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BRAIN TUMOR CLASSIFICATION USING DEEP LEARNING

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Abstract: By categorizing MRI pictures according to the existence of brain tumors, this study has been done to create an efficient and effective model for medical image analysis. The suggested method may replace current manual methods for classifying brain cancers by being able to find and extract robust features from MRI images. This project has the potential to aid physicians and radiologists.

***Index Terms* - Python, MRI, Medical analysis, Brain Tumor.**

I. INTRODUCTION

The term "brain tumor" refers to a growth or collection of abnormal brain cells. A very rigid skull shields your brain inside of it. In such a closed environment, any overgrowth might pose issues. Malignant (cancerous) or noncancerous brain tumors are also possible (benign). Growth of benign or malignant tumors may result in an increase in intracranial pressure. This has the potential to be fatal and can result in brain damage. Primary or secondary brain tumors fall into one of two categories: Your brain is where an initial brain tumor develops. Most primary brain tumors are benign.

The development of a secondary brain tumor, also known as a disseminated brain tumor, results from the transfer of cancer cells from one organ system, including the lung or breast, to the brain. Even though a brain tumor can develop anywhere in the brain, some areas are more prone than others: Meningiomas form in the meninges, the covering that protects the brain. Pituitary tumors are those that begin in the pituitary gland, whereas gliomas are a specific type of tumor that develop in the brain and spinal cord.

The symptoms of a brain tumor will differ depending on the location of the tumor because different areas of he brain govern distinct activities. For instance, a brain tumor in the cerebellum in the rear of the head may make it difficult to move, walk, balance, and coordinate one's movements. Headaches, convulsions, seizures, trouble speaking or thinking clearly, changes in personality or behavior, loss of balance, wooziness or unsteadiness, and other symptoms are typical signs of a brain tumor. A computer-generated electromagnetic field and radio waves are used in the medical imaging procedure known as magnetic resonance imaging (MRI), which produces precise pictures of the blood vessels that carry oxygen. From a huge collection of MRI pictures, it is difficult and costly to manually separate brain tumors for diagnosis. This project will merge a machine learning algorithm with a web app on the front end to accurately identify tumor types in MRI images. An effort was made to look into artificial intelligence and machine learning in the healthcare sector. By completing this project, the workload for our healthcare experts would be greatly reduced.

The goal is to create a project that would categories whether a tumor is visible in an MRI scan image or not, and if one is, which type of tumor is present. The development of a deep learning model that would employ TensorFlow Kera's (High Level Neural Network Library) to train and categories the MRI pictures makes use of tools like OpenCV, PIL (Python Imaging Library), data mining, and cleaning procedures. The most current development and the most advanced in the field of machine learning, CNN, is used to diagnose diseases using medical pictures, particularly CT and MRI imaging. Due to the fact that CNN does not require feature extraction or preprocessing prior to training, it has lately become widely employed in the classification and grading of medical imaging. Machine learning applications for classifying brain cancers may generally be separated into two areas: Most primary brain tumors are benign. The development of a secondary brain tumor, also known as a disseminated brain tumor, results from the transfer of cancer cells from one organ system, including the lung or breast, to the brain. Even though a brain tumor can develop anywhere in the brain, some areas are more prone than others: The CNN has been used to detect and classify brain tumors, and researchers are paying close attention to it as a powerful tool in the field of disease detection and classification, which will improve the precision of the detected brain tumor and assist doctors in coming up with the ideal therapeutic approach, thereby raising the ability to heal fraction of a percent.of the detected brain tumor and assist doctors in coming up with the ideal therapeutic approach, thereby raising the ability to heal fraction of a percent.

II. LITERATURE REVIEW

[1] Brain tumor classification using deep learning neural networks. In recent years, the topic of deep learning in machine learning has attracted a lot of attention. It was widely used in numerous applications and demonstrated to be an effective machine learning technique for many of the challenging issues. In this study, a dataset of 66 brain MRIs was classified into four classifications, including normal, glioblastoma, sarcoma, and metastatic bronchogenic carcinoma tumors, using a Deep Neural Network classifier, one of the DL architectures. The discrete wavelet transforms (DWT), a potent feature extraction method, principal components analysis (PCA), and the classifier were integrated, and the performance was evaluated as being pretty good across all performance parameters.

