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Multi-Class Classification of Brain Disease using Machine Learning-Deep Learning approaches and Ranking based Similar Image Retrieval from Large Dataset

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Abstract: A brain tumor is a very serious and life-threatening disease that requires immediate medical attention. Idetification and determination of an appropriate tumor type is the most important and challenging aspect of treating a patient with a brain tumor. This step takes considerable time and multiple tests are required for accurate identification. It is crucial to design the best treatment plan as soon as possible to improve the patient's chances of living a long and healthy life because brain tumors can have long-lasting and devastating effects on a patient's physical, mental, and emotional well-being. Using advanced technology, the proposed solution aims to identify the type of brain tumor quickly and accurately, which can save valuable time for doctors to provide additional treatments and ultimately save patients' lives. The dataset used in the study consists of 7023 T1-weighted contrast-enhanced images that have been cleaned and enhanced, and the proposed method encompasses the use of various deep learning models based on various kinds of Neural Networks (CNN, TL) and classifiers (SVM) to classify brain tumors into Glioma Tumor, Meningioma Tumor, No Tumor, and Pituitary Tumor i.e., CNN got an accuracy of 95% where as for TL i.e., MobileNetV2 gives an accuracy of 90% and SVM 90%. Apart from proposed work comparison of different TL models is done that can be suitable for developing a full robust application for Brain Tumor Detection and Classification.

***Keywords**: Python, Data Augmentation, Deep Learning, Convolutional Neural Network, Transfer Learning, Support Vector Machine, Magnetic Resonance Imagining,*

1. Introduction

The complexity and seriousness of brain excrescences can significantly affect a person's quality of life. A lump or development of abnormal cells that occurs in the brain or the surrounding apkins is known as a brain excrescence. Despite the fact that some brain excrescences are benign, meaning they don't spread to other body parts, others can be unpleasant and even life-threatening..

According to current statistics, brain excrescences regard for roughly 15 of all cancers diagnosed in the United States. Each time, an estimated 80,000 new cases of primary brain excrescences are diagnosed in the United States alone, and roughly 32,000 people die from the complaint. Brain excrescences can do at any age, but they're more common in aged grown-ups, with the loftiest prevalence rates being in individualities over the age of 65.

There are numerous different types of brain excrescences, which can be distributed grounded on their position, cell type, and how snappily they grow. Some common types of brain excrescences include gliomas, meningiomas, schwannomas, and pituitary excrescences. Each type of brain excrescence can have unique symptoms and treatment options, which can depend on the position and size of the excrescence, as well as the overall health of the existent.

The indications of a brain excrescence can vary extensively depending upon the position and size of the excrescence, but some common symptoms include headaches, seizures, weakness or impassiveness in the arms or legs, difficulty with speech or vision, and changes in geste or personality. Because numerous of these symptoms can be associated with other medical conditions, diagnosing a brain excrescence can be grueling , and frequently requires a combination of imaging tests, similar as MRI or CT reviews, and a vivisection of the excrescence towel.

Treatment for brain excrescences may include surgery, radiation remedy, chemotherapy, or a combination of

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these approaches. The choice of treatment will depend on the type and position of the excrescence, as well as the overall health of the existent. While treatment for brain excrescences can be grueling , advances in technology and medical exploration have led to significant advancements in issues for individualities with brain excrescences in recent times.

Overall, brain excrescences are a complex and serious medical condition that can have a significant impact on an existent's life. still, with early opinion and applicable treatment, numerous individualities with brain excrescences are suitable to achieve good issues and maintain a good quality of life.

Detection of Brain Tumor is an important part based on which the treatments for the patient depends and to simplify and make the process fast new technology called Deep Learning is used. An artificial neural network-based sub-field of machine learning is deep learning. It is a sspecial kind of artificial intelligence that lets computers learn itself from a lot of data and make decisions based on it. Complex problems can be solved and predictions made by deep learning algorithms that would be difficult or impossible for humans to make without computers.

The human brain, which is made up of interconnected neurons that process and transmit information, serves as a model for deep learning. Conventional artificial neural networks are used in deep learning to mimic the behavior of natural neurons. Multiple layers of interconnected nodes, or artificial neurons, that process and transmit information between layers make up these networks.

One of the vital benefits of profound gaining is its capacity to gain from a lot of information without being expressly customized. Data patterns and features that can be used to predict or classify can be discovered automatically by deep learning algorithms. Because of this, applications like speech or image recognition that require a large amount of unstructured data can benefit greatly from deep learning.

The capacity of deep learning to extract features is yet another advantage. The process of finding important data features or patterns that can be used to predict is known as feature extraction. Typically, a human expert performs feature extraction manually in general machine learning algorithms. However, in deep learning, the neural network handles feature extraction on its own. As a result, deep learning becomes more cost-effective and less dependent on human expertise.

