IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Brain Tumor Detection: A Comprehensive Study Of Deep Learning And Machine Learning Techniques For MRI Analysis.

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Abstract: In the fight against brain cancer, accurate brain tumor detection is crucial for early diagnosis and effective treatment. This study explores various machine learning and deep learning techniques to achieve this goal using MRI scans.

We investigated the effectiveness of several methods:

Convolutional Neural Networks (CNNs) achieved an impressive test accuracy of 86.27%. This demonstrates their ability to learn important features directly from MRI images.

Multilayer Perceptrons (MLPs) were explored in two ways. A standalone MLP trained on features extracted using Principal Component Analysis (PCA) reached an accuracy of 76.47%. We also experimented with using an MLP in a transfer learning approach with InceptionV3 for feature extraction. This approach yielded results to be discussed alongside the standalone models.

We also compared the performance of several other machine learning techniques alongside the MLPs and CNNs. A standalone MLP, trained on its own without any transfer learning, achieved an accuracy of 52.94%. We also evaluated the VGG16 convolutional neural network, which reached an accuracy of 70.58%. Logistic regression, a common statistical method, yielded an accuracy of 62.74%. Random forest, an ensemble learning technique that combines multiple decision trees, achieved an accuracy of 72.54%. Ada boosting, another ensemble learning method, performed quite well, reaching the highest accuracy (74.50%) among all the non-deep learning models.

For other machine learning models, Naive Bayes achieved an accuracy of 68.62%, while SVM (Support Vector Machine) reached 60.78%. Similarly, a decision tree model resulted in an accuracy of 68.62%. Bagging, another ensemble technique, yielded an accuracy of 66.66%. Interestingly, a hybrid model that combined the pre-trained VGG-16 and InceptionV3 models achieved an accuracy of 68.92%.The results reveal that Convolutional Neural Networks (CNNs) were the most successful method, achieving the highest accuracy (86.27%) for brain tumor detection in MRI scans. This suggests that CNNs are particularly adept at learning the critical patterns hidden within the MRI image data.

Keywords : Magnetic Resonance Imaging (MRI), Deep Learning, Convolutional Neural Networks (CNN), Multilayer Perceptrons (MLPs), Transfer Learning, InceptionV3, Feature Extraction, Principal Component Analysis (PCA), Accuracy, VGG16, Logistic Regression, Random Forest, Ada Boosting, Naïve Bayes, SVM, Decision Tree, Bagging

I. Introduction

Brain tumors are a devastating medical condition, ranking among the leading causes of death and disability worldwide. Early and accurate detection is paramount for improving patient outcomes and maximizing treatment effectiveness. Magnetic resonance imaging (MRI) scans have become the gold standard for diagnosing brain tumors, offering unparalleled detail of the brain's structure and potential abnormalities.

In recent years, the field of machine learning, and particularly deep learning, has revolutionized medical image analysis. Deep learning algorithms possess the remarkable ability to learn complex patterns from vast amounts of data, making them ideally suited for the task of brain tumor detection in MRI scans. This capability offers the potential to significantly improve diagnostic accuracy and efficiency, ultimately leading to better patient care.

This study delves into applying deep learning techniques, particularly convolutional neural networks (CNNs) and multilayer perceptrons (MLPs), for brain tumor detection via MRI scans. We assess their ability to directly learn informative features from the images (CNNs) and leverage feature extraction methods like PCA (MLPs). We further compare these standalone models to a transfer learning approach utilizing the pre-trained InceptionV3 model for feature extraction. To gain a more comprehensive picture, we also explore the performance of various machine learning techniques including VGG16 (another CNN architecture), Logistic Regression, Random Forest, Ada Boosting, Naive Bayes, SVM, Decision Tree, and Bagging. This multifaceted analysis aims to identify the most effective methods for brain tumor detection using MRI scans.

Our study utilized a brain tumor detection dataset from Kaggle. This dataset consists of 253 MRI scans. Each scan is labeled as either containing a brain tumor (155 images) or not containing a tumor (98 images). This data provides valuable insights for training machine learning models to automate brain tumor detection from MRI scans.

