Diagnosing Intracranial Neoplasms through Magnetic Resonance Imaging & Convolutional Neural Networks

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Abstract:
The paper employs modelling and predicting intracranial neoplasms by implementing convolutional neural networks on magnetic resonance imaging (MRI) scans, and then assessing the probability of a malignant or benign tumor in the region. The model implemented in the paper, a convolutional neural network (CNN), utilizes 193 images of MRI scans of the brain with and without a visible neoplasm to train the weights; while 50 validation and 10 test images are applied to evaluate the effectiveness of the model. The data utilized in the model is, primarily, resized to optimum fitting through computer vision—specifically, contouring and extremity recognition. Further, the data is augmented through the use of data generators which enable the model to achieve the benefits of a larger dataset without compromising the integrity of the primary resonance scans. The model incorporates transfer learning from the reputed [1] VGG16 CNN model along with a half dropout layer to ensure maximum reliability and certainty of the outputs. The model is evaluated through the Root Mean Square method obtained from a binary cross-entropy loss observed in the training. The total parameters of the model are 14,739,777 with 25,089 trainable parameters are trained for 30 epochs subclassed into 50 steps. The predicted values of the model are compared to the pre-determined outputs of the dataset in the training, validation and test data frames. Finally, the paper will analyze possible implementations and steps that may be enacted in conjunction with the approach developed in the research—and others such—to develop a better chance of forecasting and treating the fatal neoplasm.

Keywords: Intracranial Neoplasm, Brain Tumor, Convolutional Neural Network, Medical Imaging, Magnetic Resonance Imaging, CNN, Deep Learning, MRI.

I. INTRODUCTION

An intracranial neoplasm is the occurrence of mass growth of abnormal/anaplastic cells in the cerebrum. The said abnormal growth, in the form of tumors, may stem from the brain (primary) or reach the brain from other sections of the body (metastasis). Though new methods of treatment and advances in the medical sciences are reducing the mortality of patients and improving the quality of life with identified tumors, the over 120 types[2] of tumors such as Astrocytoma, Pilocytic Astrocytoma (grade I), Diffuse Astrocytoma (grade II), Anaplastic Astrocytoma (grade III) and many other present a significant challenge. In the United States alone, approximately 80,000 new primary brain tumors cases are anticipated to be identified this year, nearly one-third (32%) of brain and CNS tumors are malignant. Moreover, it is projected that greater than 4,600 adolescents and children through the ages of 0 to 19 will be diagnosed with a primary brain tumor this year [3]. The several types of intracranial neoplasms may yield symptoms that differ depending on the section of the brain involved. These symptoms may well comprise of seizures, headaches, challenges with vision, nausea, psychosomatic disorders, among others; with a limited understanding of the cause and prevention of the tumor, medical professionals heavily rely on diagnostic procedures such as biopsy and imaging. Magnetic Resonance Imaging (MRI) scan routines a magnetic field along with radiofrequency waves to produce a comprehensive assessment of the soft tissues of the brain. It observes the brain in three-dimensionally slices which may be ascertained from the sides or from the top as a cross-section of the brain. A dye (contrast agent) may be injected into the bloodstream to clarify the image produced by the MRI and is extremely effective while evaluating brain lesions and their impact on the nearby sections of the brain.

Figure 1. Brain metastasis in the right cerebral hemisphere from lung cancer, shown on magnetic resonance imaging [4].

The obtained images may be analyzed with the ever-growing capacity of neural networks—especially convolutional neural networks of CNNs. Convolutional Neural Networks are a segment of deep neural networks that are appropriated for implementation in computer vision or analyzing visual imagery. The Convolutional Layer employs a set of trainable filters which are utilized to perceive the occurrence of definite features or patterns observed in the original image (input image). The image is generally presented as a matrix (RxCx3), wherein R and C represent the dimensions of the image, while 3 is the RGB value.

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of the same. With marked, sometimes implicit, distinctions in the image produced by an MRI, a CNN model may be employed to ascertain if there is a possibility of a tumor, which can then be assessed by a medical professional. With the poor prognosis of brain cancer and neoplasms, it is essential to rapidly and effectively identify individuals at the risk of the same. The use of computation in identifying possible cases of neoplasms in the brain will greatly promote efficiency while maintaining current standards of integrity in the diagnosis of the same. Innovation must occur in areas wherein the wellbeing of individuals is a concern. Therefore, the paper integrates the advancing knowledge of machine learning and computer vision with medical imaging to better diagnose intracranial neoplasms and improve the quality of life of those affected.

Data
The data sourced for the training, validation, and testing of the model is obtained from reliable sources to ascertain the integrity of the data being used in the model. The best practices of Extraction, Transformation and Loading were executed to heighten the integrity of the sourced data. The dataset includes 253 images of MRI scans of the top cross-sectional area of the cerebrum. 190, 50, and 10 images from the data were applied for training, validation and testing, respectively. The images were encoded in either 0 or 1, wherein 0 represented no detected neoplasm and 1 represented the inverse. The classification of images in each set is as below.

However, the images presented in the sets were not of the same size/dimensions, due to the availability of the images on different sources. This would hamper the implementation of a CNN model; therefore, the images were resized by contouring the section of the brain. This would ensure that the images were represented in the same dimensions and were capable of being introduced to a CNN model.

