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NeuroScan : Brain Tumor Detection using Convolution Neural Network

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Abstract - This paper introduces "NeuroScan-Brain Tumor Detection Using CNN," a groundbreaking project integrating Convolutional Neural Networks (CNNs) for early brain tumor diagnosis via MRI image analysis. With deep learning's burgeoning influence, CNNs emerge as potent tools for healthcare challenges. Brain tumors, with their dire implications, necessitate swift and accurate diagnosis for effective intervention. Automated CNN-based analysis overcomes manual classification limitations, promising improved patient outcomes. Building on successful CNN-based detection, this project innovatively integrates geolocation services, pinpointing patients' locations post-detection to expedite access to nearby specialist care. By harmonizing AI with geolocation, NeuroScan streamlines specialized healthcare access, potentially curbing brain tumor mortality. Employing advanced CNN architectures, NeuroScan achieves efficient tumor detection, utilizing fewer features than traditional methods. This multidisciplinary strategy is a big step forward in using technology to improve patient care and healthcare delivery.

Key Words: : Convolutional Neural Networks, Brain tumors, geolocation services, CNN architectures.

1.INTRODUCTION

The diagnosis and management of brain tumors stand as formidable challenges within the realm of healthcare, profoundly impacting patients' lives due to the intricate nature of these conditions. Brain tumors, characterized by the uncontrolled proliferation of cells, manifest in various forms ranging from benign to malignant, with the latter posing a greater threat due to their aggressive and invasive behavior.This class of tumors presents one of the most complex and life-threatening manifestations of cancer, necessitating early detection and intervention to improve patient outcomes and mitigate mortality rates. Recent strides in medical imaging technologies, notably brain magnetic resonance imaging (MRI), have revolutionized the landscape of tumor detection and characterization.MRI offers unparalleled detail and clarity, empowering clinicians to visualize abnormalities in brain tissue with exceptional precision, thus enabling more accurate diagnoses and informed treatment planning. In addition, a new era of medical image analysis has been brought about by the development of deep learning techniques, specifically neural networks using convolution (CNNs), which enable autonomous tumor identification and categorization with previously unheard-of precision and efficiency..Amidst these advancements, the paper introduces the innovative project "NeuroScan-Brain Tumor Detection Using CNN," poised to harness the power of CNNs in augmenting early brain tumor diagnosis through MRI image analysis. By leveraging CNNs, the project aims to extract meaningful features from MRI images, enabling the identification and characterization of tumors with enhanced precision and reliability. Moreover, the project endeavors to integrate geolocation services into the diagnostic process, empowering patients to locate nearby medical specialists specialized in brain tumor treatment. This integration not only streamlines the process of accessing specialized medical care but also holds promise in expediting treatment initiation, thereby fostering improved patient outcomes and bolstering overall healthcare efficiency. Through this interdisciplinary amalgamation of cutting-edge technologies with healthcare delivery, the project aspires to confront the multifaceted challenges posed by brain tumors and propel advancements in patient care and treatment strategies. In essence, the endeavor underscores a concerted effort to confront the intricacies of brain tumor diagnosis and treatment through an integrated approach that marries state of-the-art medical imaging technologies with advanced deep learning methodologies. By leveraging the capabilities of CNNs and integrating geolocation services, the project endeavors to enhance the accuracy and accessibility of brain tumor diagnosis, thereby paving the way for timelier interventions and improved patient outcomes. This collaborative fusion of technological innovation and healthcare delivery underscores a commitment to addressing the complex challenges posed by brain tumors and underscores the potential for transformative impact in the field of neuro-oncology. In conclusion, the project "NeuroScan-Brain Tumor Detection Using CNN" represents a significant stride towards addressing the intricate challenges of brain tumor diagnosis and treatment. By leveraging cutting-edge medical imaging technologies and advanced deep learning methodologies, the project endeavors to improve the accuracy, accessibility, and efficiency of brain tumor diagnosis, ultimately aiming to enhance patient outcomes and reduce mortality rates. Through the collaborative fusion of technological innovation with healthcare delivery, this interdisciplinary endeavor underscores a commitment to advancing the field of neuro-oncology and holds promise for transformative impact in the lives of patients affected by brain tumors.