Profound learning has been utilized in a great many applications, including picture acknowledgment, normal language handling, discourse acknowledgment, and independent vehicles. It has been especially effective in applications that require a serious level of exactness, like clinical conclusion and monetary determining.

While profound learning has shown extraordinary commitment in numerous applications, it likewise accompanies a few difficulties. The need for a large amount of data to train the artificial neural network is one of the main obstacles. Profound learning calculations remain information hungry and require a lot of named information to accomplish high exactness. Also, deep learning algorithms are hard to understand because they are so complicated, which can be a problem in applications where transparency is important.

Deep learning is a rapidly expanding field that is driving advancements in artificial intelligence and machine learning in spite of these obstacles. Deep learning is expected to continue to make significant contributions to a wide range of applications as more data and more powerful hardware become available.

Profound learning has shown extraordinary commitment in the field of clinical imaging, especially in the location and characterization of cerebrum growths. Conventional strategies for mind growth identification depend on manual understanding of clinical pictures by a radiologist or clinical expert, which can be tedious and emotional. The discovery and classification of tumors can be computerized by deep learning algorithms, thereby reducing the need for human interpretation and increasing accuracy.

Convolutional neural networks, or CNNs, are one way that deep learning can be used to detect brain tumors. CNNs are a kind of profound learning calculation that are especially appropriate for picture acknowledgment and characterization. CNNs can be trained on huge datasets of medical imageries to automatically detect and classify tumors based on their type and location in brain tumor detection.

Support vector machines (SVMs) are another way that deep learning can be used to find brain tumors. SVMs are a type of machine learning algorithm that excel at classification tasks. SVMs can be used to classify tumors according to their type and location, as well as predict their growth rate and response to treatment, in brain tumor detection.

Also the Hybrid development of Convolutional neural networks with Support Vector Machine are yet another way one can use to properly find brain tumors. The method has been significantly given results that are astonishing which is very beneficial to treatment outliner.

The capacity of deep learning to learn from a large amount of data is one of its main advantages in the detection of brain tumors. Profound learning calculations can be prepared on enormous datasets of clinical pictures, permitting them to consequently find examples and elements that are applicable to growth location and characterization. Because of this, applications involving large amounts of unstructured data, such as medical images, are ideal candidates for deep learning.

All in all, profound learning can possibly upset the field of cerebrum growth location and grouping. Deep learning algorithms can make tumor detection and classification more accurate and less dependent on human interpretation by automating the process. With proceeded with innovative work, profound learning is supposed to keep on making huge commitments to the field of clinical imaging and mind growth recognition.

With just not the use of CNN or SVM it is found that transfer learning to be good and pre-trained model to be used for a unknown task, without requiring extensive retraining from scratch. Transfer learning has shown high impact in the field of general as well as medical imaging, predominantly in the recognition and classification of brain tumors in MRI images.

In the prefered transfer learning, a model trained already on the data is first validated on a big dataset, typically from a related task, such as image recognition or natural language processing. In the next step the earlier trained model is again fine tuned on a relatively small dataset which is specific to the unkown data, such as brain tumor detection or classification. By using a trained model as a initial point, transference learning can expressively reduce the size of data and computation needed for training a new machine learning model.

One of the main advantages of transfer learning in brain tumor anamoly detection is its ability to leverage the knowledge learned from earlier training on related tasks. For instance, a earlier trained model that was originally trained on a large dataset of medical images for general image recognition can be fine-tuned on a smaller dataset of brain tumor images for specific detection and classification tasks. This allows the model to learn relevant features and patterns from the larger dataset, and apply this knowledge to the specific task of brain tumor detection and classification.

The capacity to enhance the precision and generalizability of deep learning models is yet another advantage of transfer learning in the detection of brain tumors. By beginning with an existing model that has already been trained and has learned the necessary features and patterns, transfer learning can lower the risk of overfitting, which occurs when a model becomes too specialized for the training data and performs poorly on new data. By utilizing the knowledge gained from a large, diverse dataset to enhance performance on a smaller, more specific dataset, transfer learning can also improve the generalizability of deep learning models.

Transfer learning has been used in a variety of brain tumor detection and classification tasks, including the detection of gliomas, meningiomas, and pituitary adenomas. In one study, researchers used transfer learning to train a CNN ie deep learning based model for the classification of gliomas. The model was first trained on a big dataset of natural images, and then tuned to further on a small dataset of MRI brain tumor images. The resulting model achieved high accuracy in classifying gliomas, demonstrating the efficiency of transfer learning in this application.

