of the brain's dynamic activities, allowing doctors to correlate structural abnormalities, such as tumors, 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.

* **Motivation:**

Primary brain or spinal cord tumors arise in these tissues. Primary malignant brain and spinal cord tumors will affect 24,810 Americans (10,530 women and 14,280 men) in 2023. This kind of tumor is rare, less than 1%. Brain tumors account for 85%–90% of first CNS malignancies. Worldwide, 308,102 instances of primary brain or spinal cord tumors were expected in 2020. [1]

US CNS tumor diagnoses in children under 20 are expected to reach 5,230 in 2023. The rest of this manual covers’ adult primary brain tumors. 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 tumors 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.[1]

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 tumor survival rates every five years. [1]

About 120 types of brain tumors affect different brain tissues. Benign or noncancerous brain tumors might be dangerous owing to their size or location. Brain and nerve cancers affect 30 per 100,000 Americans. Brain tumors damage healthy brain tissue by pressing on or spreading into it. Certain brain tumors 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.[2]

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 rates. [3]

In Bangladesh, according to research by Sarkar et al. (2021), Treatment of brain tumors 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. [4]

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

Early detection and therapy are crucial for the cure of brain tumors. Risky, untreated brain tumors raise healthcare expenses and suffering. However, early discovery and proper therapy may improve brain cancer. Early brain tumor 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.

* **Objective**:

The final sub-goal is to provide a rationale for our method selection from a broad range of options, detailing their functionality and our development process.

**Sub-Objective 1:** To collect a suitable dataset of brain tumor images, then enhancing the image clarity and characteristics through various augmentation and filtering techniques.

**Sub-Objective 2:** To process the gathered data, training it with chosen Convolutional Neural Network models, and categorizing them using specific classifiers. This approach is crafted to be both efficient and effective.

**Sub-Objective 3:** To develop a model capable of detecting brain tumors from imaging data, focusing on enhancing the model's precision.

* **Orientation:**

**Literature Review**

In this thesis paper, brain tumor detection and classification have been developed using CNN, Xception, InceptionV3, ResNet50, EfficientNetB0, and VGG19. So many researchers and doctors work on it to improve brain tumor detection Using deep learning, artificial intelligence, image processing, and so many others. In this paper, they use Convolutional Neural Network (CNN), Xception, InceptionV3, ResNet50, EddicientNetB0, and VGG19. Researchers have found new ways and algorithms to improve the accuracy of brain tumor detection.

Hafiz Muhammad Tayyab Khushi et al., deep learning models include InceptionV3, Resnet50, and VGG19. ResNet50 achieved the highest validation accuracy of 89.45%, with a validation loss of 0.28. The InceptionV3 model achieved a validated accuracy of 76.33%. EfficientNetB7 model state-of-the-art model accuracy is 98.97%. That demonstrates excellent performance. [30]

Muhammed Celik el al., explained the classification of brain tumors using MRI imaging and deep learning. They achieved 97.15% mean classification accuracy and 97% recall using CNN and the proposed hybrid model. The pre-trained models used were VGG19, EfficientNetB0, InceptionV3, ResNet50, and Xception. Most of the ResNet accuracy was 96%, and The accuracy of the proposed Generic CNN model was 81.05 % Das et al. (2019) [31]

Ahmeed Suliman Farhan el al., introduced brain tumor 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 pre-trained Inceptionv3 model extracts features from the different Inception modules, which are passed to a softmax to diagnose the brain tumor. Total accuracy was 94.77% for a fast table. And the second table's accuracy was 97.1%. [32]

Ranit Sen et al., proposed a novel approach for datasets and categories of brain tumors and also employed state of the art CNN like architectures, like EfficientNetB0, ResNet50, Xception, MobileNetV2, and VGG16, using transfer learning to detect and classify three types of brain tumors. The MRI images across 4 classes and image enhancement methods. The EfficientNetB0 architecture performed the best, giving 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 tumor types. [33]

R. Tamilarasi proposed delves into brain tumor highlight and detection to improve patients' quality of life. There are used two models to achieve high accuracy in brain tumor classification. One identifying tumor accuracy of 98.6% and another pituitary tumor accuracy of 98%. The proposed CNN models are used ResNet-50, Inceptionv3. Overall Multi-Classification accuracy was 98%. [34]

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 tumor detection and 98% in tumor Classification. This includes custom CNN models, VGG, ResNet, and EfficientNet. CNN-based deep learning techniques were published on PubMed and Scopus in the years from 2015 to June 2022. At last, it reaches a remarkable accuracy of 98%. [35]

Saif Ahamad et al., seven transfer learning methods, such as VGG-19, ResNet50, InceptionResNetV2, InceptionV3, and Xception. For instance, VGG19-SVM achieved a height accuracy of 99.39%, That is the height classification accuracy. On the other hand, InceptionV3-Decision Tree shows the lowest accuracy score of 75.67%. The section covers the dataset data augmentation, description, image pre-processing, and CNN models [36]

Naeem Ullah proposed the critical need for timely detection of brain tumors. To identify and classify three major brain tumor types glioma, meningioma, and pituitary. In this classifications are evaluated including Inceptionv3, Xception, and Resnet50. The Accuracy of Inceptionv3, Resnet50, Xception are 94.48%, 67.03% and 98.37%. The time limit is too high. And resnet50 accuracy was not good. [37]

Md Ishtyaq Mahmud et al., application of AI, specifically deep learning algorithm. This thesis paper used the dataset of 3264 MR images with 80% of the data used and 20% for testing. Identify brain tumors using CNN architectures, also against established models like CNN, ResNet-50, and Inception V3. The CNN model accuracy of 93.3% AUC of 98.43%, recall of 91.19%, and less than 0.25. Using Deep learning models’ performance on brain tumor detection modes are CNN, ResNet-50, and Inception V3 accuracy are 93.30%, 81.10%, and 80.00%. [38

Ahmad Osman proposed highlights the importance of early and easy brain tumor detection and mortality rates impact. 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 stressing and healthcare both their potential benefits. [39]

Muhammad Naeem Tahir extensively explores various classifications for MRI brain tumor photo analysis using classifications such as SOM, KNN SVM, and others. Focusing on brain tumor MRI images for tumor diagnosis, the study aims to extract and select features (texture, color, tumor region, location, and edge) from images. Pre-processing includes segmentation and image filtering, and post-processing includes resizing, classification, and tumor area calculation using DNN. Achieving 90% classification accuracy using DNN is possible and has revealed the efficiency of the algorithm. [40]

Anjaneya Teja Sarma Kalvakolanu et al., focus on non-invasive brain tumors 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 tumor 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. Used ResNet50 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 tumor classification. [41]

Feature extraction from MRI images means picking out important information, such as unique patterns that indicate brain tumors. Classification is the process of sorting patterns into categories – identifying whether this is a tumor 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 tumors were better at being identified accurately and with fewer errors. The way these subjects are selected and combined works very well in finding brain tumors from MRI images.

The datasets are used to teach computers about brain tumors 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 tumor, 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 tumor detection. By examining different types of datasets and metrics, we can understand which classifiers performed better in correctly classifying brain tumors. 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 tumors for which otherwise complex MRI data can be interpreted. Future directions involve different models to handle different tumors 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 tumors. Collaborative efforts between medical experts and AI researchers can address this situation and advance the accuracy and reliability of brain tumor detection using MRI.

The literature review summarised has explored the Six CNN models, Xception, InceptionV3, ResNet50, EfficientNetB0, and VGG19, in brain tumor 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 come well. The three models incorporate combined 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.