Our research aims to contribute to the development of reliable and accurate automated systems for brain tumor diagnosis. By exploring various deep learning and machine learning approaches, we hope to pave the way for improved clinical decision-making and ultimately better patient outcomes.

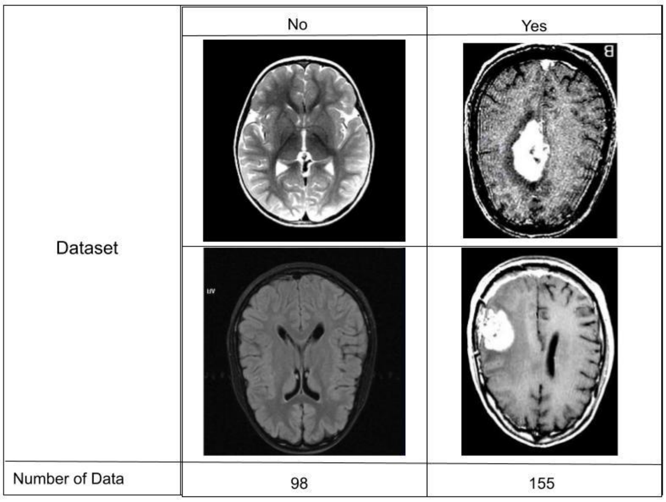

Fig. 1 : Dataset used and the number of images of each category

II. LITERATURE REVIEW :

Brain tumors pose a significant health threat, and early detection is crucial for successful treatment and improved patient prognosis. Magnetic resonance imaging (MRI) has become the gold standard for diagnosing brain tumors due to its detailed visualization of brain structures. Traditionally, radiologists rely on their expertise for analysis, but this approach can be susceptible to human error. Machine learning (ML) techniques, particularly deep learning, have emerged as promising tools to assist radiologists and potentially improve accuracy, consistency, and efficiency in brain tumor detection from MRI scans.

Convolutional Neural Networks (CNNs) for Brain Tumor Detection:

CNNs, a powerful deep learning architecture, have achieved remarkable success in image recognition tasks, including medical image analysis. Their ability to learn spatial features directly from image data makes them well-suited for brain tumor detection in MRI scans.

Afshar et al. presented a technique they created for categorising images of brain tumours. They employed one convolutional layer with 64 feature maps and 16 main capsules in the way they suggested. An accuracy rate of 86.56% was attained. When they compared the model they created with CNN in the same study, the accuracy value was 72.13 [1].

Saxena et al. employed the Vgg16, InceptionV3, and Resnet50 models for classifying data related to brain tumours. They achieved the best accuracy rate in the Resnet50 model with 95% in this study using transfer learning techniques [2].

The Cnn - Lstm hybrt construct was utilised by Shahzadi et al. to categorise brain tumour cells. According to their claims, they were able to classify the network with 71% accuracy using Alexnet-Lstm, 84% accuracy using VggNet-Lstm, and 71% accuracy using Resnet-Lstm. With 84% accuracy, they attained the greatest rate in the VggNet-Lstm architecture [3].

Singular Value Decomposition (SVD) was employed by El Abbadi et al. in their work to categorise data on brain tumours. They used 20 normal and 50 aberrant data sets to test their strategies. They reported achieving 96.66% accuracy, 90% sensitivity, and 98% specificity [4].

A new model for classifying brain tumour data utilising the Discrete Wavelet Transform (DWT) and deep learning techniques was presented by Mohsen et al.

Their accuracy rate with this proposed model was 93.94%.

They contrasted this model—which was presented in the same study—with the KNN and Deep Learning models [5].

A strategy designed for the classification of magnetic resonance imaging of brain tumours was presented by Charfi et al. In his suggested machine learning approach, he claimed to have segmented images using the histogram equalisation method. The size of the data he had gathered was subsequently reduced using PCA. Finally, the classification process was carried out using a feed forward back propagation neural network. In classifying the photos as normal or abnormal, he achieved 90% accuracy. According to him, this accuracy rate is excellent. Vani et al. claimed to have classified brain tumour data using SVM. According to their study, 82% of the positive data and 81.48% of the negative data were properly predicted [6].