2. Literature Survey

The literature review delves into a comprehensive exploration of studies dedicated to the intricate domain of brain tumor detection and classification. Each study unfolds a unique set of objectives, datasets, algorithms, results, and insightful remarks, collectively enriching the understanding of advancements in this critical field. One such study aimed to optimize feature selection methodologies specifically tailored for brain tumor detection. Employing the BraTS 2020 dataset, the study meticulously curated a Convolutional Neural Network (CNN) framework integrated with a hybrid feature selection mechanism. Impressively, this approach yielded promising results, achieving an accuracy rate of 92.2% for discerning tumor presence/absence and 90.5% for segmenting tumor core/enhancing core regions. Noteworthy was the utilization of pre-trained VGG16 features, which not only underscored the potential of transfer learning but also hinted at the efficacy of leveraging existing knowledge for enhanced diagnostic precision. In a parallel pursuit, another investigation undertook a comparative analysis of various deep learning techniques for brain tumor detection. Leveraging datasets like BraTS 2020 and MICCAI 2012, the study meticulously scrutinized a diverse spectrum of CNN architectures, prominently featuring the Inception-ResNet V2 model. The study yielded remarkable insights, showcasing the highest accuracy of 95.1% for tumor core segmentation. The key takeaway was the profound effectiveness of employing deeper models, accentuated by the integration of multi-modal MRI data (T1, T2, Flair), which substantially augmented the discernment capability, underscoring the importance of holistic data integration for robust diagnostic outcomes. Furthermore, a study delved into the classification of brain tumors through CNN methodologies. Employing the BraTS 2020 dataset, this investigation meticulously engineered a 15-layer CNN with Batch Normalization, primarily focused on achieving accurate whole tumor segmentation. Despite its relatively simple architectural framework, the study demonstrated commendable performance, attaining an accuracy rate of 91.3%. Particularly noteworthy was its adaptability for resource-constrained environments, highlighting the potential for widespread applicability across diverse healthcare settings. 3 Furthermore, a fascinating combination of CNN and an attention mechanism was discovered during an investigation on the identification of brain cancers in MRI pictures By using the BraTS 2020 dataset, this study was able to achieve an exceptional tumor core segmentation correctness rate of 94.2%. This was made possible by the attention mechanism's capacity to selectively focus on relevant image regions. Such meticulous attention to detail in identifying and delineating tumor regions suggests promising prospects for refining diagnostic accuracy and treatment planning in neuro-oncology. In addition to optimizing feature selection and comparing deep learning techniques, several studies have emphasized the significance of ensemble methods, fine-tuning pre-trained models, and developing explainable deep learning approaches. For instance, one study showcased the potential of ensemble methods by achieving a remarkable accuracy of 98.1% for tumor core segmentation, highlighting the synergistic benefits of combining multiple CNNs. Moreover, the incorporation of fine-tuned CNNs, such as ResNet50 and U-Net, has demonstrated promising results in tumor type classification, underscoring the effectiveness of transfer learning in leveraging pre-trained models for smaller datasets. Furthermore, the integration of explainable deep learning techniques, such as hybrid feature selection with CNNs, has enhanced interpretability and model transparency, contributing to the trustworthiness of diagnostic outcomes. These advancements collectively signify a concerted endeavor towards harnessing the power of deep learning and innovative methodologies to address the complex challenges inherent in brain tumor diagnosis and classification, ultimately striving towards improved patient outcomes and advancements in neuro-oncological research

3. Methodology

3.1 Population and Sample

The population of interest in this study consists of people who had brain MRIs, more especially those that show instances of brain tumors. The sample selected for analysis consists of 253 Brain MRI Images obtained from Kaggle. This dataset is divided into two partitions, first containing images representing tumorous and other representing non-tumorous brain images respectively. There are 155 images displaying tumorous brains and 98 images depicting non-tumorous brains.