**Method:**

* **Dataset:**

The dataset, Br35H (2020), is specifically designed for brain tumor localization. Accurate identification and categorization of brain tumors, which are severe conditions that impact individuals of all ages, are essential for appropriate medical therapies.[1] Brain tumours account for a vast majority, around 85 to 90 percent, 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 tumors, 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.[1]

[1] <https://www.kaggle.com/datasets/ahmedhamada0/brain-tumor-detection?select=no>

* **Data Preprocessing:**

The datasets undergo just a minimal amount of preparation, which consists of picture augmentation and scaling.[2] 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. The act of scaling an image is a frequent preprocessing procedure, particularly when dealing with convolutional neural networks (CNNs) or other deep learning models.[2] 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.[1] 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.[1]

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[1] https://machinelearningmastery.com/how-to-control-the-speed-and-stability-of-training-neural-networks-with-gradient-descent-batch-size/

* **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 [1]. 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 [2]. 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 [3].

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 [10], Xception [9], InceptionV3 [7], ResNet50 [8], EfficientNetB0 [4], and VGG19 [6] 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. [10]

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* **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 [1]. 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 [2]. 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 [3].

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.

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* **Xception:**

Xception convolutional neural network (CNN) architecture dominates deep learning for brain MRI processing (Chollet et al., 2017) [1]. A 2017 extension to Inception, Xception, uses depth-wise separable convolutions to separate cross-channel and spatial correlations [1]. This unique approach reduces parameter count and enhances feature extraction, boosting computation efficiency without reducing predictive performance.

In this code, the Xception deep learning model and conventional machine learning classifiers classify brain MRI images. MRI brain pictures are preprocessed 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. [2] 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. [3]. Prasoon et al. [4] segmented knee cartilage using Xception, demonstrating its deep feature learning in numerous anatomical circumstances. Brain MRI interpretation is difficult; thus, adaptation is crucial.

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**Tools and Libraries Used**

* **TensorFlow**

Deep learning for brain MRI processing requires TensorFlow, an open-source framework. Flexible library (2) enables neural networks and deep learning (3). TensorFlow built advanced brain MRI image segmentation, sickness classification, and picture-generating solutions (4). Due to its adaptability, community support, and hardware accelerator interoperability, TensorFlow is vital for brain disease deep learning research (6).

A large ecosystem of tools and extensions makes TensorFlow useful for brain MRI research (9). TensorFlow's integration with Keras (10) expedites neural network design (11) and prototype (12). Data preparation, model training, deployment, and monitoring in brain MRI deep learning applications are repeatable and scalable with TensorFlow Extended (TFX) (13) (14). Researchers can process giant brain MRI datasets with TensorFlow's GPU and TPU compatibility (15). Brain MRI analysis has significantly increased since TensorFlow lets researchers explore new deep learning algorithms and accelerates data preparation and model deployment (16).

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* **Kaggle**

Kaggle, a known community for data science and machine learning (1), proves to be valuable for researchers working on brain MRI analysis using deep learning techniques. With its collection of available datasets and competitive machine learning challenges Kaggle provides ample support for data driven research in processing brain MRI scans (2). Researchers can leverage a range of neuroimaging datasets from modalities and clinical scenarios to develop and validate deep learning models for tasks such as image segmentation, disease diagnosis and treatment planning (3).

The collaborative nature of Kaggle fosters exchanges among data scientists machine learning practitioners and domain experts. This platform encourages the sharing of insights, code snippets and experiences leading to strategies in learning applied to brain MRI analysis (4). Thanks to Kaggle’s user interface and efficient tools for model evaluation and comparison the scientific community enjoys model development processes, with improved assessment capabilities (5).

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* **Scikit-Learn**

The analysis of NeuroMRI using learning has made progress thanks to Scikit Learn (1) a well-known machine learning library. This Python package, which is source provides tools, for data preprocessing feature extraction, model selection and assessment in the field of machine learning. Researchers working with brain MRI data benefit from Scikit Learns image segmentation, classification and regression algorithms. Its interface is user friendly and well documented enabling researchers to experiment with machine learning models and conduct learning on brain MRI datasets.

Scikit Learns adaptability has played a role in the development of interpretable deep learning models for analyzing brain MRI data. It offers an ecosystem for creating deep learning pipelines by integrating with other libraries such as NumPy, SciPy and Matplotlib. Moreover, it also supports network architectures like TensorFlow and PyTorch. As a result Scikit Learn has become a tool for researchers who employ learning techniques to gain insights, into brain related diseases through MRI scans(3).

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* **OpenCV**

OpenCV, a used library and toolkit, for computer vision plays a role in deep learning research focused on brain MRI. With its functions and methods OpenCV simplifies tasks such as preprocessing feature extraction and image manipulation. These steps are vital in preparing MRI data for learning models (1). Researchers have successfully employed OpenCV to address challenges related to image registration, noise reduction and the extraction of structures from brain MRI data. Thanks to its user interfaces and compatibility with programming languages OpenCV proves adaptable for both researchers and practitioners (2).

In the realm of learning analysis for brain MRI OpenCV is indispensable as it enables researchers to diversify their training datasets through data augmentation techniques (3). By leveraging OpenCVs transformations brightness adjustments and noise injection on MRI data researchers can enhance training effectiveness. Promote better generalization of deep neural networks (4). Data augmentation helps reduce overfitting issues while ensuring that deep learning models trained on brain MRI perform in real world scenarios (5).

Given its versatility feature set and support for programming languages; OpenCV is an essential tool for analyzing brain MRI with deep learning techniques (6). Through its utilization, in data preprocessing, augmentation procedures and image manipulation tasks; neuroimaging researchers and medical professionals can leverage the power of learning to accurately analyze brain MRI scans efficiently (7).

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* **NumPy**

The NumPy package, a part of the Python ecosystem plays a role, in analyzing brain MRI using deep learning techniques. Known as Numerical Python NumPy is an library that allows researchers and practitioners to effectively handle multidimensional arrays and matrices. It also offers mathematical functions for performing array operations. By combining operations with data manipulation capabilities NumPy empowers researchers and practitioners to preprocess, analyze and modify MRI data within the learning pipeline.

When it comes to brain MRI analysis NumPy proves invaluable for tasks such as normalization, scaling and transformation. These operations prepare the input data for learning models. Moreover, NumPy seamlessly integrates with deep learning frameworks like TensorFlow and PyTorch simplifying data preparation well as model training and evaluation processes. Researchers heavily rely on NumPys robust linear algebra capabilities and statistical calculations to extract features from brain MRI datasets and gain insights. The ability of NumPy to handle data manipulation along with its prowess makes it an essential tool for learning based brain MRI analysis (1).

Scientists and machine learning enthusiasts have an affinity towards NumPy due to its versatility, performance and extensive documentation. The simple syntax of the language coupled with its array operations makes it particularly attractive for brain MRI researchers dealing with image collections. Moreover, being an open-source library promotes cooperation and simplifies the sharing of code within the community as a whole. The collaborative nature of this environment resulted in creating a system that includes customised tools and procedures designed particularly for analysing MRI data (2).

When it comes to analyzing brain MRIs using learning techniques NumPy is indispensable in enabling data manipulation along, with advanced mathematical operations.

With its abilities to manipulate data and perform operations along, with its seamless integration into well-known deep learning frameworks NumPy plays a crucial role as a valuable research tool in this domain. As scientists continue to make advancements in MRI based diagnosis and treatment NumPy continues to serve as a tool, for data preprocessing, analysis and extracting meaningful features (3).

References:

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* **Joblib**

Joblib, a used Python package provides a solution, for computationally demanding tasks. It proves valuable when working with learning models. The Scikit learn ecosystem [1] makes use of Joblib to parallelize and cache Python routines. This feature greatly assists researchers and practitioners, in managing memory and computational resources [2]. With Joblib experts can easily serialize Python objects allowing them to store and retrieve machine learning models and data [3]. The integration of learning within this library significantly enhances the speed and reproducibility of brain magnetic resonance imaging research.

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* **Matplotlib**

Matplotlib, a used Python tool, enables the creation of high-quality data visualizations, including brain MRI patterns. This program offers users a user interface to create static, animated and interactive graphs and plots. Deep learning and neuroimaging researchers rely on Matplotlib to visually represent their findings, making it easier to understand the architecture and patterns of MRI brain scans.

