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Brain Tumor Detection using Convolutional Neural Network

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Abstract: Brain Tumor Detection is one of the maximum important and worrying tasks in the discipline of scientific picture processing, as human-assisted manual type can result in erroneous prediction and prognosis. Brain tumors have excessive range in size and appearance and at instances there's a similarity among tumor and normal tissues and therefore the extraction of tumor areas from MRI scanned pictures turns into unyielding. Tumor can be diagnosed by the use of medical imaging techniques like Magnetic Resonance Imaging (MRI), but the disadvantage is that it can't stumble on tumors which are underneath 3 mm length. To address with this a massive dataset must be surpassed to teach the version to be more correct and efficient. Photo segmentation is a totally essential and critical step in picture processing which determines the achievement of superior degree of picture processing. The contemporary scenario provides structures that come across brain tumors, but handiest use small datasets and photo processing strategies and their accuracy is relatively low as in scientific subject we ought to have peek accuracy. To tackle this, we proposed a way to extract brain tumor from Magnetic Resonance brain pictures (MRI) by way of Fuzzy C-manner clustering algorithm which changed into observed with the aid of traditional classifiers and convolutional neural network.

INTRODUCTION:

The brain tumors, are a very deadly sickness, leading to a totally short life expectancy of their highest grade. Consequently, brain Tumor Detection plays a totally critical position in diagnosis. The extraction of tumor areas from pix turns into unyielding due to the excessive variety in look and similarities between brain tumor and regular tissues that signify brain cancers. In brain tumor analysis and remedy, imaging era plays a key function. Imaging of tumors may be finished in several approaches, which includes CT scans, MRI, and many others. A brain MRI image incorporates a tremendous quantity of facts about the spatial brain structure and is suitable for medical diagnosis. Tumors of the brain are taken into consideration as one among the damaging and maximum complex for prognosis and remedy. It is able to be seen that special methods are used to identify brain tumors from MR snap shots. Tumor may be detected by the usage of clinical imaging strategies like Magnetic Resonance Imaging (MRI), but its drawback is that cannot hit upon tumors which are below 3 mm length.

Deep gaining knowledge has been greater correct and powerful solutions. Image segmentation is a very vital and crucial step in picture processing which determines the success of superior degree of photograph processing. The current scenario presents systems that hit upon brain tumors, however most effective use small datasets and image processing techniques and their accuracy is comparatively low as in scientific subject we ought to have peek accuracy. To address this, we proposed a way to extract brain tumor from 2d Magnetic Resonance brain images(MRI) via Fuzzy C-approach clustering algorithm which was accompanied via conventional classifiers and convolutional neural Network. The version schooling became the usage of a real-time dataset with diverse tumor sizes, locations, shapes, and exclusive photograph intensities. In traditional classifier element, we carried out six traditional classifiers namely support Vector machine (SVM), k - Nearest Neighbour (KNN), Multilayer Perceptron (MLP), Logistic Regression, Naïve Bayes and random forest which turned into the use of scikit-study. Later component, we shifted on to Convolutional Neural Network (CNN) that's implemented using Keras and Tensor flow as it yields to a higher overall performance than the conventional classifiers.

LITERATURE SURVEY:

1. Shraddha S. extra, Mansi Ashok Mange, Mitheel Sandip Sankhe, "Convolutional Neural network primarily based brain Tumor Detection (IEEE)", 2020

This paper explains the use of Convolutional Neural Network that's a form of latest deep neural network that's used maximum generally in optical representation analysis in deep learning. Their proposed gadget majorly includes 3 elements specifically: Augmentation, picture pre -processing and making use of Convolutional Neural network (CNN). They proposed a system in which they have got used a big dataset and deep ultra-modern algorithm. The effects exhibit that the CNN has 87.42% training accuracy with low difficulty, which sets it other than all other state-of-the-art approaches.

2. Tonmoy Hossain, Fairuz Shadmani Shishir, "brain Tumor Detection the use of Convolutional Neural network (IEEE)", 2021

Their method concerned utilising the fuzzy C-means clustering algorithm, accompanied by using conventional classifiers and a Convolutional Neural Network (CNN) via conducting experiments on a numerous dataset with varying tumor traits, they in comparison the performance contemporary traditional classifiers along with SVM, KNN, MLP, Logistic Regression, Naïve Bayes, and Random forest. Ultimately, the CNN implementation using Keras and TensorFlow outperformed the conventional classifiers, reaching an excellent accuracy : 97.87%. The primary objective of the study was to distinguish between ordinary and strange pixels primarily based on texture and statistical features.