In conclusion, transfer learning is a better technique in deep learning that has shown great promise in the field of MRI brain tumor recognition and classification. By leveraging the knowledge learned from pre-training on related tasks, transfer learning can improve the accuracy, generalization, and efficiency of deep learning models for brain tumor detection and classification. With continued research and development, transfer learning is expected to continue to make significant contributions to the field of medical imaging and brain tumor detection.

Instead of just using CNN or SVM experimental research on different type of transfer learning pre-trained model namely VGG16, VGG19, ResNext50, InceptionResNetV2, MobileNetV2, EfficientNetB0 is done . And the accuracy for this model is 88.04%, 73.76%, 60.33%, 85.65%,90.61%, 30.89%. The best model among all was MobileNetV2 and the worst was EfficientNetB0.

2. Related Work

The researchers in [1] developed application of deep learning algorithms for the classification of brain tumors. The study explores the implementation of convolutional neural networks (CNNs) and transfer learning to classify brain tumors using their type and location. The researchers conduct experiments on a database of brain tumor images and compare the accuracy and performance of different CNN models. The outcomes demonstrate the effectiveness of deep learning algorithms for brain tumor classification, with high accuracy achieved using CNNs and transfer learning. The study highlights the use of deep learning in improving the accuracy and efficiency of brain tumor diagnosis and treatment planning.

In[2] the research work deals with the comparison of two popular machine learning techniques for image classification, namely Support Vector Machines (SVM) and Convolutional Neural Networks (CNN). The researchers conduct experiments on a dataset of images and evaluate the performance of SVM and CNN models for image classification tasks. The results demonstrate that CNNs outperform SVMs in terms of accuracy and efficiency for image classification. The study shows the use of CNNs for improving the accuracy of image classification tasks and has implications for a range of applications in computer vision, including medical imaging for diseases like cancer.

The authors in[3] worked on the comparative analysis of two popular machine learning algorithms, Support Vector Machines (SVM) and conventional Convolutional Neural Networks (CNN), for the classification of brain tumor images. The study evaluates the accuracy of both algorithms using several performance indicators such as model accuracy, precision, recall, and F1 based score. The results indicates that CNNs perform better than SVMs in relation with classification accuracy and F1 score. The study also highlights the importance of appropriate feature selection and hyperparameter tuning for improving the performance of machine learning models for brain tumor classification. The study provides valuable insights into the performance of different machine learning algorithms for the classification of brain tumors, with implications for the development of more accurate and efficient diagnostic tools for brain tumors.

In[4] the authors use deep neural networks for the classification of brain tumor images into different categories. The authors proposed a multi-classification framework that involves the use of a deep neural network architecture consisting of many convolutional layers, then later followed by fully connected layers that is used for classification. The study evaluates the performance of the given framework on a dataset of brain tumor images and compares it with other deep learning models. The results indicate that the proposed framework achieves high accuracy for the classification of brain tumors into different categories, outperforming other deep learning models. The study highlights the potential of deep neural networks for improving the accuracy and efficiency of brain tumor diagnosis and treatment planning, with insinuations for the advance of more accurate and effectual diagnostic tools for brain cancers.

In[5] the researchers deals with the development of a content-based image retrieval algorithm for medical dataset images. The authors propose a novel method that involves the extraction of features from medical images using deep learning techniques, followed by similarity matching for retrieval. The study evaluates the performance of the proposed algorithm on a dataset of medical images and compares it with other retrieval methods. The results demonstrate that the proposed algorithm achieves high accuracy and efficiency for medical image retrieval, outperforming other retrieval methods. This study effectively used for medical image retrieval, with implications for the development of more effective diagnostic tools for various medical conditions, including brain tumors.

In[6] The research paper provides a comprehensive review of different content-based image retrieval models and their feature extraction techniques for efficient data analysis. The authors explore the application of these models in various fields, including healthcare, and highlight their potential for improving the accuracy and efficiency of medical image retrieval and analysis. The study compares the performance of different content-based image retrieval models and discusses the advantages and limitations of each. The authors also identify key challenges and opportunities for future research in this field, such as the development of more efficient and accurate feature extraction techniques and the integration of deep learning methods for better image analysis. The study provides valuable insights into the state-of-the-art techniques for content-based image retrieval and their potential for improving data analysis in various domains, including healthcare.

In[7] the research paper proposes a feature selection approach for content-based image retrieval using K-nearest neighbor (KNN) supervised learning. The authors introduce a novel method that involves the selection of optimal features from images using KNN algorithm, followed by similarity matching for retrieval. The study evaluates the performance of the proposed algorithm on a dataset of images and compares it with other feature selection methods. The results demonstrate that the proposed algorithm achieves high accuracy and efficiency for content-based image retrieval, outperforming other feature selection methods. The study highlights the potential of KNN supervised learning for improving the accuracy and efficiency of content-based image retrieval, with implications for the development of more effective diagnostic tools for various medical conditions, including brain tumors.