One of the reasons Matplotlib is highly regarded is its versatility in customizing plot visuals and properties [1]. Researchers have the flexibility to adjust colors, line styles, markers and annotations in their visualizations to depict their results and meet publishing requirements accurately. Additionally, Matplotlib seamlessly integrates with deep learning frameworks like NumPy and Pandas to visualise numerical data.

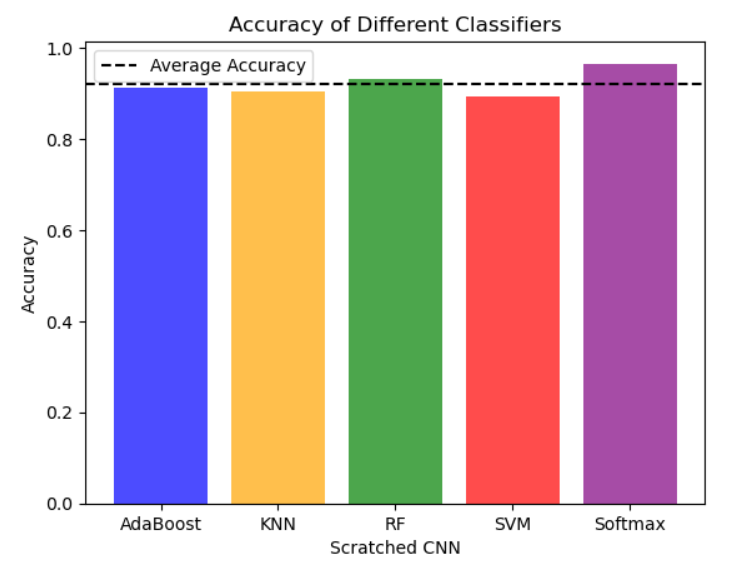
Regarding learning-based brain MRI analysis [1], Matplotlib becomes indispensable. Its flexibility empowers researchers to create visually appealing graphics that simplify the communication of neuroimaging data. Medical image analysis researchers can enhance readability and impact by leveraging the capabilities offered by Matplotlib.

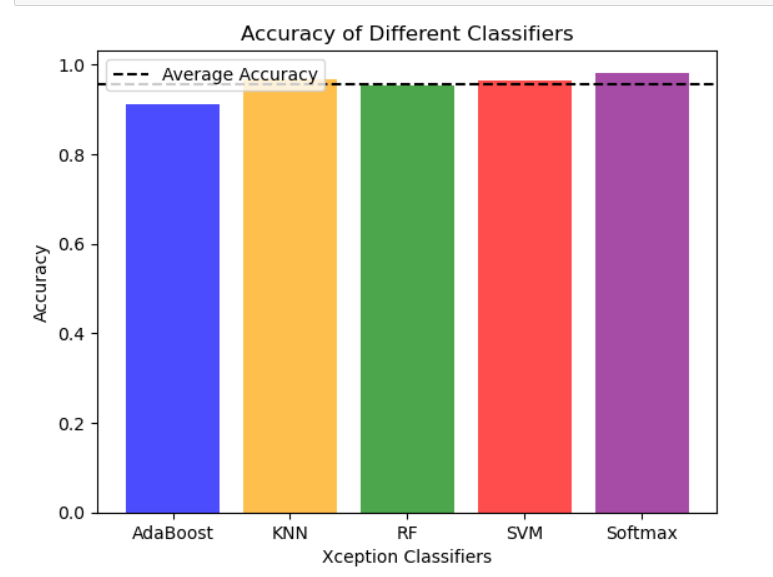
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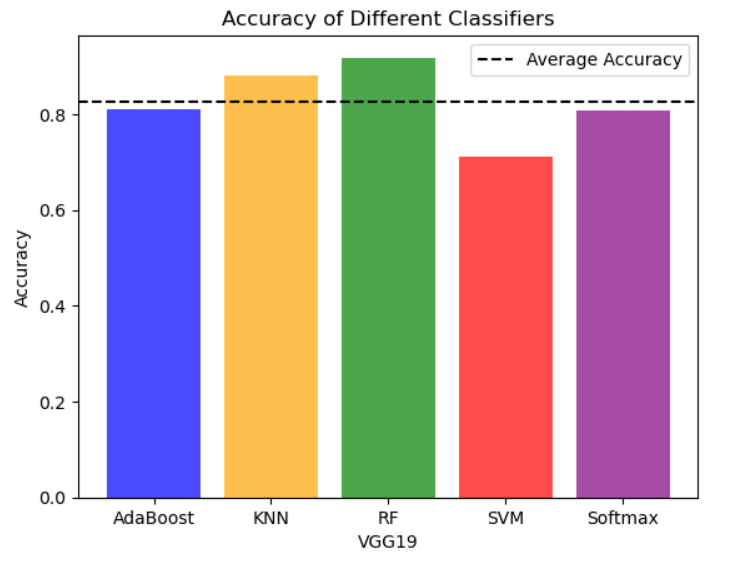
[1] Matplotlib, https://matplotlib.org/, Accessed: [Date].

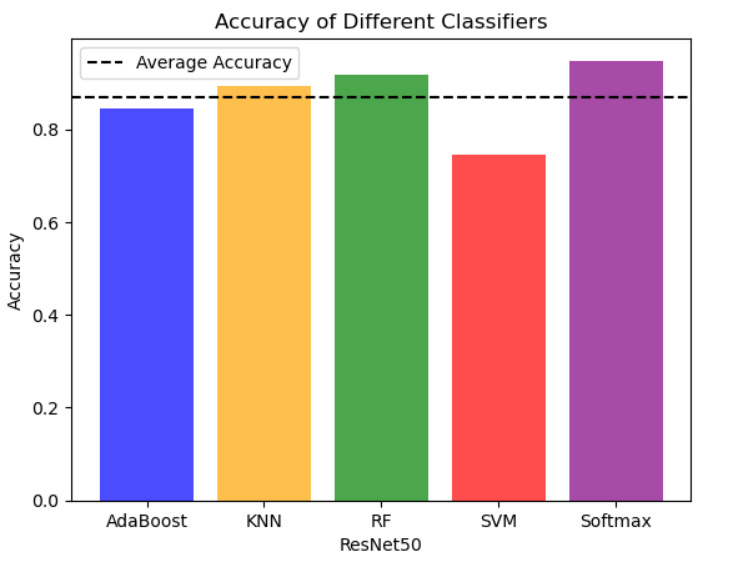
**Results:**

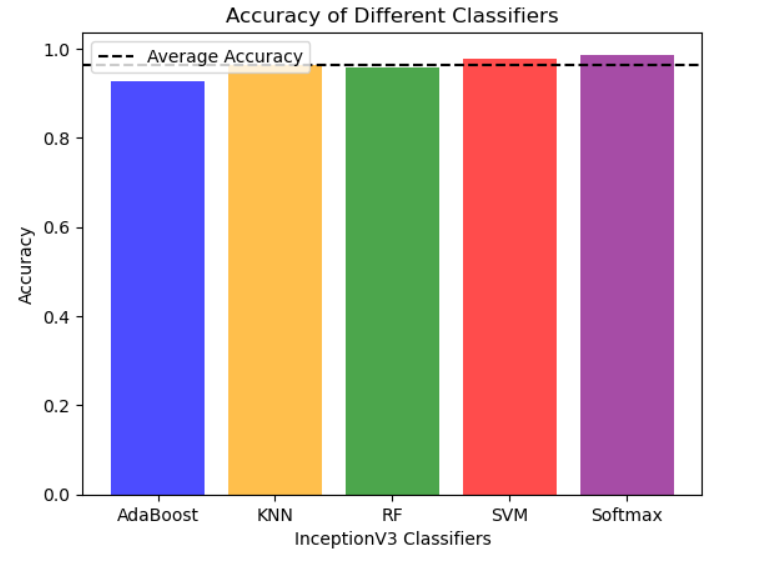
All Feature Extractions & Classifiers Accuracy:

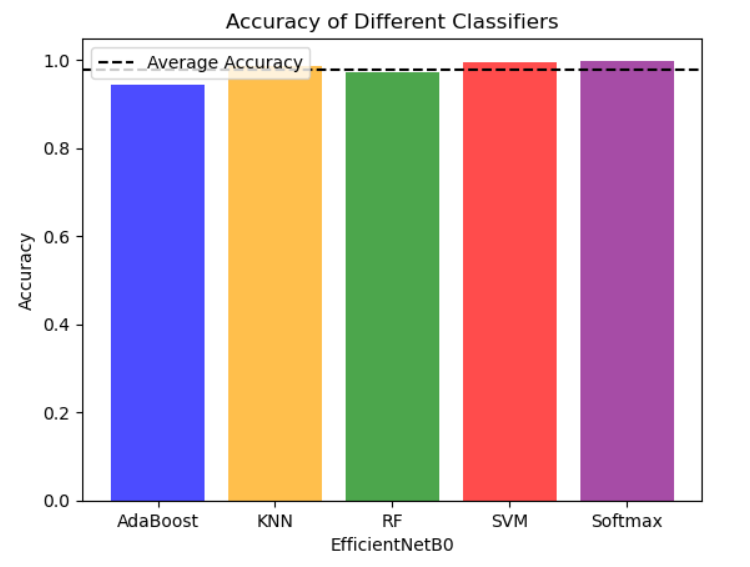


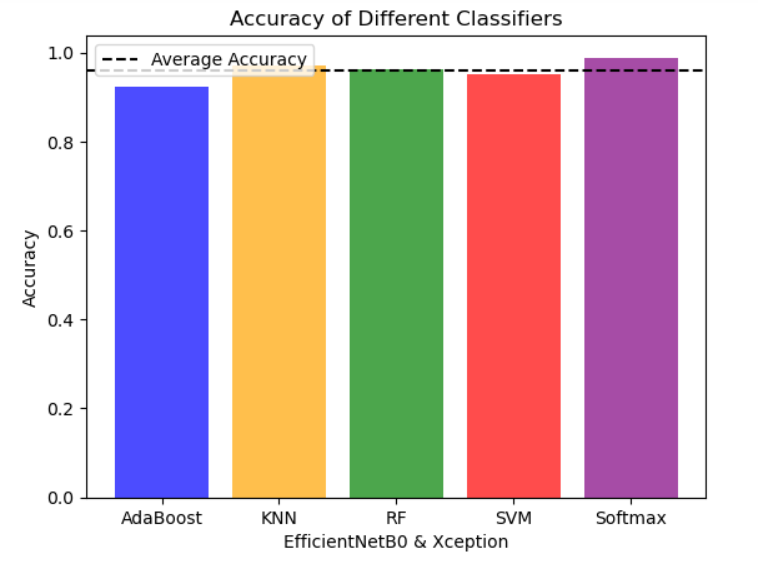


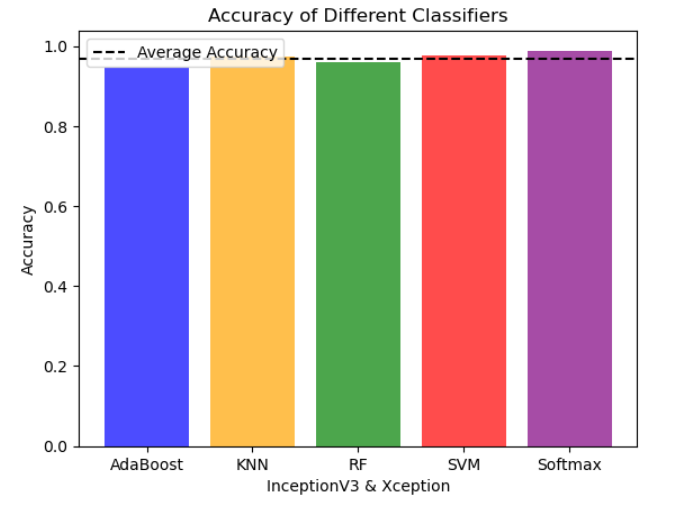


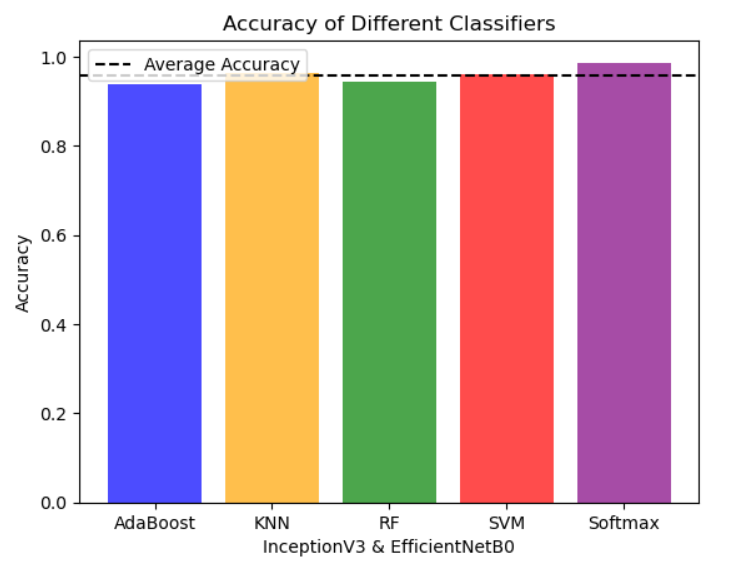