[2] Machine learning for the identification and categorization of brain tumors: a comprehensive survey Javaria Amin1, Muhammad Sharif, Anandakumar Haldorai, Mussarat Yasmin, Ramesh Sundar Nayak
Brain tumors are the result of cells developing fast and erratically. If not treated in the early stages, it might result in death. Despite several significant efforts and positive outcomes in this area, exact delineation and categorisation remain challenging challenges. It is quite challenging to diagnose brain tumors because of the variations in tumor location, shape, and size. This study's goal is to provide researchers with a thorough literature review on brain tumor detection using magnetic resonance imaging. The anatomy of brain tumors, datasets that were made accessible to the public, augmentation methods, segmentation, extraction and classification, classification, and pattern recognition, learning techniques, and quantum computer vision for the study of brain tumors were all included in this survey.
Finally, this review presents all relevant material for the identification of brain tumors together with their benefits, drawbacks, advancements, and outlook.

[3] Brain tumor segmentation based on deep learning and an attention mechanism employing MRI multimodality brain pictures Ramin Ranjbarzadeh, Abbas Bagherian Kasgari2, Saeid JafarzadehGhoushchi , ShokofehAnari4, Maryam Naseri, and Malika Bendechache.
Brain tumor localization and segmentation from magnetic resonance imaging (MRI) are difficult and crucial challenges for a variety of medical analytic applications. Because each brain imaging modality provides distinct and important information about each area of the tumor, several recent techniques utilized four modalities: T1, T1c, T2, and FLAIR. Even though several of them showed promise in their segmentation results on the BRATS 2018 dataset, their complicated structures make them more difficult to train and assess. In order to create a flexible and effective brain tumor segmentation system, we initially did the following in this paper. So, in order to acquire a flexible and effective brain tumor segmentation system, we suggest a preprocessing strategy that works just on a small portion of the image rather than the entire image. With this method, the overfitting problems in a Waterfall Deep Learning model are fixed while also cutting down on computation time. In the second step, a quick and effective Channel Convolutional Neural is introduced because we are working with a smaller percentage of each slice's brain images. The CCNN model uses two separate approaches to mine both local and global characteristics. A unique Distance-Wise Attention (DWA) mechanism is also implemented in order to increase the segmentation accuracy of brain tumors in comparison to state-of-the-art models. The DWA mechanism takes into account the impact of the brain and tumor's central placement inside the model, during extensive testing on the BRATS 2018 dataset, demonstrating that it produces results that are competitive. We also present and debate other quantitative and qualitative evaluations.

[4] Examining and Researching Brain Glioma Imaging deep learning-based Tao Luo1 and YaLing Li 2-e the incidence of glioma is growing year by year, putting people's health at risk. Magnetic resonance imaging (MRI) can efficiently provide intracranial pictures of brain tumors and offer compelling evidence to support the diagnosis and management of the condition. The accurate segmentation of brain gliomas provides medical benefits. However, because to the high diversity of glioma size, form, and location, as well as the enormous variances across instances, glioma images are difficult to recognition. Single-modal MRI pictures are unable to offer full information on gliomas, and conventional approaches are labor-intensive, time-consuming, and inefficient. - therefore, it is important to synthesis multimodal MRI pictures in order to detect and segment glioma MRI images. -This study uses multimodal MRI imaging and deep learning technologies to enable automated and efficient glioma segmentation.3D U-Net, a deep learning model built on thick blocks of holes, is suggested. It can segment multimodal MRI glioma pictures automatica lly. With its excellent performance, the U-Net network is frequently employed in image segmentation. The UNet model, however, is unable to successfully gather further information because to the glioma's extreme specificity. As a result, the suggested 3D U-Net model in this study may incorporate both empty convolution
and densely linked blocks