3.2 Data and Sources of Data

The primary data utilized in this research consists of brain MRI images sourced from Kaggle, accessible at the provided link. Comprising 253 images, these data are categorized into tumorous and non-tumorous classes, with 155 and 98 images, respectively. Methods for data augmentation were used to speed up the neural network's learning process. Because of the dataset's restricted size, data augmentation was judged required in order to address the problem of data imbalance and enrich the dataset by producing additional samples.

3.3 Theoretical framework

Data Augmentation: Data augmentation was essential in addressing the constraints posed by the relatively small dataset. By artificially expanding the dataset, the neural network's ability to generalize from limited examples was significantly enhanced. In particular, the data augmentation procedure significantly increased the sample size—from 253 to 2065—thereby resolving the data shortage problem.

Data Preprocessing: Prior to model training, each image underwent preprocessing steps to ensure uniformity and enhance model performance. These actions included standardizing the values of pixels to a range of 0-1, cropping the photos to focus on the brain region, and scaling them in a consistent form of (240, 240, 3). This preprocessing standardization was imperative to enable seamless integration of the images into the neural network architecture.

Data Split: The dataset was divided into three separate subsets: a test set with 15% of the data that was collected, a validation set with 15% of the data, and a training set with 70% of the data. This division facilitated rigorous evaluation of the model's performance while ensuring independence between the training and evaluation phases.

Neural Network Architecture: The study's neural network design was carefully developed to strike a compromise between model efficacy and computing complexity. The chosen architecture featured a series of layers, including convolutional, batch normalization, activation, pooling, and dense layers. Notably, the decision to forego complex pre-trained models in favor of a simpler architecture was motivated by computational constraints and the observed overfitting tendencies of more intricate models.

Understanding the Architecture: The architecture of the neural network employed in this study is meticulously designed to effectively process and analyze brain MRI images for tumor detection. Each input image, denoted as x, possesses a shape of (240, 240, 3), indicating a resolution of 240 pixels in width and height, with 3 channels corresponding to the RGB color space. The image x undergoes sequential processing through various layers, each serving a specific function:

Zero Padding Layer with a Pool Size of (2, 2): The zero padding layer ensures that the spatial dimensions of the input image are preserved during convolution operations. By padding the input with zeros, the convolutional operations can be applied without altering the image size. The pool size of (2, 2) indicates that pooling operations will be performed over non-overlapping 2x2 regions of the input image.

Convolutional Layer with 32 Filters: Characteristics from the input image are extracted by the convolutional layer. With 32 filters, this layer convolves across the input image, performing a dot product operation to generate feature maps. The filter size of (7, 7) signifies that each filter spans a 7x7 region of the input image, capturing spatial patterns. Additionally, the stride of 1 ensures that the filters move one pixel at a time.

Batch Normalization Layer: The batch normalization layer is introduced to stabilize and accelerate the training process by normalizing the activations of the previous layer. By standardizing the input to subsequent layers, batch normalization mitigates issues such as internal covariate shift, thereby enhancing the network's convergence rate and generalization ability.

ReLU Activation Layer: The rectified linear unit's (ReLU) function of activation is applied element-by-element to the feature maps after the batch normalizing layer. ReLU gives the network non-linearity, which enables it to pick up intricate patterns and representations. It replaces negative values with zeros, facilitating faster convergence and reducing the likelihood of vanishing gradients.

Max Pooling Layer with Pool Size (4, 4): The most important information is preserved while the physical dimensions of the map features are decreased by the max pooling layer. With a pooling size of (4, 4), the layer aggregates information within non-overlapping 4x4 regions, effectively downsampling the feature maps and increasing computational efficiency.

Flatten Layer: The three-dimensional feature maps are then converted into a one-dimensional vector by using the flatten layer. This transformation is essential for connecting the convolutional layers to the densely connected layers, enabling further feature extraction and classification.

Dense (Output) Layer with Sigmoid Activation: The single neuron with a gaussian activation function makes up the neural network's last layer. Since brain tumor detection is framed as a binary classification task (tumor or non-tumor), a sigmoid activation function is employed to produce output probabilities ranging from 0 to 1. A value closer to 1 indicates the presence of a tumor, while a value closer to 0 signifies the absence.

