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Efficacy of Algorithms in Deep Learning on Brain Tumor Cancer Detection
(Topic Area: Deep Learning)

Eliackim MUHOZA Master's, Dr. Musoni Wilson PhD,
Master of Science in Information Technology (MSCIT), University ofKigali, Rwanda

Abstract:- In today's world, manually examining a large number of MRI (magnetic resonance imaging)images and detecting a brain tumor is a time-consuming and incorrect task. It may have an impact on the patient's medical therapy. It might be a time-consuming task because to the large amount of image data sets involved. Because normal tissue and brain tumor cells have a lot in common in terms of appearance, segmenting tumor regions can be difficult. As a result, a highly accurate automatic tumor detection approach is required. In this study, I useda convolutional neural network to segregate brain tumors from 2D magnetic resonance brain images (MRI) and then compared the results. Moreover, I conducted the research on the six traditional classifiers namely- Support Vector Machine (SVM), K-Nearest Neighbor(KNN), Multi-layer Perceptron (MLP), Logistic Regression, Naive Bayes and Random Forest and deep learning approaches then compared with a convolutional neural network(CNN).To properly train this algorithm, I took a variety of MRI pictures with a variety of tumor sizes, locations, forms, and image intensities. We used «TensorFlow" and" Keras "in" Python" to develop the solution because it is an efficient programming language for performing rapid work. I also performed a literature review on this topic, and the study concluded with a recommendation for additional researchin this area.

I. INTRODUCTION

Of all the parts that make up the human body, the brain is the most important and significant. One of the common reasons of brain dysfunction is brain tumors. Simply said, a tumor is a collection of uncontrolledly expanding cells. The development of brain tumor cells causes brain failure because they eventually eat up all the nutrients meant for healthy cells and tissues. The location and size of the patient's brain tumor are currently determined by clinicians manually examining the patient's MR images of the brain. This is time-consuming and results in inaccurate tumor detection (Cheng et. al. 2015).

A lot of people lose their lives to brain cancer each year. The technique for identifying and categorizing them allows for the early diagnosis of brain cancers. The tasks that include classifying cancers in clinical diagnosis are the most challenging.

This study focuses on a system that uses a convolution neural network (CNN) algorithm to analyze MRI scans of distinct patients to locate tumor blocks and categorize the type of tumor.

A number of image processing techniques, such as picture segmentation, image enhancement, and feature extraction, are used to find brain tumors in MRI scans of cancer patients.

Using image processing methods, the four processes of image pre-processing, picture segmentation, feature extraction, and classification are involved in the detection of brain cancers. Image processing and neural network techniques help to detect and classify brain cancers in MRI images more accurately. (Hinton et al.2006).

II. METHODOLOGY

A. Data analysis

Data analysis is the process of finding answers through research and interpretation. Data analysis is necessary for understanding survey and administrative source results and for displaying data information. It is expected that data analysis will provide light on the study's topic and respondents' perspectives, as well as deepen readers' grasp of the subject and ignite their interest in this area of the study. Using data analysis techniques used in scientific analysis, Jupyter notebook will be utilized to analyze the data and display the findings. (Burns, 2022)

B. Deep Learning Models Convolutional Neural Networks model (CNN)

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A neural network could consist of hardware and computer code and function like the neurons in the brain. Image processing is not a task that artificial neural networks are ideally suited for. A CNN uses a mechanism akin to a multilayer view-point that has been created for less intensive processing. A system that is significantly more efficient and simpler to train data for linguistic communication and image processing emerges from the removal of restrictions and improvement in image processing potency. We made changes to the core CNN model and predicted a vastly enhanced version of it. The nine layers of our CNN model, along with the hidden layers, consist of fourteen phases that provide us the best tumor detection results. The figure below presents the methodology.