In[8] The research paper proposes a commodity image retrieval method using convolutional neural networks (CNN) and score fusion. The authors introduce a new approach that utilizes deep learning algorithms to extract features from images, followed by score fusion to improve retrieval accuracy. The study evaluates the performance of the proposed method on a dataset of commodity images and compares it with other state-of-the-art retrieval methods. The results show that the proposed method achieves high accuracy and efficiency in retrieving commodity images, outperforming other methods. The authors also discuss the potential applications of the proposed method in various fields, including e-commerce and online shopping. The study provides valuable insights into the use of deep learning algorithms and score fusion for improving the accuracy and efficiency of image retrieval, with implications for various domains, including e-commerce, healthcare, and education.

In[9] the research paper presents an analysis of machine learning algorithms used in content-based image retrieval (CBIR). The authors examine the performance of various machine learning algorithms, including k-nearest neighbor (KNN), support vector machine (SVM), and random forest (RF), for feature extraction and classification of images. The study evaluates the algorithms using a dataset of images and compares their performance in terms of accuracy and efficiency. The results demonstrate that SVM outperforms other algorithms in terms of accuracy, while KNN and RF achieve high efficiency. The authors discuss the potential applications of the analyzed algorithms in various domains, including healthcare, e-commerce, and education. The study provides useful insights into the performance of machine learning algorithms in CBIR and their potential applications in different domains.

The researchers provides a comprehensive review of content-based image retrieval (CBIR) and its importance in the current era [10]. The authors discuss the various aspects of CBIR, including its architecture, feature extraction techniques, similarity measures, and evaluation metrics. They also present the challenges faced in CBIR and the recent advancements in this field. The paper highlights the importance of CBIR in various domains, such as healthcare, security, and e-commerce, and how it can help in solving real-world problems. The study provides a detailed analysis of the various techniques and algorithms used in CBIR and their applications. The authors also identify the future directions of research in this field and the potential areas of improvement. The study provides a valuable resource for researchers and practitioners interested in CBIR and its applications in various domains.

In[11] the research paper proposes a method for content-based image retrieval (CBIR) using convolutional neural networks (CNNs). The authors utilize a pre-trained CNN model for feature extraction and train a support vector machine (SVM) classifier for image retrieval. The proposed method is evaluated on two benchmark datasets, namely, Caltech-101 and Caltech-256. The study compares the performance of the proposed method with state-of-the-art methods in CBIR and shows that the CNN-based method outperforms the traditional methods in terms of accuracy and computational time. The authors also perform ablation experiments to analyze the impact of different CNN architectures and feature selection methods on the performance of the proposed method. The study demonstrates the potential of CNN-based methods for CBIR and provides insights for improving the performance of such methods. The study can serve as a useful reference for researchers and practitioners interested in CBIR and its applications using deep learning techniques.

The research paper proposes in [12] a content-based image retrieval (CBIR) system based on convolutional neural networks (CNNs). The authors employ a pre-trained CNN model, VGG16, for feature extraction and use these features for image retrieval by computing the cosine similarity between query and database images. The proposed system is evaluated on the Caltech-101 and Caltech-256 benchmark datasets, and the results are compared with other state-of-the-art CBIR systems. The study shows that the proposed system outperforms traditional methods and achieves better retrieval accuracy. The authors also conduct experiments to analyze the effect of different CNN architectures on the retrieval performance of the proposed system. The study provides useful insights into the use of CNNs for CBIR and demonstrates the potential of deep learning techniques for image retrieval applications.

In[13] the research paper presents a study that comparing the effectiveness of different distance measures for content-based image retrieval (CBIR). The study used a dataset of 1000 images, and three different feature extraction methods (color histogram, texture, and shape) were applied to extract features from the images. The distance measures used in this study include Euclidean distance, Manhattan distance, Cosine similarity, and Hamming distance. The results of the study showed that the Euclidean distance and Cosine similarity measures performed better than the other distance measures in terms of retrieval performance. The study provides useful insights for selecting appropriate distance measures in CBIR applications.

In[14] the research paper provides an extensive review of the application of Content-Based Image Retrieval (CBIR) in various fields. The paper discusses the potential of CBIR to improve the performance of various systems and applications in different fields. The authors have explored various aspects of CBIR such as feature extraction, indexing, and retrieval techniques. The paper presents a comprehensive analysis of the different approaches and techniques used in CBIR and their effectiveness in various applications. The authors have also discussed the challenges and future directions of CBIR research. The paper provides valuable insights into the potential and challenges of CBIR and its importance in different fields, such as medicine, surveillance, and security.

