

BRAIN TUMOR CLASSIFICATION AND DETECTION USING CNN WITH MRI IMAGES

Ranabothu Srija ¹, Pachineelam Pranathi², Masina Karthik Reddy³, Maragouni Ashrith Goud⁴

Mr. V. Basha Assistant Professor, Department of CSE, AVN Institute of Engineering and Technology, Koheda Road, M.P.Patelguda Post, Ibrahimpatnam (M), Rangareddy Dist-501510.

ABSTRACT:

The fundamental subject of the undertaking is to perceive the cerebrum harmful development in human with the progression of huge learning. From that point, we can utilize convolutional brain organizations (CNN's) to make an enlightening record with the end goal of connection. We were unable to use the CNN's to achieve higher levels of exactness in the previous study. Thus, we utilized CNN's with extra three models, for example, Thick, to make a more far reaching file utilizing further developed component examination and the division utilizing upscale innovation. Here by utilizing CNN we are getting extraordinary accuracy. We have cutoff points of Responsiveness Examination Metrics(Accuracy,Sensitivity,Specificity), Computational time, Preparing execution graphs, Execution with different preparation degrees.

INTRODUCTION:

The disease is basically an uncontrolled improvement of cancer-causing cells in any piece of the body, however a brain malignant growth is an uncontrolled improvement of cancer-causing cells in the frontal cortex. A harmless or threatening mind growth can happen. The innocuous frontal cortex development has a consistency in structure and doesn't contain dynamic (illness) cells, while compromising brain diseases have a non-consistency (heterogeneous) in structure and contain dynamic cells. The glioma and meningioma are the cases of low quality developments, named innocuous diseases and glioblastoma and astrocytomas are a class of high-grade developments, designated undermining malignant growths.

LITERATURE REVIEW:

Sure, here are some literature survey papers with abstracts and published years for brain tumor classification using image processing:

1.Title:A Comprehensive Survey on Brain Tumor Classification Techniques with MRI Images

Abstract:This survey paper provides a comprehensive overview of various techniques and methodologies used for brain tumor classification using MRI images. It covers different image processing methods, feature extraction techniques, and classification algorithms employed in the field. Additionally, it discusses the challenges and future directions in brain tumor classification.

Published Year: 2018

2.Title:Review on Brain Tumor Detection and Classification Techniques

Abstract:This paper presents a review of recent advancements in brain tumor detection and classification techniques using image processing. It discusses the importance of accurate diagnosis and the role of image analysis in aiding medical professionals. Various approaches such as machine learning, deep learning, and hybrid methods are examined along with their strengths and limitations.

Published Year:2020

3.Title:A Review of Brain Tumor Classification Methods Using Magnetic Resonance Imaging

Abstract:This review paper surveys the state-of-the-art methods for brain tumor classification utilizing magnetic resonance imaging (MRI). It analyzes different stages of the classification pipeline, including preprocessing, feature extraction, and classification algorithms. The paper also highlights emerging trends such as the integration of advanced machine learning techniques and the incorporation of multi-modal imaging data.

Published Year:2019

4.Title:A Comprehensive Review of Brain Tumor Classification Techniques Based on MRI Data

Abstract:In this comprehensive review, various techniques for brain tumor classification based on MRI data are explored. The paper covers traditional machine learning approaches as well as recent advancements in deep learning models. It also discusses the importance of feature selection and dimensionality reduction in improving classification accuracy.

Published Year:2017

5. Title:Recent Advances in Brain Tumor Classification: A Survey

Abstract:This survey paper presents recent advances in brain tumor classification techniques, focusing on the use of image

processing and machine learning methods. It discusses the challenges associated with accurate tumor classification and reviews state-of-the-art algorithms and frameworks. Additionally, it identifies potential research directions for future work in the field.

Published Year: 2021

These papers should provide you with a good starting point for your literature survey on brain tumor classification using image processing techniques.