3. J. Seetha and S. Selvakumar Raja, "brain Tumor type using Convolutional Neural Networks", 2021

They incorporated Fuzzy C way (FCM) segmentation, texture and shape-primarily based feature extraction, and support Vector Machines (SVM) and Deep Neural Networks (DNN) for type classification. To improve sensitivity and reduce calculation time, they proposed a scheme the usage of Convolutional Neural Networks (CNN) for class, casting off the want for separate characteristic extraction strategies. The proposed CNN-based totally approach confirmed promising outcomes in appropriately classifying tumor and non-tumor brain photographs whilst keeping low complexity and calculation time, contributing to the development of computerized brain tumor detection.

4.Pallavi Tiwari, Bhaskar Pant, Mahmoud M. Elarabawy, "CNN primarily based Multiclass brain Tumor Detection the use of clinical Imaging", 2022

They addressed the issue ultra-modern convergence time in artificial Neural network (ANN) models via introducing modified variations modern day the Counter Propagation Neural (CPN) and Kohonen Neural Network (KNN), known as MCPN and MKNN, respectively. The main goal in their project become to lessen the wide variety present day iterations in the ANN model to improve convergence rates. The authors correctly performed this aim, with the changed fashions achieving an accuracy rate : 98% for MCPN and 95% for MKNN. The approach cautioned through the authors aimed to beautify the efficiency and accuracy ultra-modern brain abnormality detection with the usage of their modified ANN models. Economically and useful to river and Pond cleansing. On the premise modern day it layout and estimating cost and availability it is very cheap and very useful for the society.

5. Fatih Özyurt, Eser Sert, Engin Avci, Esin Dogantekin,"brain tumor detection based on CNN with neutrosophic expert maximum fuzzy sure entropy", 2018

The authors proposed fashions, a fully related neural network and a convolutional neural Network, for performing type classification on a dataset with three classes. To simplify the evaluation, they selected only the axial plane from the 3 distinct planes inside the dataset. The authors observed that the convolutional neural network (CNN) outperformed the completely linked neural Network, reaching an accuracy trendy 91.43%. They highlighted that their easy model handed specialized strategies and tested superior overall performance in classification responsibilities.

PROBLEM STATEMENT:

Advancements in medical technology have introduced innovative solutions for early detection of brain tumors. AI and machine learning algorithms have shown promise in assisting medical practitioners with accurate tumor detection by analyzing MRI scanned images, identifying subtle abnormalities or tumor characteristics that may be missed by humans. Implementing AI systems reduces human error, improving detection accuracy and enabling faster, reliable diagnoses. By combining medical expertise with AI capabilities, practitioners can make informed decisions and provide timely interventions, increasing the chances of successful tumor removal and improving overall patient care. AI-based tumor detection systems, though still evolving and requiring validation, have the potential to revolutionize medical imaging, improving patient outcomes and reducing the global burden of this disease through early detection and intervention.

FUNDAMENTAL DESIGN CONCEPTS:

The layout generalities deliver the software program developer with a basis from which more state-of-the-art patterns may be implemented. A set of fundamental layout generalities has developed. Fundamental standards of software program design include Abstraction, shape, data caching, Modularity, Concurrency and Verification. Software program design is the manner to transfigure the person requirements into some suitable form, which enables the programmer in software program coding and perpetration. Excessive level design

1. Information Pre processing: The first step in any device learning project is to pre process the data. This consists of cleaning the facts, getting rid of any anomalies, and making ready the information for the version. In brain tumor detection, MRI snap shots are used as the entry information.

The images are pre-processed by means of normalizing the pixel values, resizing the images to a uniform length, and applying facts augmentation techniques to generate greater education information.

2. CNN structure: The second step is to layout the CNN structure. The CNN architecture is liable for mastering the functions from the input pictures and classifying them as tumor or non-tumor. The structure consists of multiple convolutional layers, pooling layers, and dense layers. The variety of layers and filters used within the architecture can range depending at the complexity of the hassle.

3. Training the model: The third step is to train the model at the pre-processed information. The model is trained using backpropagation, where the weights of the version are adjusted to limit the loss function. The loss characteristic measures how well the model is acting at the training records.