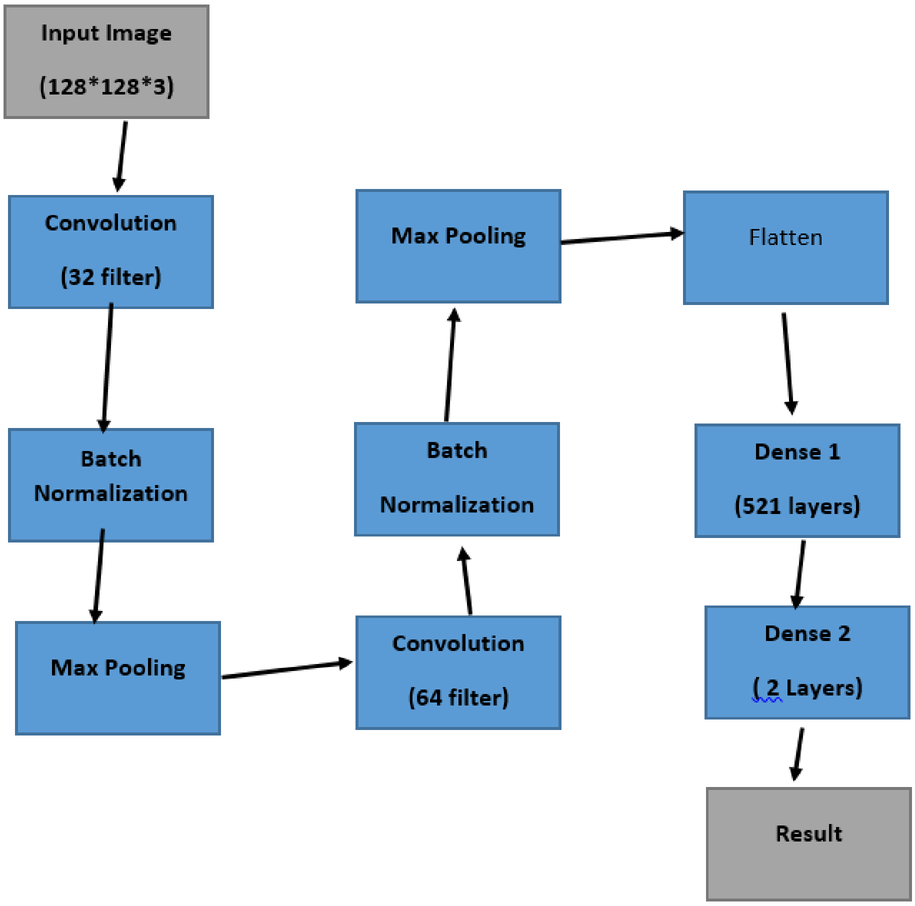

Fig. 1: Methodology for tumor detection using 9 - Layer Convolutional Neural Network

C. Layers to a Build CNN Model

Each layer in a simple CNN consists of a differentiable function that transforms one volume of activations to another. The following are the three main categories of layers used to build CNN architectures.

D. Convolutional Layer

The core component of a convolutional neural network is the convolutional layer. It has certain distinctive qualities. The majority of the computational labor is handled by it. The parameters of the CONV layer are a set of learnable filters. Each filter has a tiny width, height, and depth, yet it covers the whole input volume.

For instance, a typical 3X3 filter on the first layer of a ConvNet may be 5*5*3. (i.e., 5 pixels wide and high, and 3 color channels because images have a depth of 3).

Each filter is convolved across the width and height of the input volume during the forward pass, and dot products are calculated anywhere between the filter entries and the input. owing to the filtering A 2-dimensional activation map with the responses of that filter at each spatial position is produced as the sliders are moved across the width and height of the input volume. The network will intuitively learn filters that turn on if it spots a visual feature, such an edge with a specific orientation. To create the output volume, these activation maps are stacked along the depth axis.

Moreover, the Convolutional layer contains some fundamental qualities like:

- **Parameter Sharing:** In parameter sharing, each neuron in a certain feature map shares weights.
- **Local Connectivity:** The notion that each neuronal is only connected to a portion of the input image is known as local connection (as opposed to a neural network in which all neurons are fully connected). These traits contribute to the overall system's reduced parameter count and the computation's increased efficiency. Three hyper-parameters regulate the output volume of the convolutional layer. The criteria are as follows:
- **Depth:** The number of color channels in the input image are represented by the depth of the input volume in the first layer. If the input image is colored, the depth will be 3, which consists of the red, green, and blue channels. The depth is 1 if the image is in grayscale or black and white. The quantity of filters we apply to the input determines how deep the output volume is.
- **Stride:** Stride moves the cursor along the supplied image's width and height. The filters are moved one pixel at a time when the stride is 1. The filters will leap 2 pixels at a time as we move them when stride is set to 2.