Training the Model: The model was developed over 24 epochs, with the training process guided by the optimization of loss and accuracy metrics. Notably, the model achieved its highest validation accuracy on the 23rd 5 iteration, showcasing its proficiency in learning from the dataset.

3.4 Statistical tools and econometric models

In the realm of medical image analysis, statistical tools and econometric models play a pivotal role in elucidating relationships, identifying patterns, and making informed decisions. In this section, we delve into the statistical methodologies and econometric frameworks employed in the analysis of brain MRI images for tumor detection.

3.4.1 Descriptive Statistics Descriptive statistics offer valuable insights into the characteristics of the dataset, enabling a comprehensive understanding of its distribution, central tendency, and variability. Key descriptive statistics include:

Mean: It is determined by dividing the total amount of observations by the total of all values, offers a measure of the center of gravity $\mu = (1/n)\sum(x_i)$

Standard Deviation (σ): Describing the dispersion of data points around the mean, the standard deviation quantifies the variability within the dataset. $\sigma = (x_i - \mu)^2/n$

Skewness: The distribution's asymmetry is measured by skewness. A symmetric distribution is shown by a skewness of zero, but a right or left skew is indicated by a positive or negative value.

Kurtosis: Kurtosis describes how peaked or flat the distribution is. A normal distribution has a kurtosis of zero, whereas peaked distributions have positive values and flat distributions have negative values.

3.4.2 Inferential Statistics: Using a sample to support inferences or predictions about the population, inferential statistics make the process easier. Typical methods for inferring include:

Hypothesis Testing: Creating null and alternative hypotheses, then utilizing sample data to evaluate the viability of the null hypothesis, is the process of hypothesis testing. Techniques such as t-tests, chi-square tests, and ANOVA are utilized for hypothesis testing in various contexts.

Confidence Intervals: Confidence intervals offer a range of likely values and a corresponding degree of confidence for an ensemble parameter, like the mean or proportion. To get an interval of confidence for the overall mean (μ), use the following formula: $x \pm z\left(s/\sqrt{n}\right)$

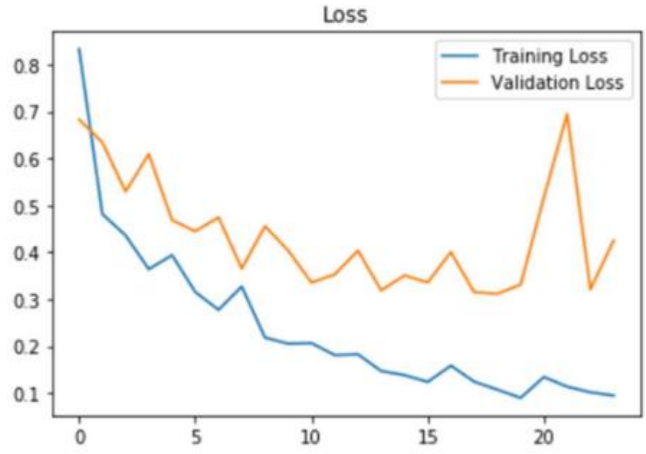
Regression Analysis: The link between a variable that is dependent and one or more separate variables is investigated using regression analysis. The linear regression model is represented as: $\mathrm{y} = \beta_0 + \beta_1 \mathrm{x}_1 + \beta_2 \mathrm{x}_2 + \cdots + \beta_n \mathrm{x}_n + \varepsilon$