In[15] the research paper provides a comparative study of various Content-Based Image Retrieval (CBIR) techniques. CBIR is a method of retrieving similar images based on their visual content such as color, texture, shape, and spatial arrangements. The paper compares the effectiveness of various CBIR techniques such as color-based, texture-based, shape-based, and hybrid approaches. The authors also discuss the strengths and limitations of these techniques in terms of accuracy, speed, and retrieval time. The study concludes that hybrid techniques that combine multiple features provide better results compared to individual techniques. The paper is useful for researchers and practitioners in the field of CBIR who seek to improve the performance of image retrieval systems.

In[16] the paper presents a comprehensive review of recent trends in content-based image retrieval (CBIR). The authors discuss the importance of CBIR in various applications, including medical imaging, surveillance, and remote sensing. They provide an overview of the CBIR system and the image representation techniques, including low-level and high-level features. The paper also covers the retrieval methods, such as similarity measures, indexing, and relevance feedback. The authors discuss the challenges and future directions of CBIR research, including scalability, user interaction, and deep learning-based approaches. Overall, the paper provides a valuable insight into the recent developments and challenges in the field of CBIR.

The work presented in [11] does an evaluation of various distance measures used in content based image searching. Authors compare the accuracy of four distance measures, namely, Euclidean distance, cosine similarity, Pearson correlation coefficient, and intersection similarity, on three image datasets, namely, COIL-100, ETH-80, and Brodatz. They use the Mean Average Precision (MAP) based on confusion matrix and Normalized Discounted Cumulative Gain (NDCG) indicator to check the retrieval performance. The results show that the cosine similarity and intersection similarity measures perform better than Euclidean distance of images and Pearson correlation coefficient used for most of the experiments. Additionally, the study highlights the importance of selecting appropriate distance measures in CBIR systems for better performance.

The work of authors in [18] presents a similar image retrieval system that employs convolutional neural networks (CNNs) for feature extraction and image retrieval. The proposed system uses a earlier trained CNN for feature extraction and further tunes it based on a large image database to improve its accuracy in identifying and extracting features from images. The system then calculates the resemblance between query and database images using the extracted features, which are fed into a similarity measure algorithm. The presented system is checked on several datasets, and the analysis indicates that it outperforms many CBIR systems in terms of retrieval performance. The authors suggest that the proposed system has the potential to be used in various applications, including medical imaging, object recognition, and multimedia content analysis.

3. Proposed Methodology

3.1. Database

In this work ,the brain tumor database used which was available online but it was small dataset so after proprocessing and applying data augmentation the dataset was made. The database contains total 7023 T1 weighted and contrast improved brain MRI's images and contains four

classes of tumors viz glioma, meningioma, notumor and pituitary tumor. Table.1 lists the number of images of each class in the dataset.

Table 1: Summary of Used Image DataSet

Class Name	No. of Sample Images
Glioma	1621
Meningioma	1645
No Tumor	2000
Pituitary	1757
Total	**7023**

3.2 Preprocessing

Like any other pre-processing step before giving to the proposed neural network following steps are followed:

1. Loading the data: The dataset is loaded into the script using the os library. The training and testing data are stored in two separate arrays, X_train, Y_train, X_test, and Y_test, respectively. The image size is also set to 150 for all the images.

2. Shuffle and split the data: The training and testing data are shuffled randomly, and then the training data is further split into training and validation sets in a 80:20 ratio using the train test split method.

3. Encoding the labels: Since the labels of the dataset are strings, they need to be converted to numerical form for the model to learn effectively. This is done using the LabelEncoder method from the sklearn library.

4. Converting labels to categorical form: The labels are further converted to categorical form using the to_categorical method from the keras.utils library. This is done to improve the performance of the model while training.

5. Preprocessing the data: Since the images are in the form of numpy arrays, no additional preprocessing is done on the images. The data is directly fed into the model for training.

3.3 Image Augmentation

Image augmentation is used in many machine learning and computer vision related applications to increase the number of images in a database by transforming available but slightly modified versions of the original images. This is performed to increase the diversity of the dataset, which in turn can improve the accuracy of a machine learning model.

Data augmentation method can include a wide range of operations, depending on the type of data being processed. In image augment, common techniques include:

- Horizontal or vertical flips: Invert the image horizontally or vertically.
- Rotation: Rotate the image by a certain number of degrees.
- Zoom: Zoom in or Zoom out on the image.
- Crop: Crop a smaller portion of the image.
- Translation: Shift the image left, right, up, or down.

These techniques can be applied randomly to the original data to create new, slightly different versions of each image.