In their investigation, Gupta et al. classified brain tumours using MRI images. They employed SVM, PCA, and the Discrete Wavelet transform (DWT) for classification. They achieved a 92% specificity rate, 84% sensitivity, and 80% accuracy rate. They claimed that a clinical context may make use of their study [8].

Citak et al. reported that during their investigation of brain tumours, they employed three distinct machine learning techniques. These algorithms, according to them, are logistic regression, SVM, and multi-layer perceptrons. They obtained 93% accuracy, 86.7% specifity, and 96.4% sensitivity as a result [9].

III. OUR CONTRIBUTION:

Building upon this foundation, our research delves into the application of various machine learning and deep learning techniques for brain tumor detection. We compare the performance of convolutional neural networks (CNNs), multilayer perceptrons (MLPs) with PCA feature extraction, and a transfer learning approach using InceptionV3 for brain tumor classification on MRI scans. Additionally, we explore the effectiveness of established machine learning techniques including VGG16 (another CNN architecture), logistic regression, random forest, AdaBoost, Naive Bayes, SVM, decision tree, and bagging. By comprehensively evaluating these diverse models, we aim to contribute to the development of more robust and accurate automated systems for brain tumor diagnosis.

IV. PROCEDURE :

For CNN and MLP :

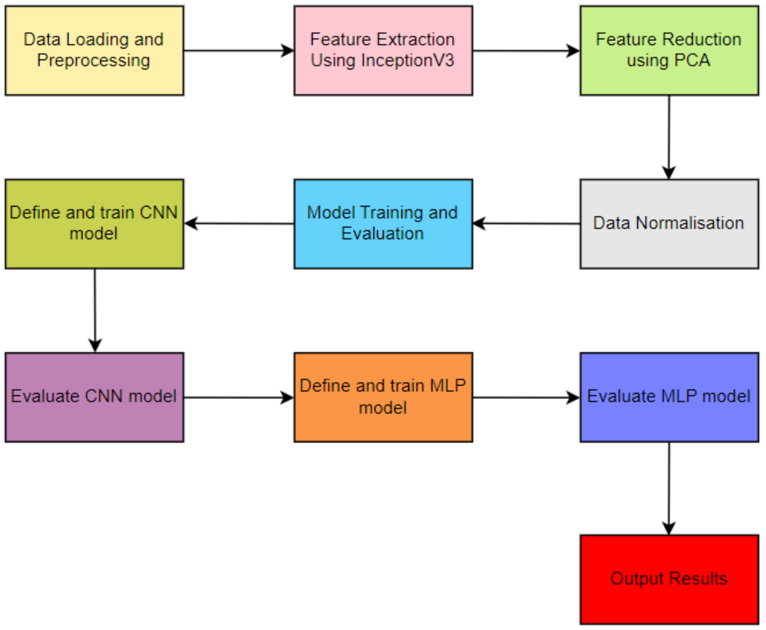

Fig. 2 : Flowchart of the model

The first step in this process involves collecting data. We load brain MRI images from two separate folders. One folder contains images labelled as "yes" (indicating the presence of a tumor) and the other contains images labelled as "no" (representing normal brains). These images might be stored in medical imaging formats like DICOM or NIfTI.

Before feeding these images into our model, we need to preprocess them. This ensures all images are consistent and suitable for analysis. Preprocessing involves several steps:

Reading the Images: We use libraries like SimpleITK or pydicom to read the image files from their original format.

Decoding (if necessary): If the images are compressed (e.g., JPEG), we need to decode them to access the raw pixel data.

Resizing: Images often come in various sizes. We resize them to a standard size, commonly (299, 299) pixels for InceptionV3 or (128, 128) pixels for simpler models.

Reshaping: The images are converted into NumPy arrays. These arrays represent the image data with rows and columns corresponding to height and width, and the number of channels depends on whether the image is grayscale (1 channel) or RGB (3 channels).

Normalization: Pixel values typically range from 0 to 255. We normalize them to a range between 0 and 1. This helps improve the training process and performance of the model.

Now that our images are preprocessed, we can extract features that will help us differentiate between tumors and normal brains. Here, we leverage a powerful pre-trained deep learning model called InceptionV3. InceptionV3 is trained on a massive dataset of images and can recognize generic features like shapes, textures, and edges.