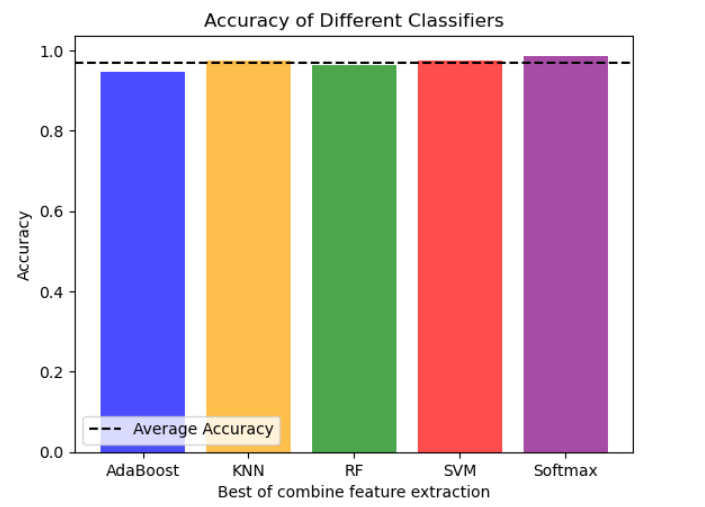




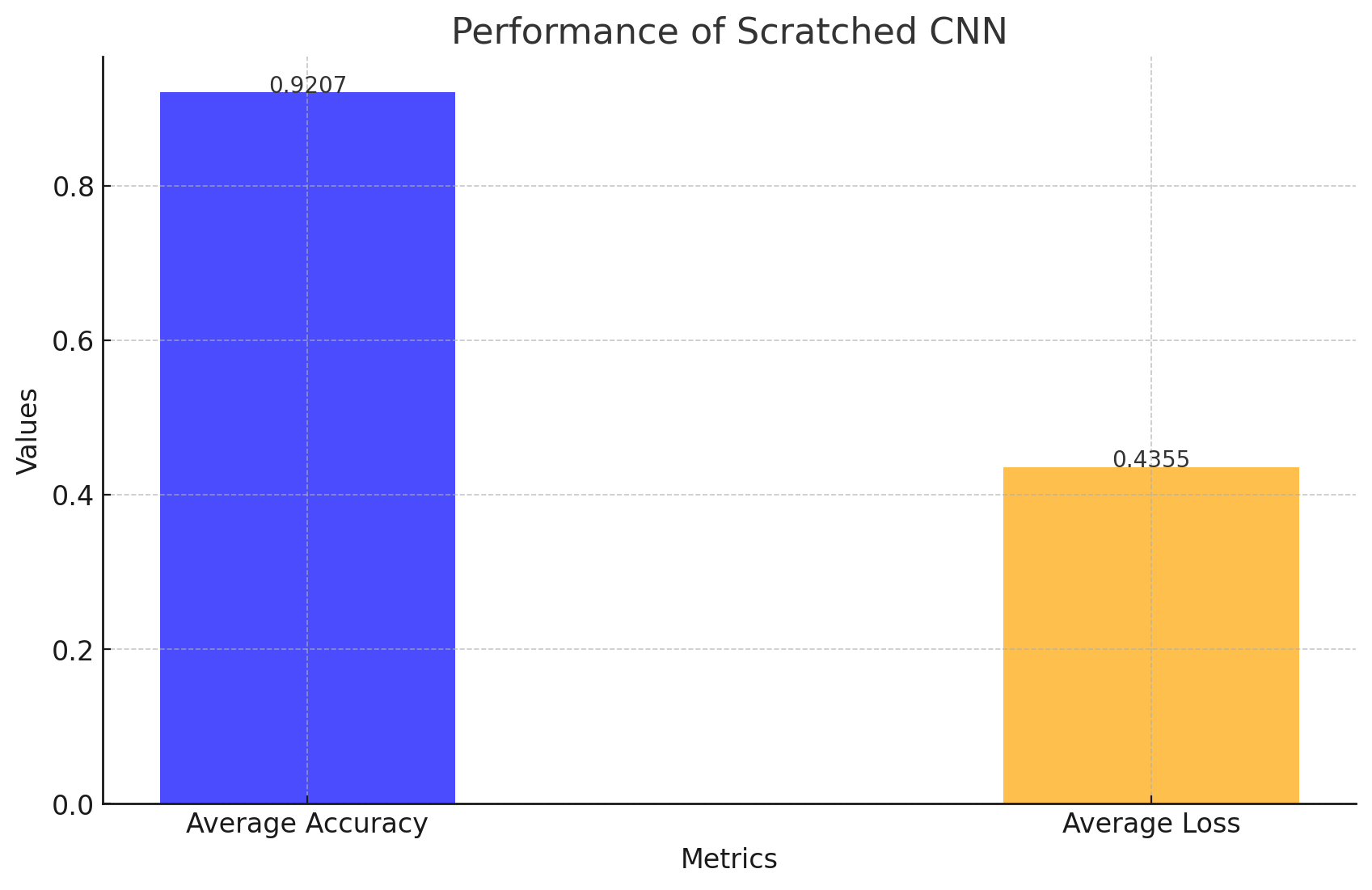


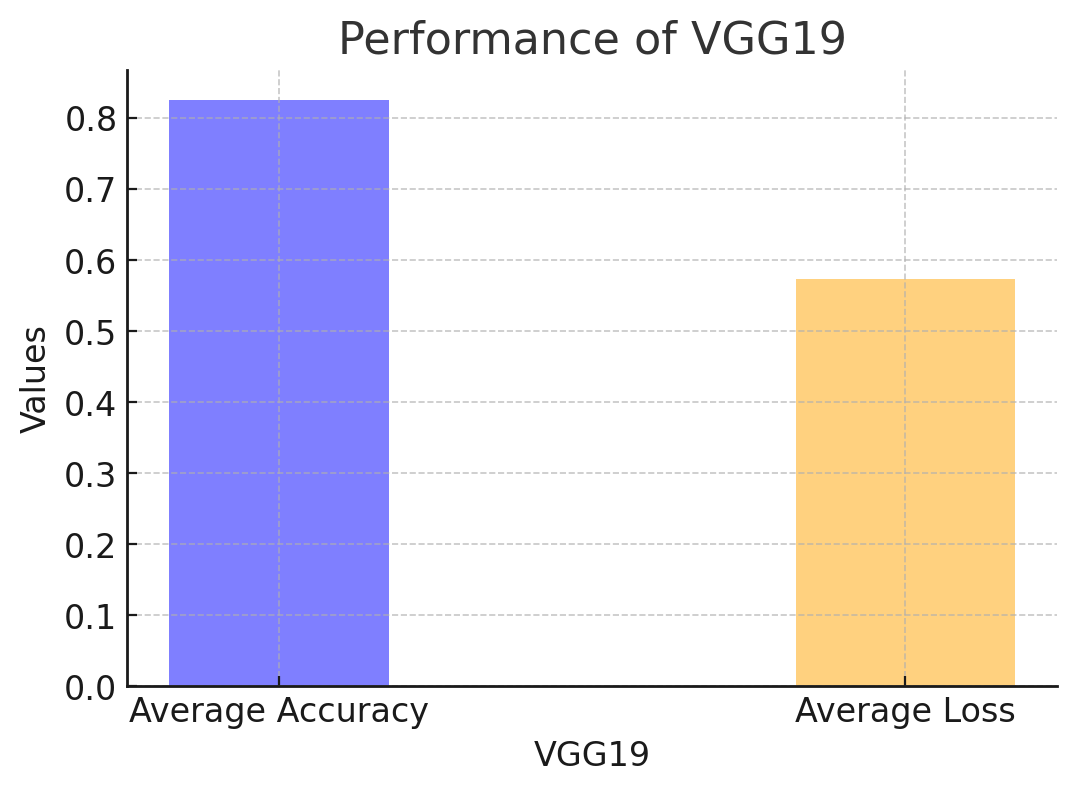