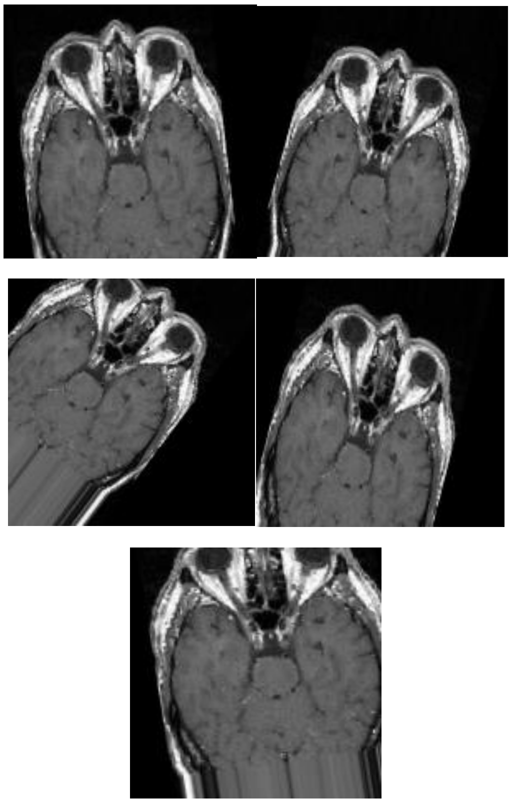

Fig 1: Data Augmented

3.4 Proposed Research Model

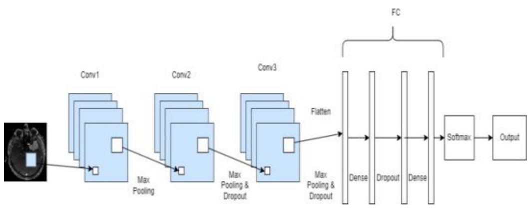

Fig 2: Proposed CNN Architecture

This proposed work uses a Convolutional Neural Network (CNN) model to classify brain MRI images into four different classes, glioma, meningioma, notumor, and pituitary. CNN is a deep learning architecture that is widely used for image classification, object recognition, and computer vision tasks. It is particularly useful for image classification as it can automatically learn features and patterns from the images.

The model consists of several layers that process the input images and produce output in the form of class probabilities. The layers are arranged in a sequential order in which the output of one layer is used as the input for the next layer.

The first layer in the model is the Conv2D layer, which performs the convolution operation on the input image with a set of learnable filters. The number of filters is defined by the user, in this case, 32 filters of size 3x3 are used. The activation function used is 'relu' (rectified linear unit) which is commonly used in CNNs.

The next layer is the MaxPooling2D layer which performs a down-sampling operation by taking the maximum value of the input pixels in a window of size 2x2. This layer helps in reducing the spatial dimensions of the output from the previous layer.

The above two layers are repeated again with a higher number of filters, i.e., 64 filters, and the same size kernel and activation function are used.

The next layer is a Dropout layer, which randomly drops out some of the neurons during the training process to prevent overfitting. The above three layers are repeated again, but this time with even higher filters, i.e., 128 filters. The next layer is a Flatten layer that converts the output from the previous layer to a one-dimensional array. Next is a Dense layer, which is a fully connected layer, with 128 neurons and 'relu' activation function. Another Dropout layer is used to prevent overfitting. The final Dense layer has the number of neurons equal to the number of classes in the dataset, i.e., 4, and uses a 'softmax' activation function, which produces output in the form of class probabilities as shown in figure 2.

The model is then compiled with 'categorical_crossentropy' as the loss function, 'adam' as the optimizer, and 'accuracy' as the metric to monitor. During training, the model is trained for 10 epochs with a batch size of 32. The training data is split into a training set and validation set with 80:20 ratio. After training, the model is evaluated on the test set, and the test loss and accuracy are reported. Finally, the model is saved to the disk.

Overall, the model used a CNN architecture with multiple Conv2D and MaxPooling2D layers, along with Dropout and Dense layers. The model achieved an accuracy of 95% on the test set, indicating that it is a useful model for classifying brain MRI images.

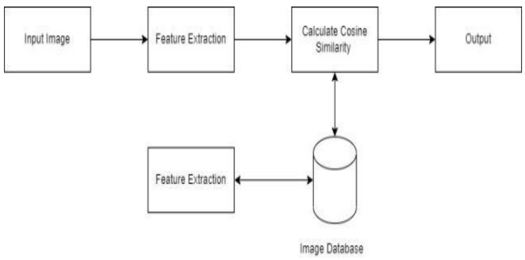

Fig 3: CBIR Architecture

Content-based image retrieval (CBIR) is a technique used to search for digital images by their visual content. Unlike traditional image retrieval systems, which rely on metadata such as file names or text descriptions, CBIR systems use features such as color, texture, shape, and spatial information to index and retrieve images. CBIR has various applications such as medical image retrieval, criminal investigation, and e-commerce. With the exponential growth of digital images, CBIR has become an essential tool for image management and retrieval. The success of CBIR systems depends on the efficiency and effectiveness of the feature extraction and matching algorithms used. Researchers are continuously exploring new methods to improve the performance of CBIR systems, including using deep learning techniques like convolutional neural networks (CNNs) to extract image features.