SYSTEM ANALYSIS:

EXISTING METHOD:

- Head Part Assessment
- Neighborhood matched model and shape highlights
- KNN and FNN classifier

KNN:

A popular methodology for request and backslide in artificial intelligence is the K-Nearest Neighbors (KNN) computation. It is contingent on the possibility that scores or values from comparable data sources will typically be comparable.

During the preparation stage, the KNN assessment stores the whole arranging dataset as a kind of perspective. While making presumptions, it settle the distance between the information data of interest and

all the arranging models, utilizing a picked distance metric like Euclidean distance.

Portrayal and backslide insightful issues can both advantage from the utilization of the KNN Estimation. In any case, it is significantly more normally utilized in social affair issues in the business. We typically take into consideration three primary points of view when evaluating a method:

1. capacity to understand yield Computation time
3. Insightful Capacity To put KNN on the scale, we ought to look at two or three models:

Differentiating models and the KNN computation, the KNN classifier performs well across all of the limits suitable. It is every now and again utilized because of its low assessment time and simplicity of understanding.

DISADVANTAGES:

- Less accuracy
- Less dataset only taken

PROPOSED METHOD:

- CNN with DENSE
- Preprocessing
- Feature extraction

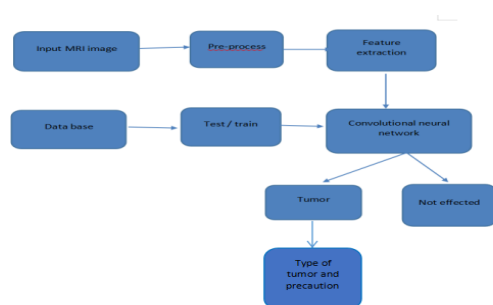
ADVANTAGES:

- Accuracy is more by using algorithm with models
- More training process
- More data
- With in the less time we will get more accuracy

APPLICATIONS:

- Research and Development
- Medical Applications

SYSTEM ARCHITECTURE:



MODULES IMPLEMENTATION:

IMAGE ACQUISITION:

Image acquisition is the process of capturing visual information, typically in the form of digital images, using various devices such as cameras, scanners, or medical imaging equipment. It involves converting the optical signals from the scene being captured into electronic signals that can be processed, stored, and manipulated by computers. This process encompasses not only the physical capturing of the image

but also the conversion and transfer of data into a digital format. Image acquisition is a fundamental step in many fields, including photography, medical imaging, remote sensing, and computer vision.

DATA PRE-PROCESSING :

Pre-processing is done to improve the image's quality so that we can better analyze it. We can improve a few important highlights for the application we are working on and get rid of unwanted bends by preprocessing. A crucial step in the process of data mining is the preprocessing of the data. Data preparation for analysis includes cleaning, transforming, and integrating the data. Data preprocessing aims to improve the data's suitability for the particular data mining task by chipping away at its concept.

FEATURE EXTRACTION:

For example, in image processing, feature extraction might involve identifying edges, corners, or textures within an image. In natural language processing, it could involve extracting word frequencies, syntactic structures, or semantic meanings from a text. The ultimate goal of feature extraction is to reduce the dimensionality of the data while preserving important information, making it easier and more efficient for machine learning algorithms to process and interpret the data accurately.

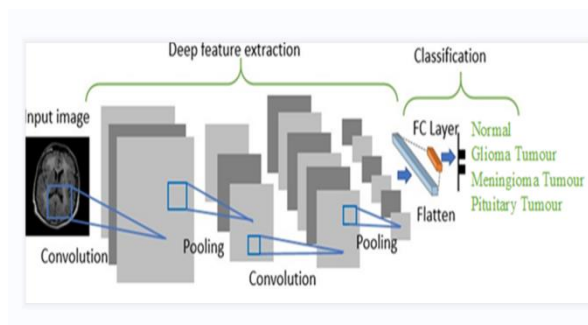
This can lead to better performance and more effective models in various applications.