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- **Zero Padding:** In the input layer, padding the input image with zero is sometimes used, and this technique is known as zero-padding. We can regulate the size of the input layer by using zero padding. If zero-padding is not used, it's possible that some edge-related properties could be lost.

E. Pooling Layer

The pooling layer is another element of CNN. Typically, the pooling layer comes after the convolutional layer. Its objective is to gradually shrink the representation's spatial size in order to decrease the number of parameters and computation in the network and, as a result, acquire control overfitting. Each depth slice of the input is handled independently by the Pooling Layer, which also resizes it spatially. Pooling has no impact on the input volume's depth dimension.

The work of pooling is completed by summarizing the input's subregions using various techniques, such as taking the average, maximum, or minimum value of the subregions only. Pooling functions are the name of these techniques.

- **Various Pooling Function Types:** The symmetric aggregation functions in the pooling layer include: Max Pooling, which returns the highest value from its rectangular neighborhood.

F. Fully-Connected Layer

Every neuron in the fully connected layer is linked to the neuron in the layer below it, just like a neural network. Similar to a neural network, its activation is likewise calculated via matrix multiplication with weight and bias. Fully connected layer is often a column vector. The connection between two layers is shown in the image below, with the right layer being the fully connected layer.

- Data Import and Preprocessing

```
100%|██████████| 2/2 [00:00<00:00,  4.76it/s]
100%|██████████| 2/2 [00:00<00:00, 93.17it/s]
100%|██████████| 2/2 [00:00<00:00, 21.17it/s]

193 images loaded from TRAIN/ directory.
10 images loaded from TEST/ directory.
50 images loaded from VAL/ directory.
```

Fig. 2: Data Import and Preprocessing

- Distribution of classes among sets

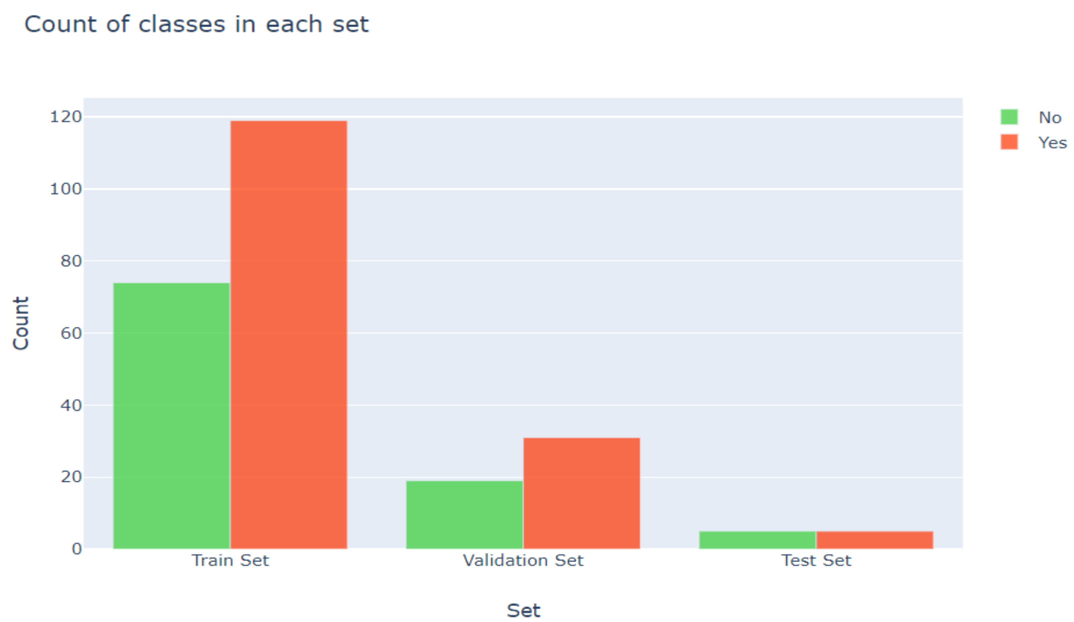

Fig. 3: Distribution of classes among sets

- Changing pixel values

As you can see, photos vary in height, width, and the size of their "black corners". Certain broad photos may appear strange after resizing since the image size for the VGG-16 input layer is (224,224). Ratio distribution histogram (ratio = width/height)