[5] Classification of brain tumors in MR images using deep spatiospatial models Soumick Chatterjee , FarazAhmed Nizamani, Andreas Nürnberger & Oliver Speck
A brain tumor is a collection of cancerous neural cells that possess the potential to kill owing to its ability to infect surrounding tissues and form tumors. A precise diagnosis is required for effective patient care, As a result, mri scan (MRI) is the principal imaging technology used to assess the amount of brain malignancies. Deep Learning methods in applications involving computer vision have already shown significant improvement in recent years, the majority of which can be attributed to the availability of a huge amount of information to train models, as well as advances in developed comprehensive produce better estimations in a controlled situation. With the availability of accessible datasets with good annotations, deep learning systems for tumor classification have made great progress. Typically, these approaches are either 3D versions that employ three dimensional MRIs or 2D models that consider each slice individually. However, By treating each spatial dimension separately or by seeing the slices as a succession of images across time, spatiotemporal systems can be employed as "spatiospatial" simulations for this task. These models can reduce computation costs while learning exact spatial and temporal interactions. To categories different types of brain cancers, this study used two spatiotemporal systems. Both of these models were found to perform better than the traditional 3D convolutional classifier. Besides that, pretraining the systems on a distinct, even unconnected datasets before having trained them for the objective of tumor classification boosts performance.

[6] Deep learning with mixed supervision for brain tumor segmentation Hervé Delingette Antonio Criminisi Nicholas Ayache, Pawel Mlynarski.
The majority of today's cutting-edge Approaches for segmenting malignancies are based on AI techniques that have been thoroughly trained using segmented images. This sort of training phase data is especially expensive since manual tumor delineation is not just time demanding but also demands medical skill. Pictures with a provided universal label (that shows whether a malignancy is present or not) are less illuminating but may be created at a much lower price. They advise making use of both types of training data (complete and partial). To create a deep learning segmentation model. Their method entails adding an additional branch to segmented circuits so they may do picture categorization. In order to take use of the information present in poorly annotated images while preventing the network from gaining extraneous features for the segmentation task, the model is simultaneously trained for segmentation and classification tasks. This method was compared to the challenging task of brain tumour segmentation in magnetic resonance images

for the Brain Cancer Segmentation 2018 Challenge. They demonstrate that, as compared to conventional supervised learning, the recommended method greatly improves segmentation accuracy. The proportion of badly annotated to fully annotated images that are available for training is connected to the improvement that has been found.

[7] Hyperspectral Images of the Human Brain Used as a Deep Learning-Based Framework for In Vivo Identification of Glioblastoma Tumor, Himar Fabelo, Martin Halicek, Maysam Shahedi , Adam Szolna , Carlos Espino , Mariano Márquez, Mara Hernández , David Carrera , Jess Morera.
The basic objective of brain cancer surgery is to accurately remove the tumor while conserving as much of the patient's normal brain tissue as is feasible. A current clinical need is the creation of a non-contact, label-free technique to offer trustworthy support for tumor removal in real-time during neurosurgery procedures. Without utilizing a contrast agent,
hyperspectral imaging is a non-contact, non-ionizing, and label-free imaging method that can help surgeons with this difficult task. In this study, we describe a system for analyzing hyperspectral pictures of in vivo human brain tissue that is based on deep learning. Our human picture library, which contains 26 in vivo hyperspectral cubes from 16 distinct patients, 258,810 of whose pixels were tagged, was used to assess the suggested framework. The suggested framework can produce a thematic map that shows the position of the tumor and the parenchymal region of the brain, giving the operating surgeon direction for a procedure. successful and accurate removal of the tumor. For multiclass classification, the deep learning pipeline achieves an overall accuracy of 80%, outperforming the outcomes of conventional support vector machine (SVM)-based methods. The operating surgeon can modify the final theme map in the assistance visualization system to determine the best categorization threshold for the current circumstance during the surgical procedure.

[8] A two-phase, multi-model, automated brain tumor diagnosis method from magnetic resonance imaging uses convolutional neural networks. Ali Ismail Awad, Hesham F. A. Hamed, Ashraf A. M. Khalaf, and Mahmoud Khaled Abd-Ellah
A dangerous condition, brain tumors are responsible for a rising number of fatalities. It takes a lot of effort to manually diagnose tumors using magnetic resonance imaging (MRIs), and it is ineffective for reliably identifying, locating, and
classifying the tumor type. This study suggests a brand-new two-phase multi-model automatic diagnosis technique for locating brain tumors. Preprocessing, feature extraction using a convolutional neural network (CNN), and feature classification using an error-correcting output codes support vector machine (ECOC-SVM) approach make up the system structure for the first phase. The initial system phase's goal is to identify brain tumors by dividing MRI pictures into normal and abnormal ones. The objective of the second system phase is to find the tumor by analysing the abnormal MRIs using five fully formed planes of a territory convolutional neural network (R-CNN). To assess the first phase's performance, three CNN models—AlexNet, Special Interest Group (VGG)-16, and VGG-19—were utilised. AlexNet was able to get a peak detection accuracy of 99.55percent of total using 349 pictures from the RIDER Neuro MRI collection, which is a widely used reference image library to evaluate response. Using 804 3D MRIs from the Brain Tumor Segmentation (BraTS) 2013 database, the brain tumor localization phase was assessed, and a DICE score of 0.87 was obtained. Comparing the proposed deep learning-based system to existing non-deep-learning systems in the literature, empirical research demonstrated its superior performance in detecting tumors' collected findings also show how effective the suggested technique is at both locating and detecting tumors.