Feature extraction and similarity measure are two critical components of content-based image retrieval (CBIR) systems.

Feature extraction involves analyzing the visual content of an image and extracting meaningful features that can be used to describe the image. These features can include color, texture, shape, and other visual characteristics. The goal of feature extraction is to represent the image in a way that can be easily compared to other images in the database.

In this proposed model feature extraction is done by taking the output from the second last layer, which is a Dense layer with 128 neurons, and passing it through a new model. The new model is created using the Model class from Keras, where the input is the same as the original model, and the output is the output of the second last layer. This model is then used to extract features from the test set

On the other hand, similarity measure is a method used to determine how similar two images are based on their feature vectors. In CBIR systems, similarity measure is used to match a query image with the most similar images in the database. There are many similarity measures used in CBIR systems, including Euclidean distance, cosine similarity, and correlation coefficient.

The importance of feature extraction and similarity measure in CBIR systems lies in their ability to accurately retrieve images that are relevant to the user's query. CBIR systems that use effective feature extraction and similarity measures can provide users with high-quality results and save them time and effort in searching for images manually. Additionally, these components are crucial for many applications of CBIR systems, such as medical image analysis and surveillance systems, where accurate retrieval of images is essential for diagnosis or security purposes.

Similarity measure plays a crucial role in content-based image retrieval (CBIR) systems. After extracting the features from an image, the similarity measure is used to compare these features with those of the images in the database and rank them according to their similarity score.

There are several types of similarity measures used in CBIR systems, including Euclidean distance, Manhattan distance, Cosine similarity, Pearson correlation coefficient, and Jaccard similarity coefficient. Each of these similarity measures has its own strengths and weaknesses, and the choice of a particular measure depends on the characteristics of the dataset and the application requirements.

While there are many distance measure the widly used are euclidean distance method and cosine similarity function. Euclidean distance function computes the straight line distance between two available points in a multidimensional space, while Manhattan distance measures the distance between two points along the axes of the space. Cosine similarity measures the cosine of the angle between two vectors in a high-dimensional space, while Pearson correlation coefficient measures the linear correlation between two variables. Cosine Similarity is used to calculate similarity score and then display the top similarity images with their similarity score.

Formula of Cosine Similarity.

cosine_similarity(A, B) = dot_product(A, B) / (norm(A) * norm(B))

where A and B are the two vectors being compared, dot_product is the dot product of the two vectors, and norm is the Euclidean norm of the vector.

3.5 Performance Evaluation

For performance measurement confusion matrix and classification report is computed.

The formula for evaluation metrics are as follows:

The frequency with which the classifier performs an accurate vaticination is known as accuracy. It's determined by partitioning the quantity of properly grouped cases by the all out number of cases.

Precision is a measure of how frequently the classifier correctly predicts a positive instance.

Accuracy = (TP + TN) / (TP + TN + FP + FN),

where TP is the true positive, TN is the true negative, FP is the false positive, and FN is the false negative. It is computed by dividing the total of TP and FP by the total number of true positives.

Recall is a measure of how frequently the classifier correctly predicts a positive instance out of all positive instances. Precision = TP / (TP + FP) It is determined by separating the quantity of genuine up-sides by the amount of TP and FN.

Review = TP/(TP + FN)

The F1 score is the balanced mean of perfection and recall. It is a proportion of the classifier's exactness.

F1 Score is equal to 2 x ((Precision x Recall) / (Precision x Recall))

3.6 Result Analysis

The experiments were performed on a laptop with Intel Core-I7 CPU and 8 GB of RAM. And also using Google Colab for training heavy models. The experimental results gives an accuracy of 95% for the proposed CNN model. With proved to be very good and able to properly predicted and display the similar images.