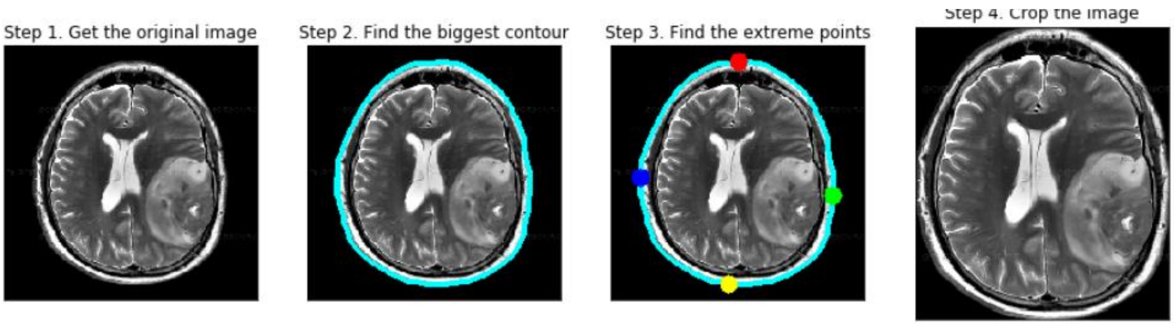

Fig. 4: Changing pixel values

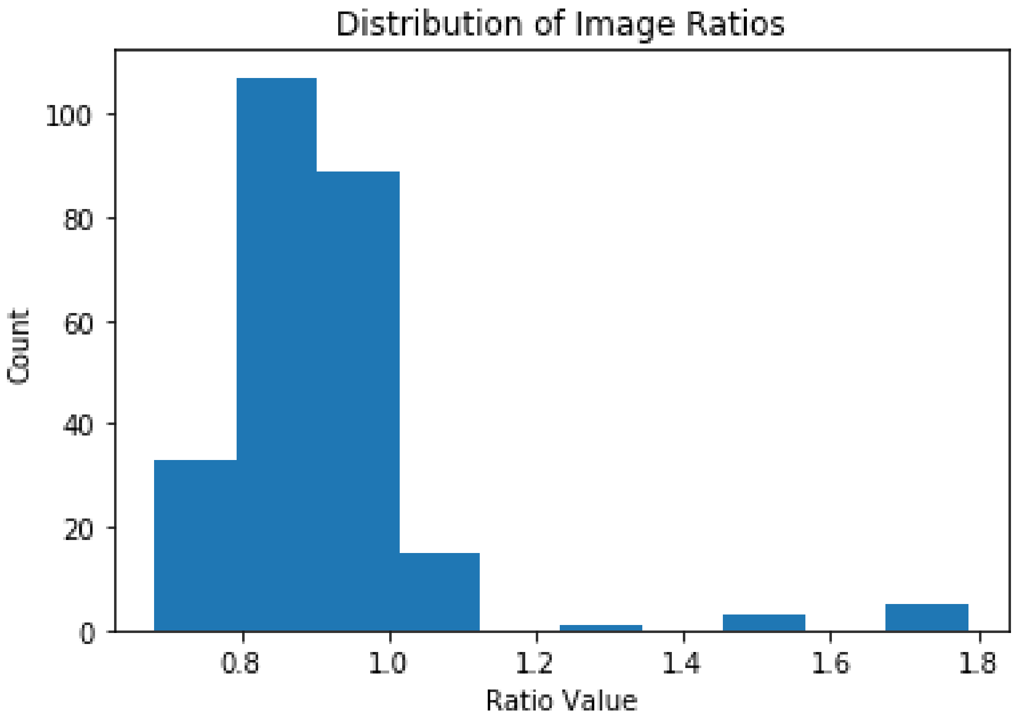

Fig. 5: Distribution of images

- Normalization

Cropping the brain from the photos would be the first stage of "normalization." Images would then need to be resized to (224,224) and preprocessed to prepare them for input into the VGG-16 model.

- CNN Model

As a foundation model, I was using Transfer Learning with VGG-16 architecture and weights.

- Visualizing the images

I employed the Data Augmentation technique, which helps to "raise" the size of the training set, because I had a tiny data collection.