[9] Data Augmentation for Brain Tumor Segmentation Jakub Nelepa, Michal Marcinkiewicz, Michal Kawulok
A common method for enhancing deep neural networks' generalization skills is data augmentation, which may be thought of as implicit regularization. It is crucial in situations where there is a shortage of high-quality ground truth data and finding new examples is expensive and time-consuming. Tumor delineation, this is a particularly prevalent issue in the interpretation of medical images. In this article, we examine recent developments in data-augmentation methods used on brain tumor magnetic resonance images. We examine the papers submitted to the Multimodal Brain Tumor Segmentation Challenge (BraTS 2018 edition), as the BraTS dataset has become a standard benchmark for validating existing and cutting-edge brain-tumor detection and segmentation methods, to better understand the practical aspects of such algorithms. We investigate which data augmentation techniques were used and how they affected the skills of the underlying supervised learners. Finally, we highlight the most potential research lines to pursue in order to synthesize high-quality artificial brain tumor cases that can improve deep models' generalization capabilities.

[10] A Review on a Deep Learning Perspective in Brain Cancer Classification Gopal S. Tandel ,Mainak Biswas Omprakash G. Kakde, Ashish Tiwari 1, Harman S. Suri, Monica Turk , John R. Laird, Christopher K. Asare , Annabel A. Ankrah, N. N. Khanna , B. K. Madhusudan , Luca Saba and Jasjit S. Suri
According to a World Health Organization (WHO) research from February 2018, the Asian continent has the greatest fatality rate from brain or central nervous system (CNS) cancer. In order to preserve many of these lives, it is crucial that cancer be discovered sooner. An essential component of targeted therapy is cancer grading. The development of non-invasive, inexpensive, and effective techniques for brain cancer characterization and grade estimation is urgently needed because cancer detection is a time consuming, costly, and very intrusive process. Brain scans employing imaging modalities like computed tomography (CT), magnetic resonance imaging (MRI), and others are quick and risk-free ways to find tumors. In this article, we attempted to provide a concise overview of the pathophysiology of brain cancer, brain cancer imaging techniques, and automatic computer-assisted approaches for characterization of brain cancer in a machine and deep learning paradigm. Finding the current problems with the engineering methodologies that are currently in use and predicting a future paradigm are other goals of this research. Additionally, in the context of machine learning and the deep learning paradigm, we have highlighted the connection between brain cancer and other brain disorders like stroke, Alzheimer's, Parkinson's, and Wilson's disease, leukoriasis, and other neurological disorders.

METHODOLOGY

3.1 Dataset

In this research, we used a 'Brain tumor classification dataset' [1] from the website https://www.kaggle.com. The dataset contains pictures of contrast-enhanced brain MRIs and is divided into four categories: glioma, meningioma, pituitary tumor, and no tumor. We segregate these images into four different folders for the labelling purposes. The MRI images included in the dataset are of one of the three axes shown below. MRI images can be taken from various axes to cover the entire portion of the brain. The images taken from these three axes are carefully examined for the presence of any tumor masses. Different axes of the MRI images show various different sections of the brain enabling the doctors to thoroughly examine all the sections. The most effective way for detecting brain cancer is magnetic resonance imaging (MRI). The scans generate a massive amount of image data. These images are examined by the radiologist. A manual examination may be inaccurate due to the intricacy of brain tumors and their features.