Train and Test :-There are two subsets for datasets. The status data, which is a piece of our ensured dataset that is used in the impersonated information model to find and learn plans, is the major subset. Therefore, it prepares our model. The other subset is known as the testing information. It produces results that are additionally evolved than those gotten by applying man-made cognizance solely to the unforgiving data.

CONVOLUTION NEURAL NETWORK

INTRODUCTION:

Yes, CNN talks about the Convolutional Cerebrum Association. It is a type of fictitious brain network that is primarily utilized for the study of visual symbolism. A succinct explanation is as follows:



1. Convolutional Layers: CNN's utilization convolutional layers to segregate highlights from input pictures. These layers apply a

progression of channels to the data picture, which are likewise called pieces. Each channel recognizes specific features like edges, surfaces, or models.

2. Pooling Layers: After convolutional layers, the spatial components of the final maps are typically reduced using pooling layers. Accordingly, the association's computational unpredictability is diminished and the learned features are more impenetrable to incorporate assortments.

3. Layers Completely Connected: These layers are for the most part arranged around the culmination of the affiliation and are utilized for social occasion or break faith undertakings. They take the colossal level elements advanced by the convolutional layers and guide them to the best result (e.g., class denotes every single together errand).

4. Capabilities at Inception: After each layer, non-straight activation capacities, as ReLU or sigmoid, are applied to the association to introduce non-linearity and enable it to learn complex data plans.

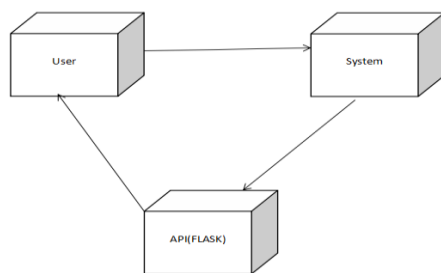
5. Training: Through regulated learning, CNNs figure out how to plan input pictures to their relating marks. Stochastic Slant Drop (SGD) is an outline of a tendency based upgrade computation that restricts a disaster capacity that activities the difference among expected and certifiable outcomes by changing the association's limits.

CNN's have changed different fields like PC vision, picture assertion, object affirmation, and, amazingly, standard language dealing with, making them perhaps of the most significant asset in man-made knowledge and man-made thinking.

Sending Chart:

The game plan for the application's runtime components is obtained by the sending graph. This chart is predominantly most strong when a framework is constructed and fit to be sent

Deployment Diagram:



FLASK:

Flask is a lightweight and versatile web framework for Python used to build web applications. It is designed to be simple, easy to learn, and flexible, allowing developers to create web applications quickly and efficiently. Flask provides essential tools and libraries to handle tasks such as routing, HTTP requests, sessions, and template rendering.

Key features of Flask include:

Routing: Flask uses decorators to map URLs to functions, making it easy to define routes and create endpoints for handling

different HTTP methods like GET, POST, PUT, DELETE, etc.

HTTP Request Handling: It offers request and response handling, allowing developers to work with incoming HTTP requests and craft appropriate responses.

Template Engine: Flask comes with Jinja2, a powerful and user-friendly template engine that enables the separation of HTML from Python code, facilitating the creation of dynamic web pages.

Extensions: Flask has a modular design, allowing developers to integrate various extensions for functionalities such as database integration (SQLAlchemy), form validation, user authentication, etc.

Scalability: While Flask is minimalistic by design, it's scalable and can be extended as needed by integrating various libraries and extensions, making it suitable for building both simple and complex web applications.

Werkzeug and Jinja2: Flask is built on top of the Werkzeug WSGI toolkit and uses the Jinja2 template engine, providing a robust foundation for web development in Python.

Overall, Flask's simplicity, flexibility, and extensive documentation make it a popular choice among developers for building web applications, RESTful APIs, and prototypes in Python.