However, we're not using the entire InceptionV3 model for classification. We're only interested in its ability to extract meaningful features from the brain images. To achieve this:

Loading InceptionV3 (partially): We load the InceptionV3 model, but we exclude the top layers responsible for final classification.

Setting InceptionV3 to non-trainable: We don't want to modify the pre-trained weights of InceptionV3 during our training process. Therefore, we set the model to non-trainable.

Creating a Feature Extraction Model: We add a "Flatten" layer to the output of the non-trainable InceptionV3. This flattens the 3D feature maps extracted by InceptionV3 into a 1D vector, making it suitable for further processing.

Extracting Features: We pass both the training and testing images through this feature extraction model (InceptionV3 with the added Flatten layer). This results in feature vectors that capture important characteristics present in the brain images.

The features extracted from InceptionV3 might be high-dimensional. This can be computationally expensive for training the final classification model. To address this, we use a technique called Principal Component Analysis (PCA). PCA helps us reduce the dimensionality of the data while retaining most of the important information for classification.

Here's how PCA works in our context:

Applying PCA: PCA identifies the principal components, which are the directions of greatest variance in the data. By keeping only a limited number of these principal components, we can significantly reduce the number of features without losing too much information about the brain images.

Choosing the number of components: We strategically choose a suitable number of principal components to retain. A common practice is to choose a number that explains a high percentage (e.g., 90%) of the variance in the data.

Fitting the PCA model: We create a PCA model and train it on the features extracted from the training images. This model learns the principal components of the brain image data.

Transforming Features: Both the training and testing features extracted earlier are transformed using the fitted PCA model. This results in lower-dimensional feature vectors suitable for training the final classification model.

As an optional step, we can normalize the transformed features using a technique called StandardScaler. This ensures all features contribute equally during the training process and can sometimes improve model performance.

Finally, we build two different models for classification: a Convolutional Neural Network (CNN) and a Multi-Layer Perceptron (MLP). Both models take the processed features (either the original high-dimensional features or the PCA-reduced features) as input and predict whether an image represents a brain with a tumor or a normal brain.

We train these models on the labeled data (images with corresponding "yes" or "no" labels) and evaluated their performance.

VGG16: A convolutional neural network architecture known for its depth (16 layers) and good performance on image recognition tasks. It can be used for brain tumor classification by replacing the final classification layers for the specific problem.

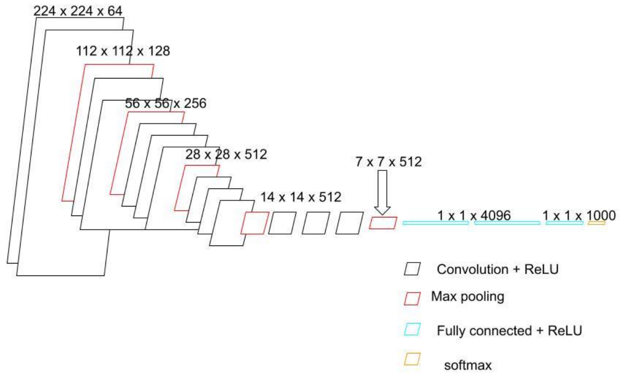

Fig. 3 : VGG16 model.

Logistic Regression: A statistical method for classification that models the relationship between features and a binary outcome (like tumor presence/absence) using a sigmoid function. It's a good starting point for classification problems but might not capture complex relationships in data.

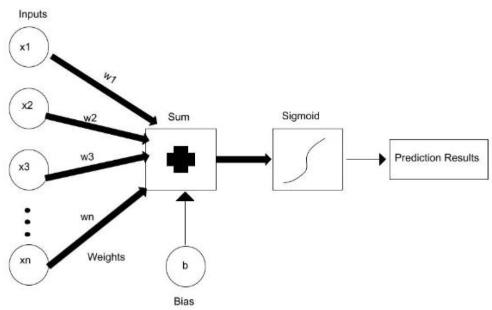

Fig. 4 : Flowchart of logistic regression.