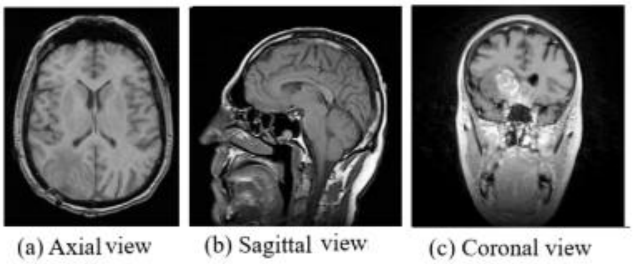

Fig.1 Axes of an MRI image (image courtesy: cancers (2019) - mdpi)

We will now examine the various images present in the dataset used for this project. We can segregate the images into one of the four classes - glioma, meningioma, pituitary tumor and no tumor images. We can see that in general it is very difficult to differentiate between a mass of tumor and the normal portions of the brain. The images below display the first instance, which is an MRI scan of a glioma tumor. In the brain and spinal cord, gliomas, a specific type of tumor, form. Gliomas are derived from the glumpy support cells (glial cells), which surround and support nerve cells.

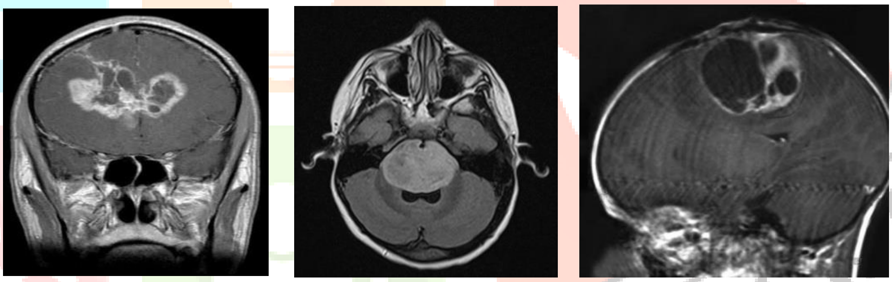

Fig.2 Glioma MRI images from the dataset

The second case is shown in the pictures below, which is Meningioma tumor. The brain is covered by three layers or membranes called the meninges. These layers cover and protect the brain and the spinal cord. When tumor cells arise from these outer layers or meninges, it is called meningioma. The MRIs show the tumor arising from the meninges of the brain.

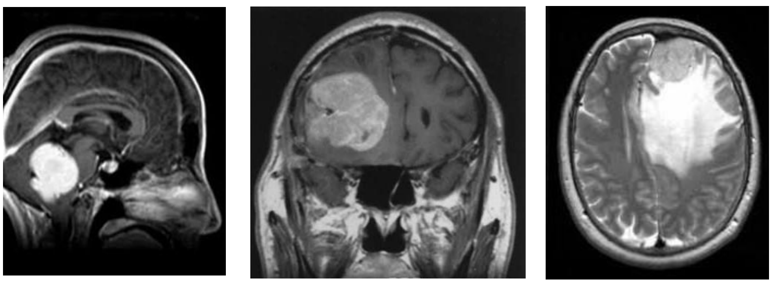

Fig.3 Meningioma MRI images from the dataset

The third case of tumor is Pituitary tumor, shown in below pictures. The pituitary gland is located near the bottom of the brain. It regulates the formation, growth, and function of the other endocrine glands. It is generally a pea-sized organ, but in the case of a pituitary tumor, the size unnaturally grows, as depicted below.

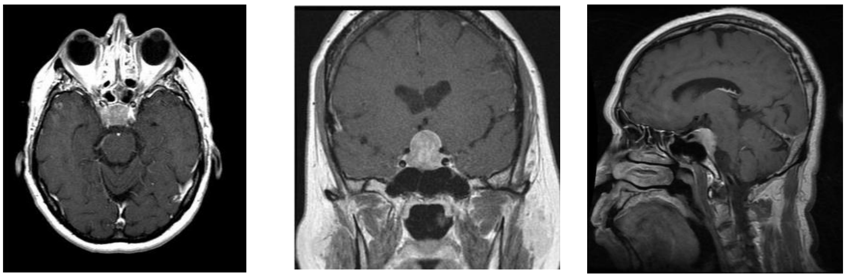

Fig.4 pituitary tumor mri images from the dataset

The last case shown in below pictures is of the category No Tumor MRI images. The below scans do not show the presence of any tumor cells. This is how a normal MRI scan is supposed to look like. The dataset includes this class of MRIs to provide a larger overall classification. The model is meant to detect the presence of a tumor and then to classify it