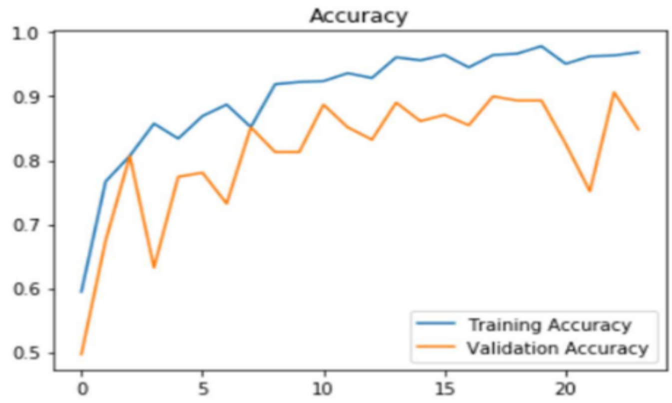
Survival Analysis: Survival analysis techniques, such as Cox proportional hazards model, are pertinent for assessing time-to-event data, such as patient survival rates or time until tumor recurrence. These models account for censoring and covariates to analyze the impact of various factors on survival outcomes.

Cox Proportional Hazards Model: The instant risk of an occurrence occurring at a specific time is represented by the hazard function, which is estimated by the Cox model as an expression of 6 covariates. The risk ratios are assumed by the model to remain constant over time. The Cox paradigm can be stated mathematically as:

$$h(t|x) = h_0(t) \times e^{(\beta_1 x_1 + \beta_2 x_2 + \cdots \beta_n x_n)}$$

When analyzing brain MRI pictures, the use of statistical techniques and econometric models improves the robustness and interpretability of the results. By employing descriptive and inferential statistics, researchers can gain insights into the dataset's characteristics and make valid inferences about the population. Econometric models, on the other hand, offer a framework for exploring complex relationships and identifying factors influencing diagnostic accuracy and patient outcomes. The integration of these methodologies enriches the analytical process and contributes to evidence-based decision-making in medical image analysis and healthcare management.





(The highest validation accuracy was attained during the 23rd iteration of the training process.)

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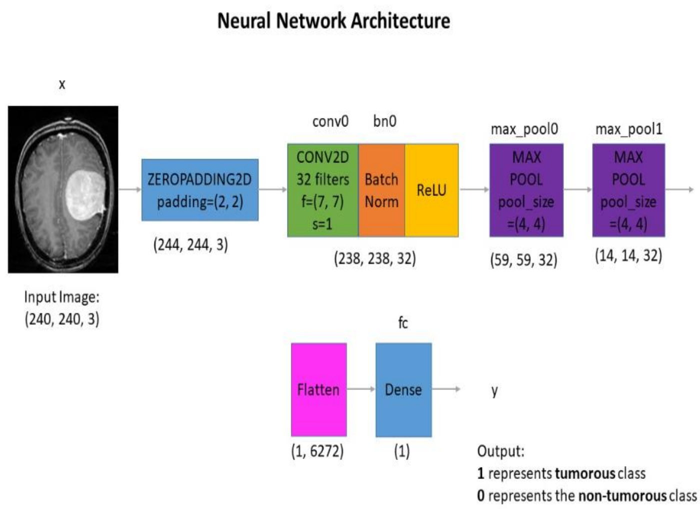

4. CONCLUSIONS

After extensive training and assessment, the result of our work is the implementation of the best model, which has outstanding performance in identifying brain tumors. The culmination of our efforts underscores the efficacy of our approach, as evidenced by the following results. Accuracy on Test Set: The best model, selected based on validation accuracy, achieves an impressive accuracy of 88.7% on the test set. This measure attests to the model's outstanding level of accuracy in correctly classifying brain MRI pictures as malignant or non-tumorous. F1 Score on Test Set: Additionally, the model attains an F1 score of 0.88 on the test set, further corroborating its proficiency in binary classification tasks. The model's efficacy in maintaining a balance between true positives and negative results is demonstrated by the F1 score, which takes precision and recall into account.The balance nature of the dataset, which uniformly distributes cases of tumorous and non-tumorous photos, makes these results very remarkable. The model's robust performance in accurately detecting brain tumors amidst this balanced dataset underscores its adaptability and reliability in real-world scenarios. Moreover, to provide a comprehensive overview of the best model's performance, we present a performance table detailing its metrics on both the validation and test sets:

Metric	Validation Set	Test set
Accuracy	91%	89%
F1 Score	0.91	0.88

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