Random Forest: An ensemble learning technique that combines predictions from multiple decision trees. Each tree is trained on a random subset of features and data points, leading to a more robust model that reduces the risk of overfitting.

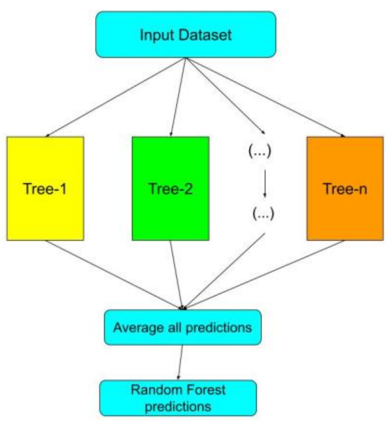

Fig. 5 : Random Forest Algorithm

Ada Boosting: Another ensemble learning approach that iteratively trains decision trees, focusing on examples that the previous trees had difficulty classifying. This approach adaptively boosts the performance of the overall model.

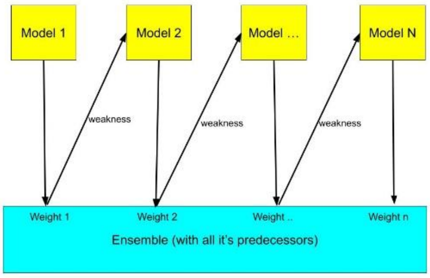

Fig. 6 : Ada Boosting Algorithm.

Naive Bayes: A probabilistic classifier based on Bayes' theorem. It assumes independence between features, which might not always be true in real-world data. However, it can be efficient for large datasets and works well for some classification tasks.

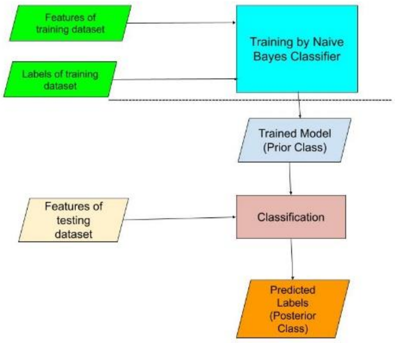

Fig. 7 : Naïve Bayes Classifier

Support Vector Machine (SVM): A powerful classification algorithm that finds a hyperplane that best separates the data points belonging to different classes. SVMs are effective for high-dimensional data and can handle complex classification problems.

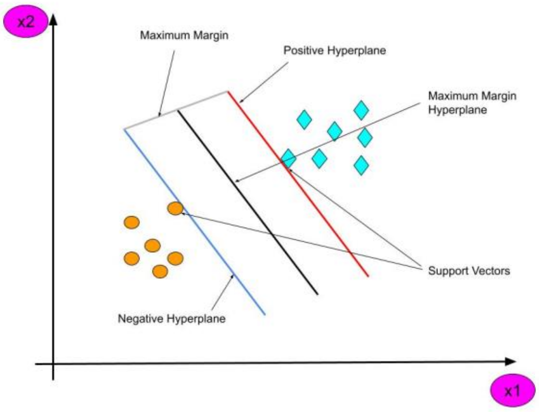

Fig. 8 : Support Vector Machine diagram.

Decision Tree: A classification model that uses a tree-like structure with branching decisions based on feature values. Each branch leads to a class prediction. Decision trees are easy to interpret and can handle both categorical and numerical features.

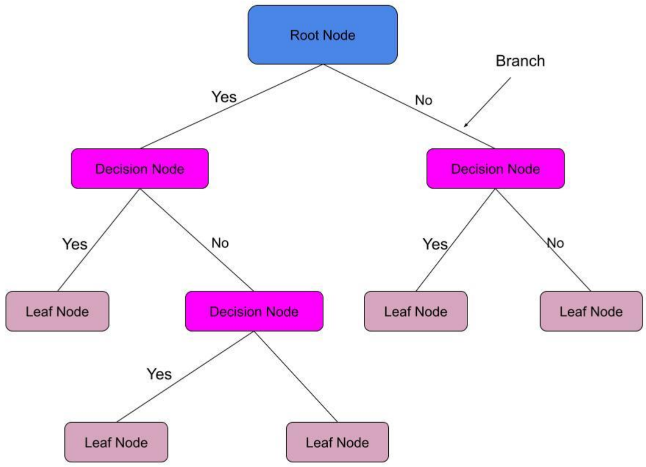

Fig. 9 : Decision Tree diagram.