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Fig. 6: Brain image

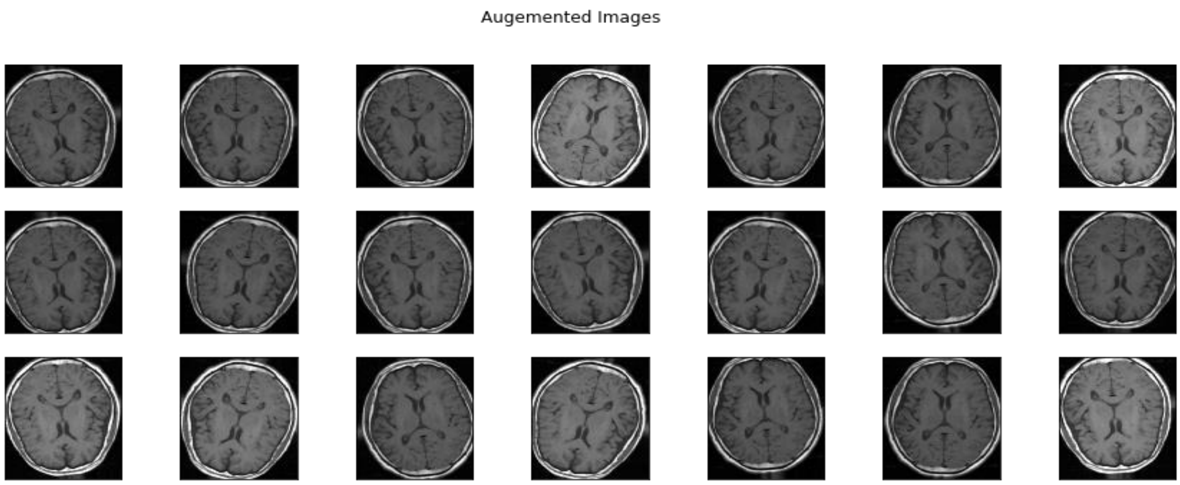

Fig. 7: Brain image augmented

* Model Building

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Model)                (None, 7, 7, 512)         14714688
_________________________________________________________________
flatten_1 (Flatten)          (None, 25088)             0
_________________________________________________________________
dropout_1 (Dropout)          (None, 25088)             0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 25089
=================================================================
Total params: 14,739,777
Trainable params: 25,089
Non-trainable params: 14,714,688