SOFTWARE REQUIREMENTS

- Anaconda navigator(Jupyter notebook)
- Opencv
- Tensor-flow
- Keras
- Matplotlib
- Numpy

HARDWARE REQUIREMENTS

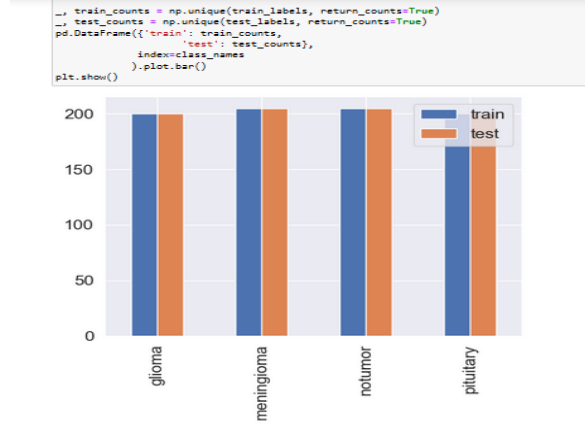
- Operating System : Windows Only
- Processor : i5 and above
- Ram : 4gb and above
- Hard Disk : 50 GB

OUTPUT SCREENS:

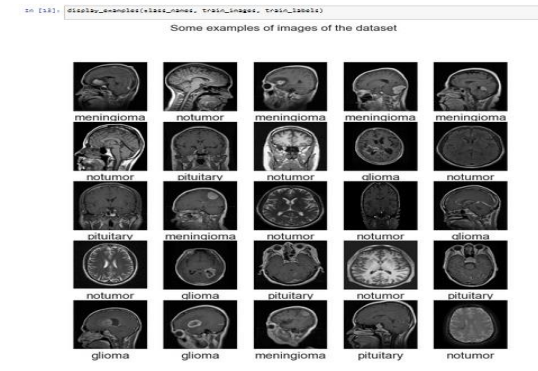
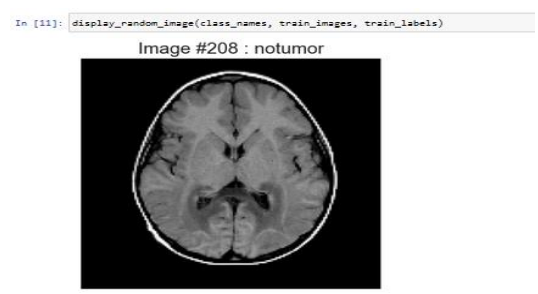
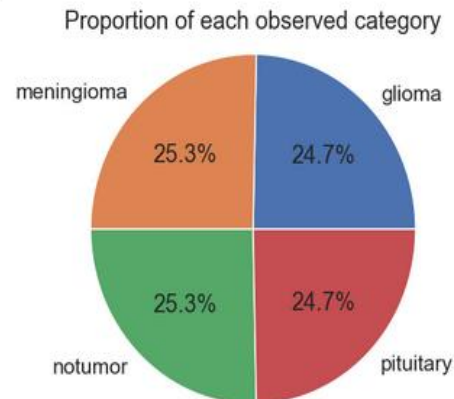
```
In [2]: (data_train, data_test) = train_test_split(data, test_size=0.2)
```

```
In [3]: (data_train, data_test) = train_test_split(data, test_size=0.2)
```

```
In [4]: (data_train, data_test) = train_test_split(data, test_size=0.2)
```



```
In [8]: plt.pie(train_counts,
               explode=(0, 0, 0, 0),
               labels=class_names,
               autopct='%1.1f%%')
plt.axis('equal')
plt.title('Proportion of each observed category')
plt.show()
    
```



```
In [25]: model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])

In [26]: history = model.fit(train_images, train_labels, batch_size=128, epochs=4, validation_split=0.2)

Epoch 1/2
6/6 [=====] - 11s 2s/step - loss: 1.8819 - accuracy: 0.6481 - val_loss: 0.9448 - val_accuracy: 0.6358
Epoch 2/2
6/6 [=====] - 11s 2s/step - loss: 0.7148 - accuracy: 0.7515 - val_loss: 0.7548 - val_accuracy: 0.7837

In [27]: test_loss = model.evaluate(test_images, test_labels)

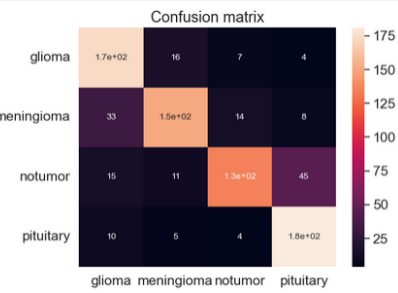
26/26 [=====] - 3s 189ms/step - loss: 0.6888 - accuracy: 0.7877
```

```
In [28]: import matplotlib.image as mimg
import matplotlib.pyplot as plt

from tensorflow.keras.preprocessing import Image
test_image = image.load_img('C:/Users/HP/Desktop/Brain-ADITYA/test/meningioma/3 (35).jpg', target_size=(128, 128))
test_image = image.img_to_array(test_image)
test_image = np.expand_dims(test_image, axis=0)
predictions = model.predict(test_image) # Vector of probabilities
pred_labels = np.argmax(predictions, axis=1) # to take the highest probability
print(pred_labels)
index = np.random.randint(test_image.shape[0])
plt.figure()
plt.imshow(test_image[index].astype('uint8'))
plt.xticks([])
plt.yticks([])
plt.grid(False)
plt.title('Brain Tumor output #' + str(index) + ' - ' + class_names[pred_labels[index]])
plt.show()
```