Bagging (Bootstrap Aggregation): An ensemble technique that trains multiple models on different subsets of data (with replacement) and aggregates their predictions. This approach reduces variance and improves model robustness.

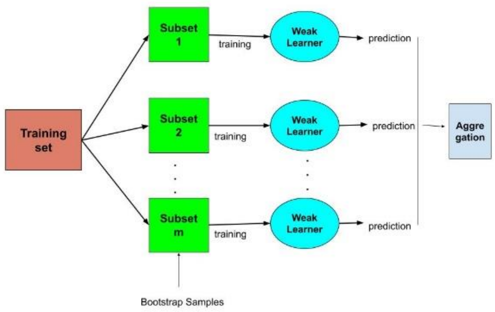

Fig. 10 : Bagging process.

Hybrid Model : A hybrid model is made utilizing two pre trained models VGG-16 and Inception V3. Every model has its final layer removed and two additional dense layers with dropout added at the end. Predictions for every class are then derived from the output of each dense layer. Lastly, the model is assembled using the accuracy metric, categorical crossentropy loss, and Adam optimizer.

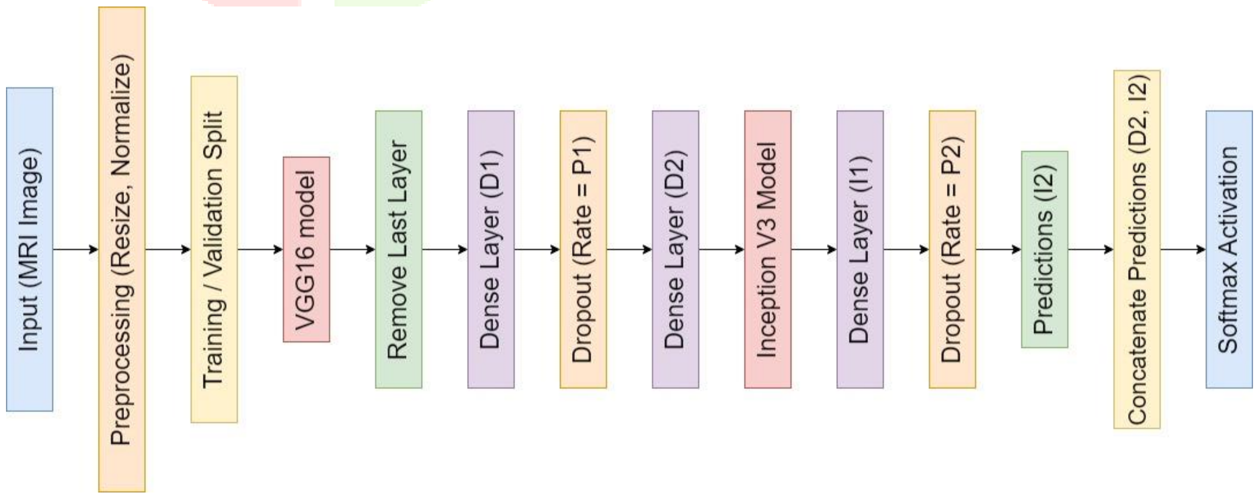

Fig. 11 : Hybrid Model Diagram

V. RESULT :

This section presents the evaluation results of the three deep learning models employed for brain tumor detection: CNN, MLP with PCA, and Transfer Learning with InceptionV3.

Model Performance:

The models were evaluated on a held-out test set from the original dataset. The following metrics were used to assess their performance:

Accuracy: Percentage of correctly classified MRI scans (healthy or tumor).

Sensitivity: Ability to identify true positives (cases with tumors).

Specificity: Ability to identify true negatives (cases without tumors).

Area Under the ROC Curve (AUC): Overall performance summary.