The cropping model utilized pre-existing extreme thresholds in lieu with erosions and dilations in the image, to contour the necessary section (the cerebrum) and resize the images. Lastly, to further ensure the reliability of the prediction of the model, the images applied in the training were augmented for data generation purposes. Through the use of a generic image data generator, the images in the model were altered—whilst not affecting inherent properties—through views from different angles, vertical and horizontal turns. This “increased” the size of the dataset without hampering the reliability of the images.
In the face of limited data available for the model to train, computer vision was implemented to optimize the current data directory. Likewise, data augmentation through generators was utilized to alter the images and enable more thorough training of the model.

**Model**
The model utilized in the paper is a transfer-alternative of the conventionally utilized CNN models. The model incorporates the benefits of the critically-acclaimed VGG16 model. VGG16 is a convolutional neural network model projected by K. Simonyan and A. Zisserman from the University of Oxford in the paper “Very Deep Convolutional Networks for Large-Scale Image Recognition”. The VGG16 model attains 92.7% test precision in ImageNet, which is a dataset of greater than 14 million images belonging to a thousand different classes. [5]

![Figure 7. Architecture of VGG16 Neural Network.](image)

The apparent depth and pre-determined weights of the VGG16 make into a very resourceful model for the paper. The use of the same would help deliver accurate and reliable results concerning the imagistic diagnostics of intracranial neoplasms. Therefore, the VGG16 model was capped with other segments of the final CNN model to perform effective transfer learning. The CNN model, after transfer learning, utilizes a flatten of the matrix, ½ dropout layer and a sigmoid-activated segmentation layer (Dense) to classify the final matrix as either consisting of a tumor or not. This appends to reducing the chances of overfitting of the training data in the model. Moreover, an early-stopping function, which measures the root mean square error in binary cross-entropy loss, is applied in the model; hence, allowing the model to achieve the optimum fit in lieu with the data and training. Throughout the training of the model, the validation generator is used alongside to enhance productivity and reduce computational complexity. The validation dataset is essentially utilized to adjust the hyper-parameters throughout the training, which ensures that the optimum—as possible through the limited data—parameters are established before the testing is conducted. Ideally, the model must be assessed on samples that were not applied to construct or fine-tune the hyperparameters of the model, so that they provide an unbiased evaluation of the model’s efficacy. Hence, the validation dataset enables the tuning of hyperparameters without repeating data in testing or training. The complete CNN is trained for 30 epochs with 50 steps, with the input being an image from the dataset while the output corresponds to the class of the images: its encoded value. However, the CNN issues a 0 to 1 probability instead of a hot-encoded value; through the same, a 0.5 or greater result is considered positive of an intracranial neoplasm.

![Figure 8. Final CNN model architecture.](image)

**II. RESULTS**
The training accuracy of the model through the resized, augmented images achieved a maximum in the 50th sub-run of the 16th epoch with a loss of 0.5057. The loss-rate corresponds to 7 incorrectly labeled images during the training of the model. It may imperatively add to the uncertainty of the predictions of the model; however, it represents the reliability achieved by using the transfer learning model.

![Figure 9. Model loss during training.](image)
After the training of the model, the testing phase outputted an accuracy of 0.9, with 1 mislabeled image in the test dataset. This depicts the optimum-fitting achieved through the set hyperparameters and high reliability of the model outside the training dataset; far surpassing the baseline 50% achieved through the general probability of random conjecture.

90% accurate prediction rate, is indicative of the high performance achieved by substituting a recognition task to computational entities.

Applications
The increasing computational power—be it transitioning to neuromorphic or quantum systems—and burgeoning quantity of data available may be channeled to applications which require greater efficiency. This is clearly visible in medical imaging, as intracranial neoplasm impacts hundreds of thousands around the globe, it is essential we deploy the influence of neural networks to aid medical professionals in effectively diagnosing the same. With larger datasets and augmentation of the same, the CNN models may be transformed into networks with—to a great extent—no loss of accuracy. With the ability to sort through thousands of medical resonance scans, CNN models can be employed to present cases with higher probability to physicians’ expert in the matter. For example, ½ standard deviation below the mean illustrates all possibilities of a metastasized or primary brain tumor in the individual scanned. This would eliminate 30.85% (considering a normally distributed dataset) of unnecessary checking; therefore, increasing efficiency and productivity of the medical professionals. Moreover, such CNN models allow for remote diagnosis after the scan, this may be especially helpful in less economically developed regions wherein immediate access to medical professionals is a challenge. Though a preliminary resonance imaging is necessary, expert opinion or analysis of the same can be implemented secondary to a remote analysis by the CNN model: significantly improving the otherwise fatal prognosis of the positively diagnosed individual. The concepts of the research, coupled with other similar, can be implemented in a plethora of other forms of medical diagnosis. Foundations fields such as Proietional Radiography and Computational Tomography along with relatively new areas like Elastography may benefit from implementing computer vision and learning for secondary diagnoses.

III. CONCLUSION& FOREWORD

The paper developed on the fused fields of medical sciences and computation through the use of computer vision in contouring the necessary section of the cerebrum for optimized model training, while convolution neural networks were implemented to forecast the likelihood of an intracranial neoplasm, simply, through the use of magnetic resonance imaging scans. The greater efficiency and reliability attained through the use of multiple segments of varied fields is a prologue to the greater horizons that lie at the intersection of the two knowledge frameworks. With incrementing computational processing ability and deepening knowledge of the medical sciences, innovations at the juncture of the two can significantly impact productivity, efficiency, and most importantly, lives for the better.

IV. REFERENCES


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