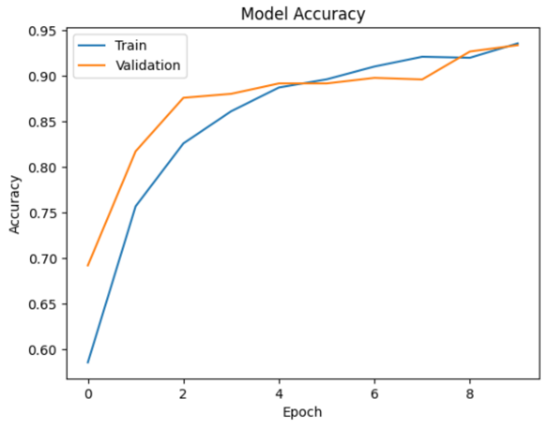

Fig 4: Model Training and Validation Accuracy

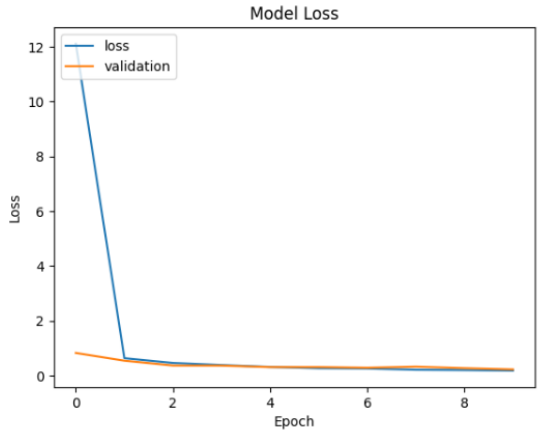

Fig 5: Model Training and Validation Loss

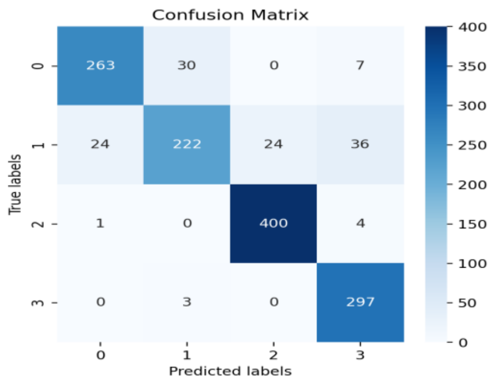

Fig 6: Confusion Matrix

4. Experiment

With this proposed model it has been experimented with different Transfer Learning model like VGG16, VGG19, ResNext50, InceptionResNetV2, MobileNetV2, EfficientNetB0. And the accuracy for this model is 88.04%, 73.76%, 60.33%, 85.65%,90.61%, 30.89%. The best model among all was MobileNetV2 and the worst was EfficientNetB0.

Table 2: Different Pre-trained Model tested on same Dataset

TL Model	Test Accuracy	Test Loss	F1 Score
VGG16	88.04	0.29	88
VGG19	73.76	0.72	71
ResNext50	60.34	0.98	55

InceptionResNetV2	85.65	0.40	85
MobileNetV2	90.61	0.25	91
EfficientNetB0	30.89	1.87	30

In the experimention with CNN - SVM model achieving an accuracy of 93%. This was an hybrid approach consists of a Convolutional Neural Network (CNN) and a Support Vector Machine (SVM) classifier for the task of brain tumor classification. The CNN is used for feature extraction, and the SVM is used for classification based on the extracted features. Overall, this hybrid CNN - SVM model provides a powerful approach for brain tumor classification, with the CNN being able to extract meaningful features from the brain tumor images and the SVM being able to classify them accurately based on these features.

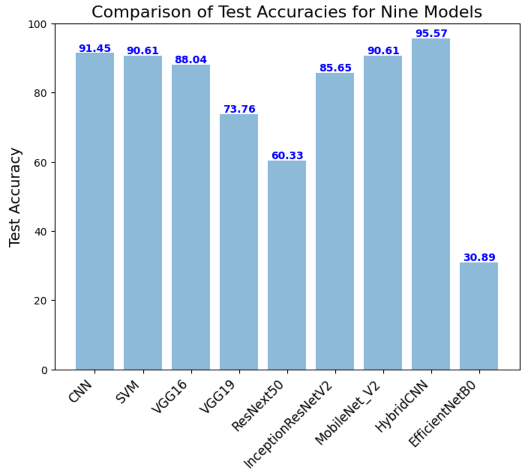

Fig 7: Comparision with Different Model

5. Conclusion

In this work, the proposed model is a novel and improvised convolutional neural network (CNN) architecture for automatic brain tumor classification. This architecture succeeded in classifying the brain tumor four classes with high performance in accuracy. The system can suggestively classify the tumor into four levels; glioma, meningioma, no tumor and pituitary tumor using the dataset of brain MR images. This architecture proficiency may even be further enhanced by including more brain MRI images with diverse weights and with several contrast enrichment techniques to allow the architecture to be possibly more generalized for big image databases and by adding new original images to the dataset rather than distorted images.

Future Scope

Although the improvisation got from the proposed model there are still many things that can be worked upon. There is always scope of improvising previous work by introducing new filters and learning fuctions in CNN that can be very helpful to the application and its field.

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