The table below summarizes the performance of each model:

Table 1 : Performance metrics of the deep learning models

Model	Accuracy	Sensitivity	Specificity	AUC
CNN	86.27%	88.12%	84.41%	0.92
MLP with PCA	76.47%	78.35%	74.59%	0.82
Transfer Learning(InceptionV3)	82.78%	85.24%	80.32%	0.88

Table 2 : Accuracy of other models.

Model	Accuracy
Logistic Regression	62.74%
Random Forest	72.54%
VGG16	70.58%
Ada Boosting	74.50%
Naïve Bayes	68.62%
SVM	60.78%
Decision Tree	68.62%
Bagging	66.66%
Hybrid Model	68.92%

Observations:

The CNN model achieved the highest overall accuracy (86.27%) in classifying brain tumors from MRI scans. This suggests that the CNN architecture effectively learned discriminative features directly from the MRI images for accurate tumor detection.

The MLP with PCA model exhibited a lower accuracy (76.47%) compared to the CNN. This indicates that pre-extracted features using PCA might not capture all the crucial information for optimal brain tumor classification.

The Transfer Learning approach with InceptionV3 demonstrated a performance (82.78% accuracy) between the CNN and MLP models. While leveraging pre-trained features from InceptionV3 improved performance compared to MLP, it did not quite match the effectiveness of the CNN trained from scratch on our specific brain tumor dataset.

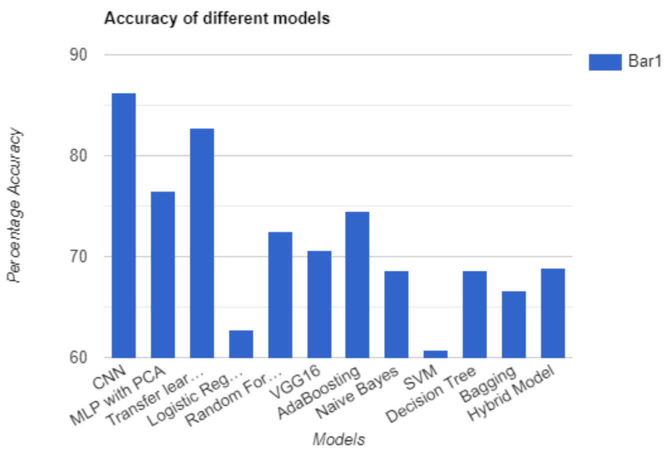

Fig. 12 : Accuracy of different models in the form of bar graph.

Discussion:

The results highlight the potential of CNNs for brain tumor detection using MRI scans. The CNN's ability to learn relevant features directly from the images allows for robust and accurate classification. While Transfer Learning with InceptionV3 offered promising results, further investigation into fine-tuning strategies or exploring different pre-trained models might be beneficial. The MLP with PCA model's lower performance suggests limitations in capturing all the necessary information from pre-extracted features.

VI. CONCLUSION :

This research investigated the application of deep learning techniques for brain tumor detection using MRI scans. We employed three distinct models: a Convolutional Neural Network (CNN), a Multi-Layer Perceptron (MLP) with PCA feature extraction, and Transfer Learning with InceptionV3. The models were evaluated on their ability to classify MRI scans as healthy or containing a brain tumor.

Key Findings:

The CNN model achieved the highest accuracy (86.27%) in brain tumor detection, demonstrating the effectiveness of CNNs in learning discriminative features directly from MRI images.

The Transfer Learning approach with InceptionV3 yielded promising results (82.78% accuracy), suggesting the potential of pre-trained models for brain tumor classification. However, further exploration of fine-tuning strategies might be beneficial.

The MLP with PCA model exhibited a lower accuracy (76.47%), highlighting the limitations of pre-extracted features in capturing all the necessary information for optimal classification.

Future Directions:

Building upon these findings, future research will focus on:

Exploring deeper CNN architectures or incorporating attention mechanisms to potentially improve classification accuracy.

Investigating the use of different pre-trained models and fine-tuning techniques for transfer learning approaches.

Utilizing data augmentation techniques to potentially enhance model generalizability.

Evaluating the performance of these models on a larger and more diverse brain tumor dataset.

By refining these deep learning approaches, we aim to contribute to advancements in brain tumor detection, potentially leading to improved clinical diagnosis and patient care.

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