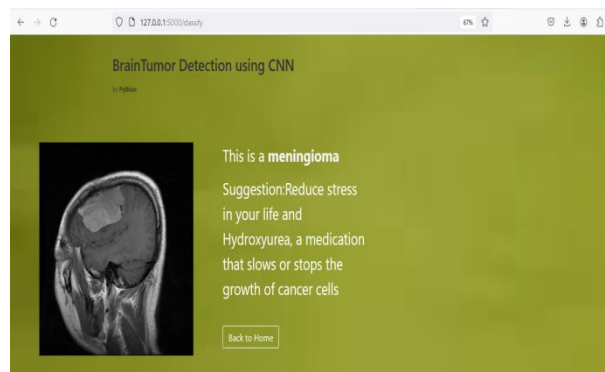


```
In [30]: CM = confusion_matrix(test_labels, pred_labels)
ax = plt.imshow(CM)
ax.set_title('Confusion matrix')
ax.set_xlabel('Actual')
ax.set_ylabel('Predicted')
plt.show()
```



```
In [32]: from sklearn.metrics import classification_report
print("\n Classification report : \n {}".format(classification_report(test_labels, pred_labels)))
```

| Classification report : | | | | |
|-------------------------|-----------|--------|----------|---------|
| | precision | recall | f1-score | support |
| 0 | 0.75 | 0.86 | 0.80 | 200 |
| 1 | 0.82 | 0.73 | 0.78 | 205 |
| 2 | 0.84 | 0.65 | 0.74 | 205 |
| 3 | 0.76 | 0.91 | 0.83 | 200 |
| accuracy | 0.79 | 0.79 | 0.79 | 810 |
| macro avg | 0.79 | 0.79 | 0.79 | 810 |
| weighted avg | 0.79 | 0.79 | 0.78 | 810 |



CONCLUSION:

In conclusion, our study demonstrates the effectiveness of Convolutional Neural Networks (CNN's) with dense in the classification and detection of brain tumors using MRI images. Through extensive experimentation and evaluation on a diverse dataset, we have shown that CNNs can achieve high accuracy, sensitivity, and specificity in identifying different types of brain tumors

FUTURE SCOPE:

important to note that ethical considerations, data privacy, and regulatory frameworks will also play crucial roles in the successful implementation of these technologies in healthcare. As technology evolves, the future of brain tumor detection holds promise for more accurate, early, and personalized diagnostics, ultimately improving patient outcomes.

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