_________________________________________________________________
```

Fig. 8: Image of CCN model build

- Model Performance

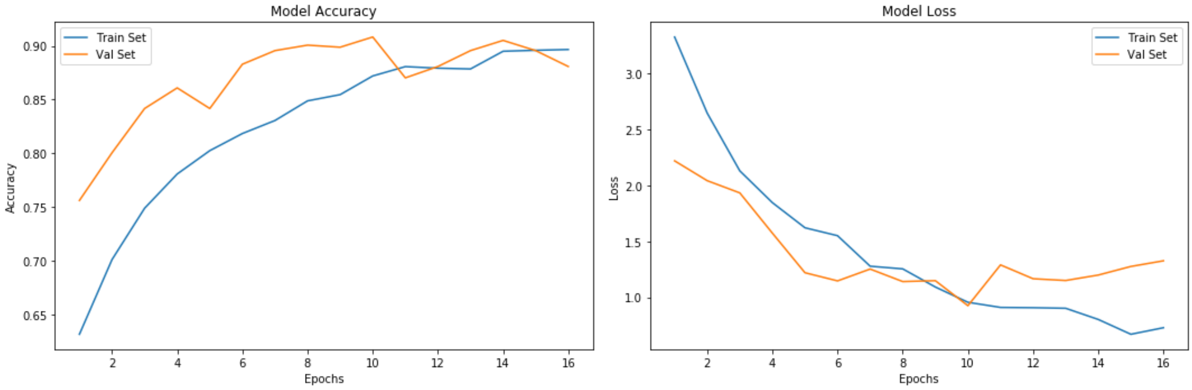

Fig. 9: Model Performance

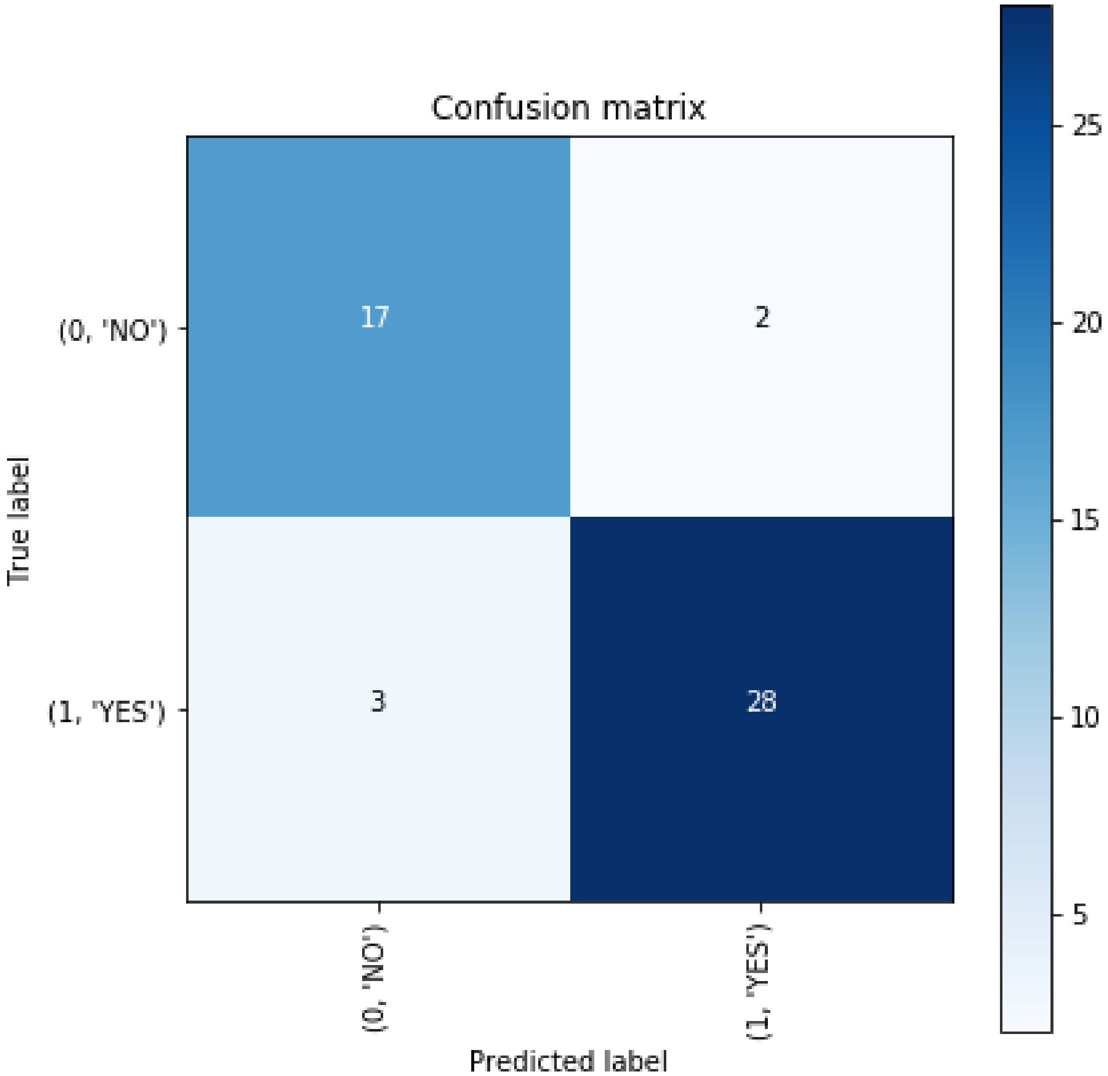

Fig. 10: Confusion matrix image

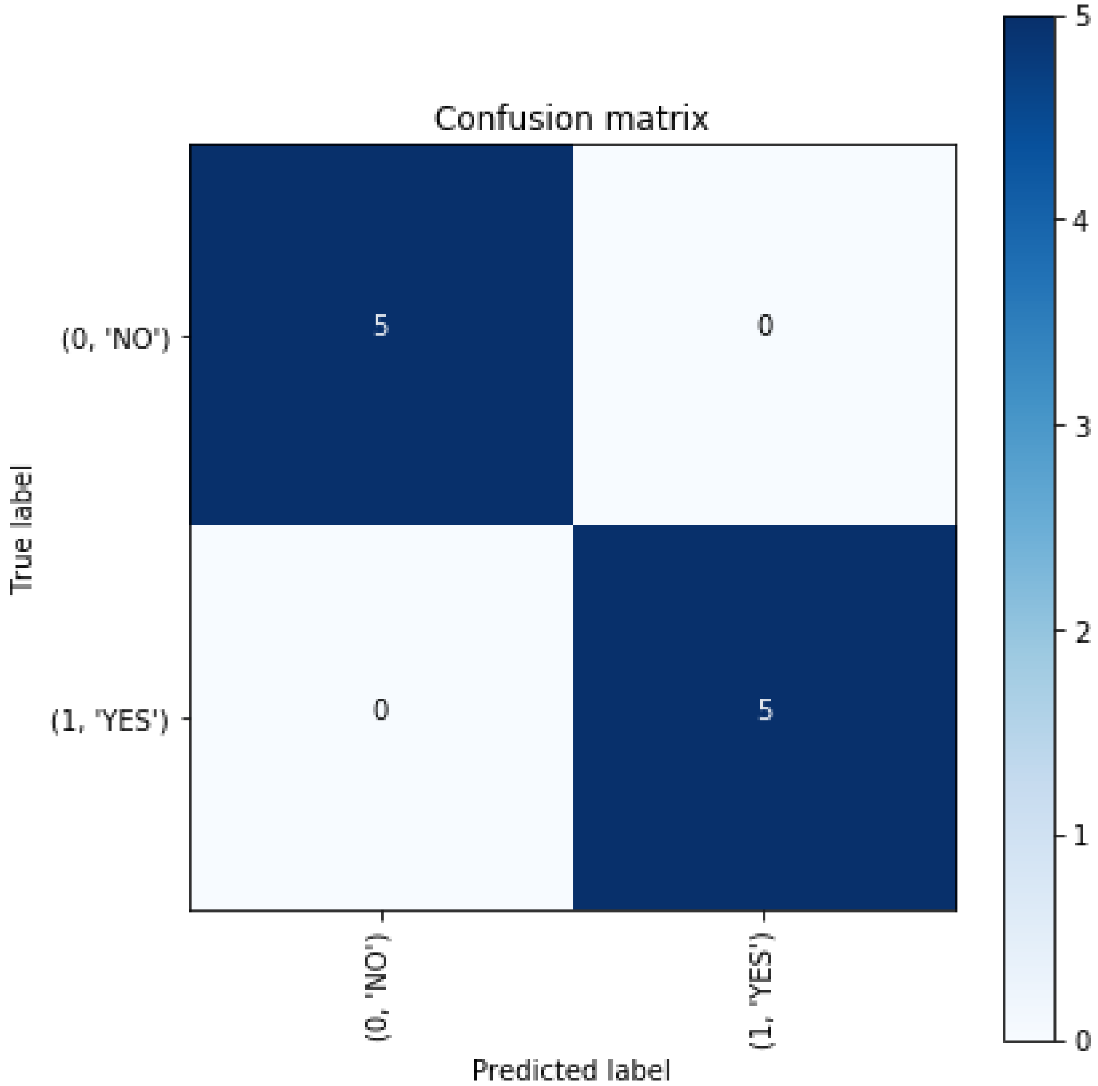

Fig. 11: Confusion matrix image

III. CONCLUSIONS OF THE STUDY

The diagnosis of brain tumors is essential for clinical therapy. It's crucial to comprehend medical images because of how differently they can be displayed. In addition to making discovery easier, the automatic brain tumor detection approach greatly increases the patient's odds of surviving. For the categorization of brain tumors, convolutional neural networks have led the way for more accurate and reliable tumor identification. Brain cancer detection and classification is the most typical use of MRI technology. Due to their apparent effective feature extraction capacity, DL-based techniques have recently attracted more attention and efficiency as compared to standard classification algorithms for medical imaging.Early cancer detection and the determination of the appropriate grade utilizing quick and affordable diagnostic tools can save many lives. Therefore, there is an urgent need for quick, non-invasive, and affordable diagnostic techniques. This work made an effort to address these needs by creating a unique method for more accurate brain tumor detection in MRI images.

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