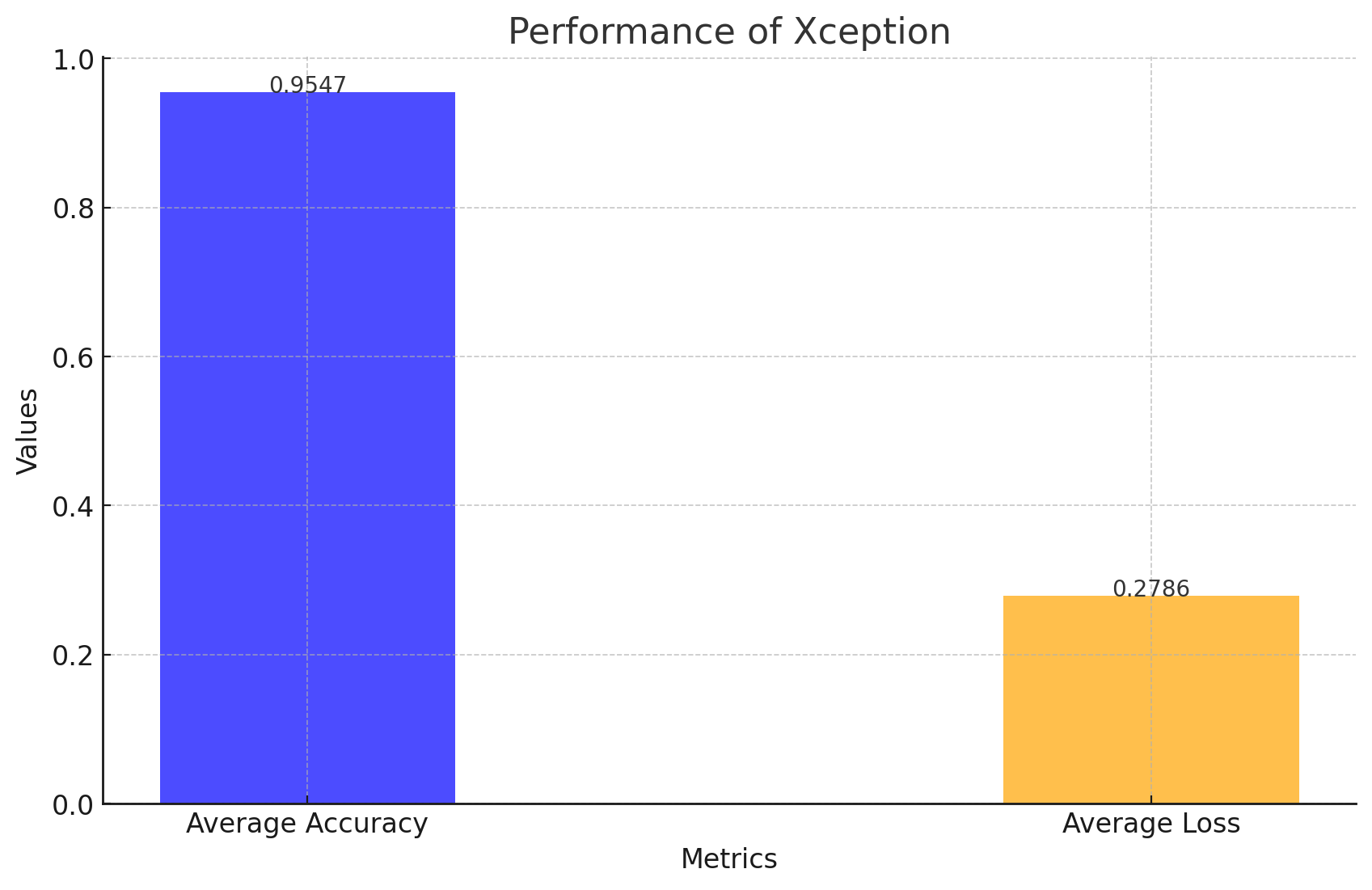


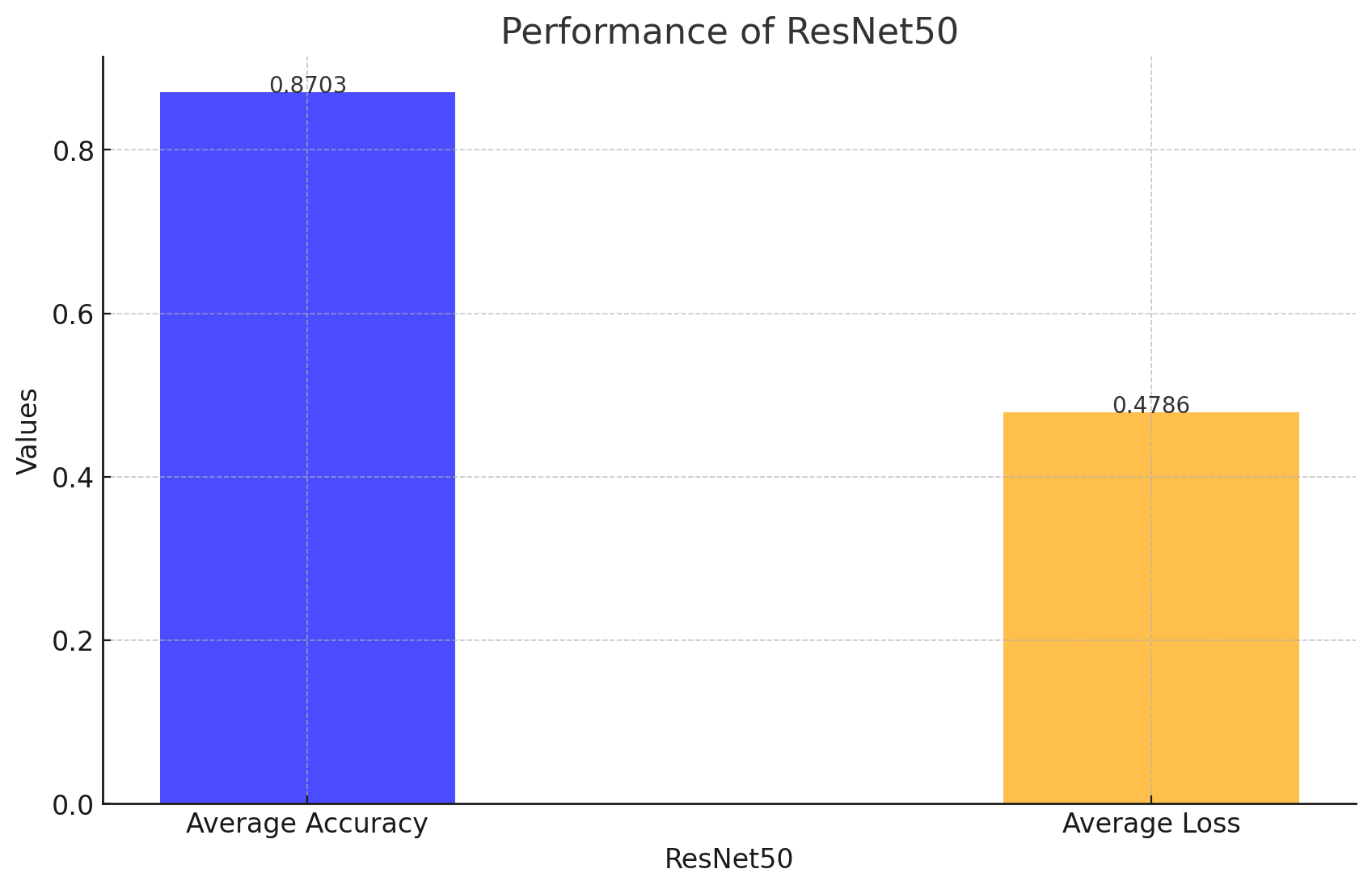


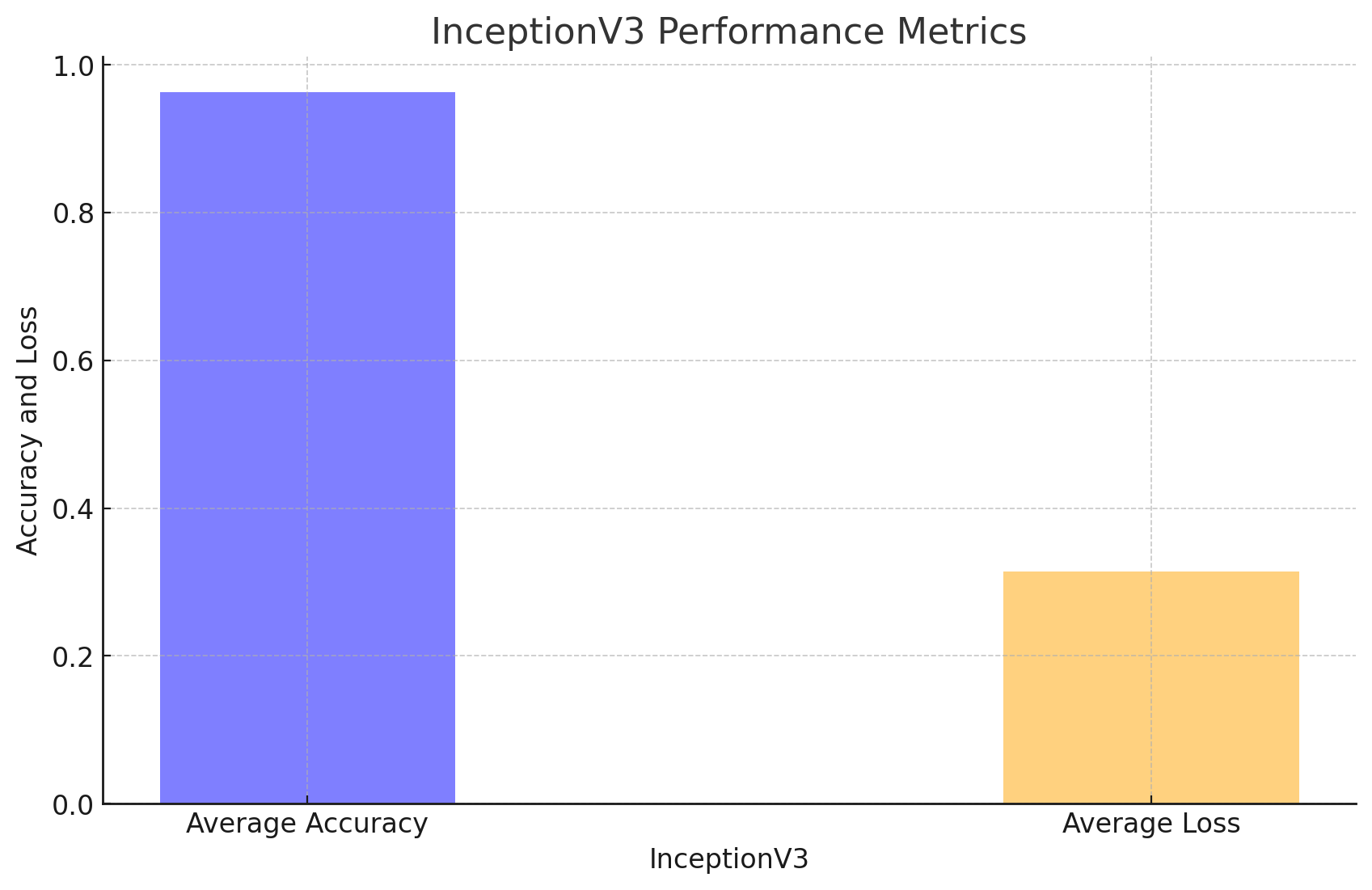
All Feature Extractions Avg Accuracy and Loss:

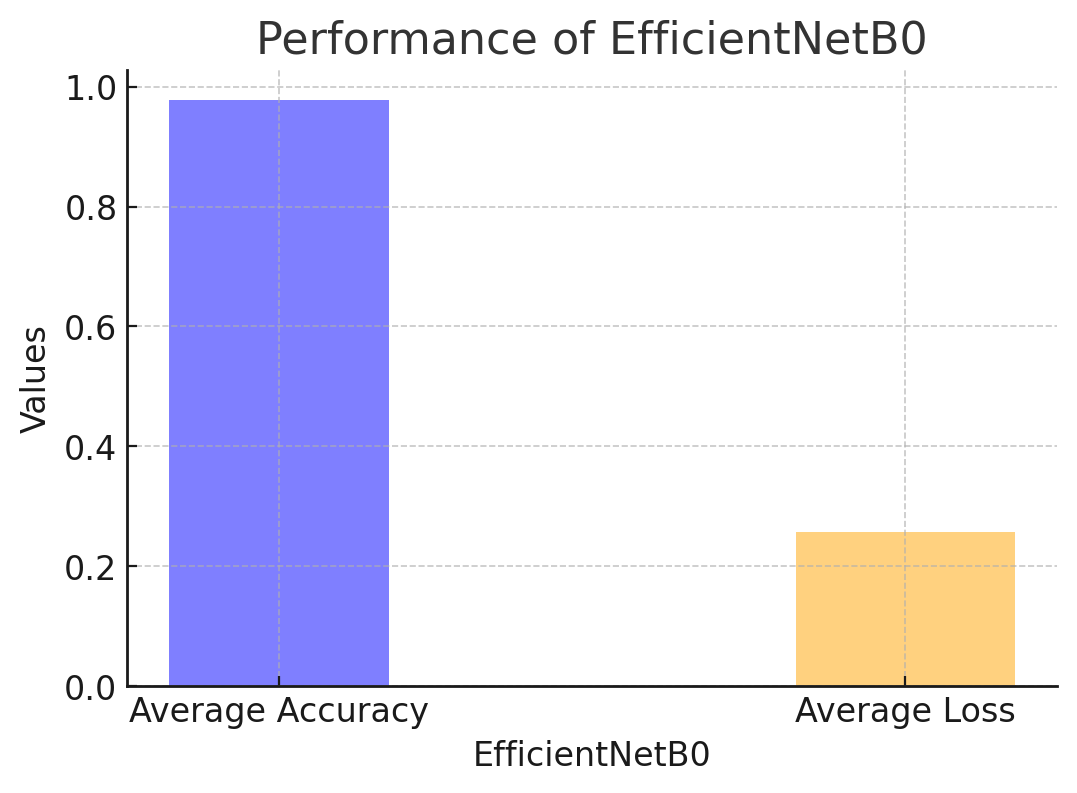


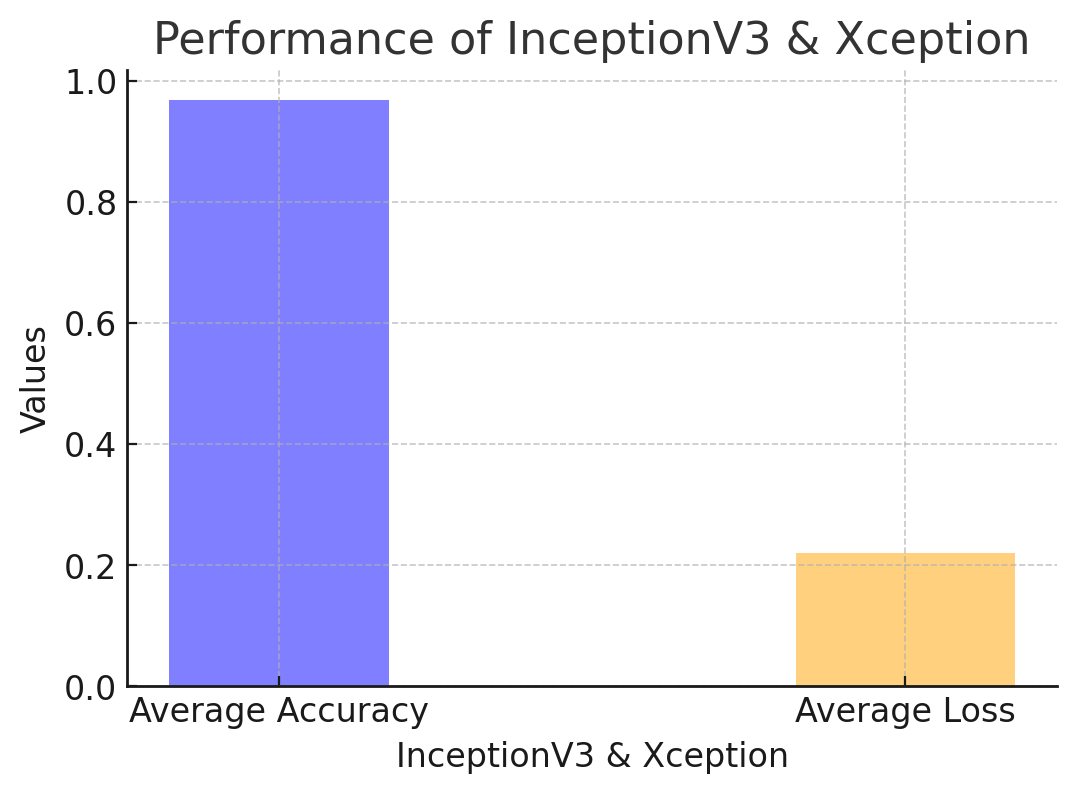
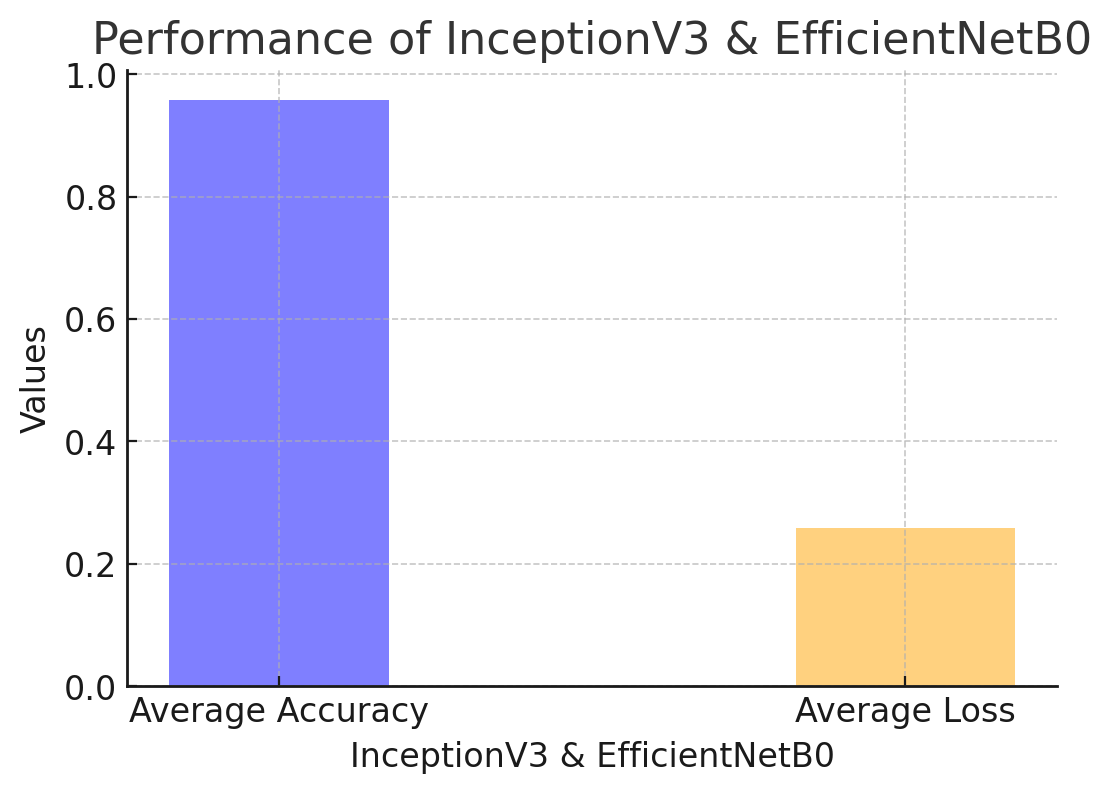
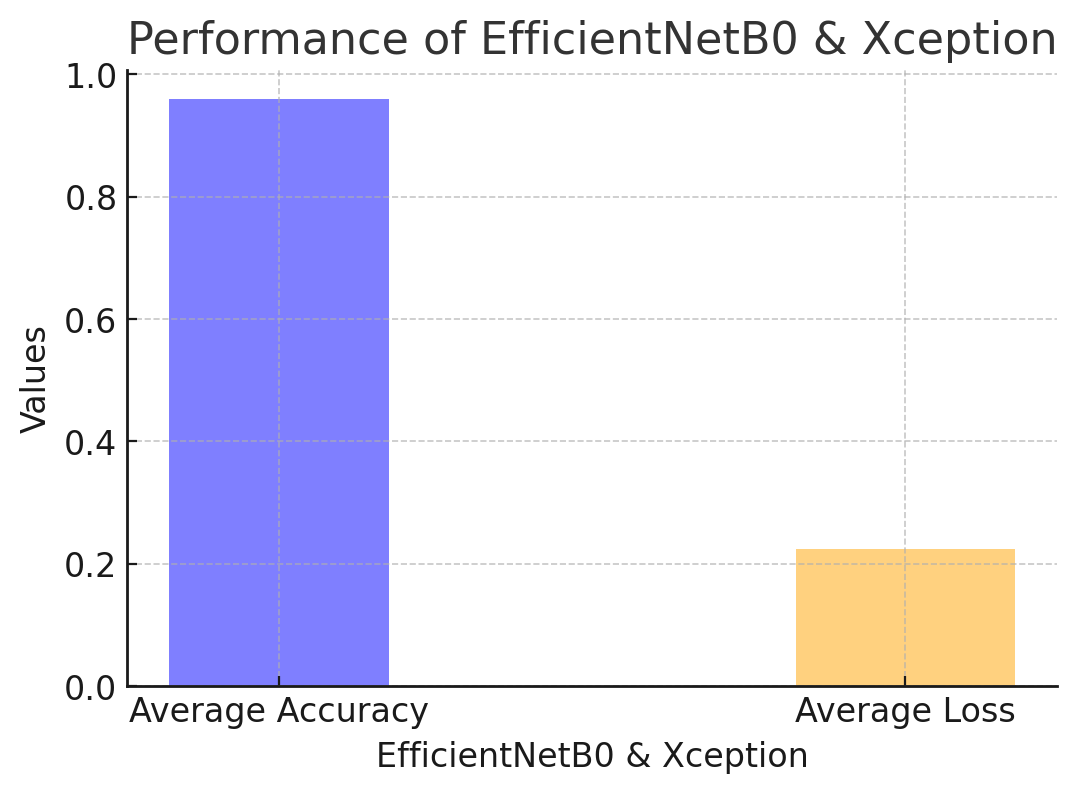


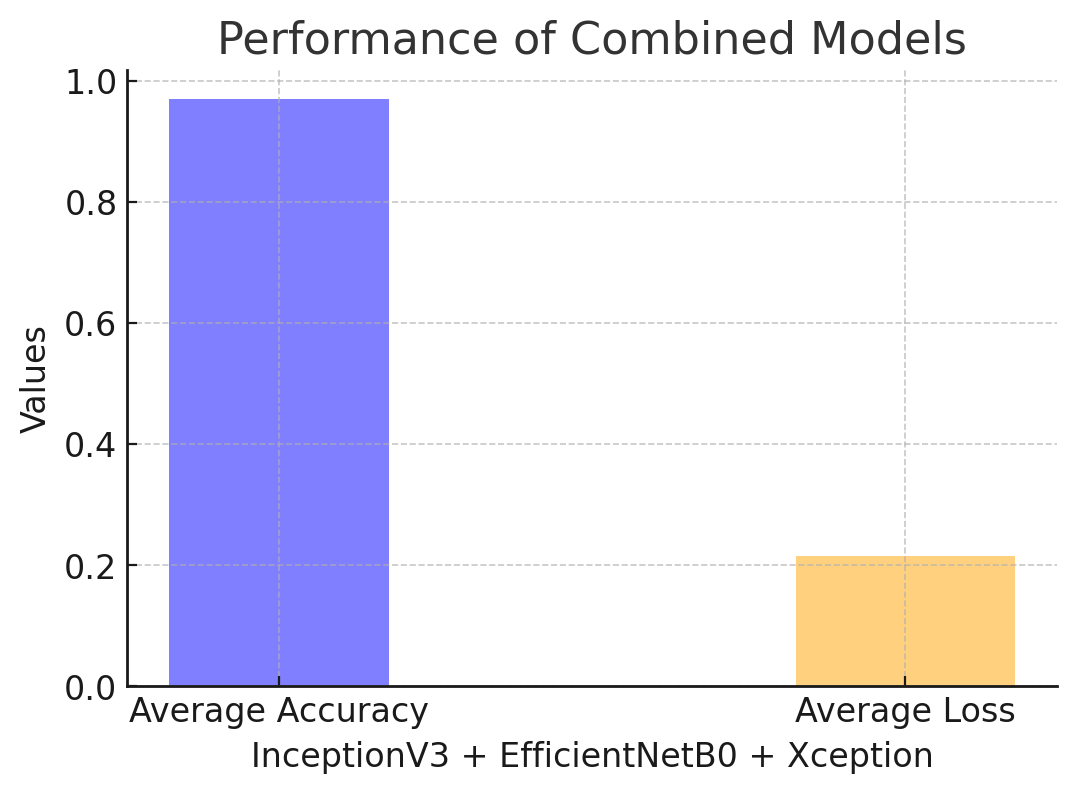












**Discussion:**

This study used image processing techniques with MRI images, which are a unique method for detecting brain tumors. Here, the filtering identifies the brain tumor part after removing the noise of the image. Here, the Softmax, SVM, RF, KNN, and AdaBoost classifiers were used. Here used 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

* **5.1.1 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 there use a small dataset, has courage, it can bring accurate results

* **5.1.2 Tumor type Scope**

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

* **5.1.3 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.

* **5.1.4 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.

* **5.1.5 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.

**Conclusion:**

Brain tumors can be very scary and deadly and 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 tumors 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 AdaBoostall, 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 tumor diagnosis and patient care.

* **Future Work:**

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 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 tumors. Moreover, also can 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 tumor at an early stage so that a better treatment plan can be made.