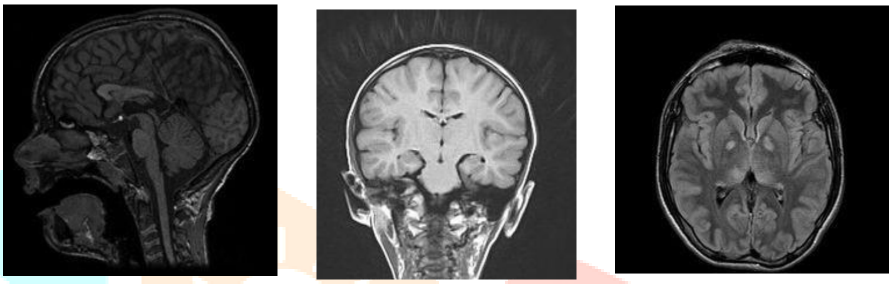

Fig.4 No tumor MRI images from the dataset

3.2 Classification Algorithm

Because of their precision and natural ability to recognize data without explicit programming, neural networks are commonly employed in practically every deep learning effort. CNN is frequently used to categorize visual data. CNN's primary benefit is its ability to automatically and without human intervention identify key elements in any image. This may be the reason that CNN would be the ideal answer to issues with computer vision and picture categorization. Therefore, feature extraction is essential for CNNs.

3.3 Method

The selected dataset is first downloaded in the form of a zip file. The data is then extracted from the zip file and properly categorized as per the requirements. The information has been organized into four folders: glioma tumor, meningioma tumor, pituitary tumor, and no tumor. Now, various modules in karas TensorFlow are used to create the neural network that will learn and classify the MRI images into one of the four categories. The presence of a tumor is first detected then it is classified into one of the four classes. Next, a frontend python web application is built and designed using flask framework. Even a mobile application can be created to carry out the same functionalities. A backend is created using python to connect the ML model. Finally, the ML model is connected to the python web application. The filtering step is carried out by the convolutional layer. ConvNet's convolutional layers hold the majority of the weights that it learns during training. We refer to these scales as cores. The image is scanned by the core, which creates a weighted pixel sum. The most important part of any neural network is identifying the features to build a feature map. Based on the information it receives, the activation function determines if a certain neuron will fire before sending it to the next layer. Because of its straightforward implementation and ability to overcome several drawbacks that are present in other activation functions like the Sigmoid, the Rectified Linear Unit, or ReLU.

Once the feature map is built it is used to figure out the differences or similarities in the images. The User will never know what the particular selected features were. The various layers of the CNN select these features. The kernels required to scan the images are also selected automatically. The user can ultimately choose and upload their own MRI picture. The feature map is contrasted with the MRI picture. The picture is initially utilized to determine if a tumor is present or not based on that.

MRI is then assigned to one of the four classes. The user receives a class label in return that contains information about the supplied MRI picture. Anyone without prior knowledge may effortlessly utilize this user-friendly UI. Patients won't be required to seek a second opinion as a result. lowers the likelihood of human mistake. Although the patients must initially contact a radiologist, this system would lessen the necessity for involving the doctors in the beginning itself. This largely reduces the burden on our healthcare workers

IV. Conclusion

The dataset used in this study contains three types of brain cancer: gliomas, meningiomas, and pituitary tumors. The proposed convolution neural network is employed in this study to carry out an efficient automated classification of brain cancers. Matplotlib for imshow (), which displays the image, and Python Imaging Library (PIL), which handles all image operations.

We use PIL's ImageOps module, which is used for a variety of imaging and image preprocessing activities. We can declare with confidence that our CNN model correctly predicts any type of brain tumor data. Any of the aforementioned brain tumor datasets may be used when using the provided model architecture. As we observe how drastically technology has altered both our way of life and society. Using technology to better our people is the best it can do.

We have the foresight to develop this technology incrementally and make it practical for daily usage. Deep Learning is the finest alternative for healthcare. We may employ all the models in the industry, such as the aforementioned Deep Learning model for brain tumor classification, by making little changes. We learnt how to utilize TensorFlow and Keras for this deep learning model as well as other approaches to assist us increase our accuracy and do visualization tool. R

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