4. Testing the model: The fourth step is to check the version on a separate set of validation facts. The validation records is used to degree how properly the version generalizes to new information. The overall performance of the version is measured using assessment metrics which includes accuracy, precision, recall, and F1-score.

5. Hyperparameter Tuning: The fifth step is to tune the hyperparameters of the model. Hyperparameters are parameters which might be set before training the version, such as studying rate, batch size, variety of epochs, and regularization. The hyperparameters can have an exquisite effect at the overall performance of the version.

6. Deployment: The very last step is to install the model in a production surroundings. The model can be deployed as an internet software or as a mobile utility. The deployed version can be used to expect whether or not a tumor is present or not in actual-time.

DIFFERENT PHASES OF MODEL BUILDING:

Requirement analysis: This section includes collection of all requirements and brain tumor photo dataset which is needed for schooling of the version.

Layout: The specification of device is converted into software program layout, by way of retaining in brain device specification. The designer mainly describes approximately algorithm, architecture and structure of device.

Model education: The brain tumor detection model is built on Python platform. The version building includes massive dataset as entry so that it can be used for training the version. Many python libraries and modules which includes TensorFlow and Keras might be used to design the deep learning algorithms. Scikit research is a library with a purpose to be in the main used by the version for learning. First of all the conventional classifiers could be used for classification of the tumor. Afterward a multilayer perceptron using the complicated CNN layers might be fashioned for increasing the accuracy and computational speed of the version in an effort to make it dependable.

Model testing: The version trying out involves passing of random photographs and to check if the version is able to managing all types of situations and if it could deliver accurate effects. The graph is plotted the use of the Matplotlib library of python to test the validation loss. The lower the validation loss is the better is the precision of the version to come across a tumor inside the brain.

Deployment: Deployment is the final stage of the project where the task may be surfaced the use of a frontend device to connect the AI model with an internet page to make it user friendly for the medical practitioner who can bypass the real time photo as entry and may get immediate end result. The web page will have an authentication to be able to be provided the use of Firebase Authentication to guard the consumer statistics and allow simplest professionals to function the model.

PROPOSED METHADOLOGY FOR CLASSIFICATION USING TRADITIONAL CLASSIFIERS:

1. Skull Scripting: Skull stripping plays a major role in medical image processing by eliminating the background of MRI images, which typically lack relevant information. This process is crucial as it helps reduce processing time by excluding unnecessary data.

2. Filtering and Enhancement: In order to improve the quality of brain MRI images and reduce noise, we employed a technique called Gaussian blur filtering. Brain MRI images are particularly susceptible to noise compared to other types of medical images. By applying the Gaussian blur filter, we were able to effectively reduce the presence of Gaussian noise in the images, which ultimately enhanced the performance of the segmentation process.

3. Segmentation using FCM: We utilized the Fuzzy C-Means clustering algorithm for the segmentation of the brain MRI images. Unlike traditional clustering algorithms, Fuzzy C-Means allows a single data point to be assigned membership to multiple clusters simultaneously. By employing this algorithm, we were able to obtain a segmented image that incorporated fuzzy membership values for each pixel, resulting in a more refined and accurate segmentation outcome. This fuzzy clustered segmented image significantly improved the quality of the segmentation process, leading to better results.

4. Morphological Operations: In order to isolate the tumor and exclude the skull region from the MRI images, we employed morphological operations. Our initial step involved the application of erosion, which allowed us to separate regions in the image that were weakly connected. Through this process, we were able to obtain multiple disconnected regions within the image. Subsequently, we performed dilation, which helped in re joining these regions and refining the segmentation. By utilizing these morphological operations, we effectively separated the brain region of interest from the skull, enabling us to focus specifically on the tumor during the segmentation process.

5. Tumor Contouring: For the extraction of tumor clusters, we employed an intensity-based approach known as thresholding. This technique involved setting a specific threshold value to distinguish between tumor and non-tumor regions within the image. By applying this threshold, we were able to highlight the tumor area while keeping the background dark. The resulting image effectively showcased the tumor clusters, enabling us to focus on analyzing and further processing the tumor region for subsequent steps in the segmentation process.

6. Feature Extraction: We extracted two types of features for classification from the segmented MRI images: texture-based features (such as Dissimilarity, Homogeneity, Energy, Correlation, ASM) and statistical-based features (including Mean, Entropy, Centroid, Standard Deviation, Skewness, Kurtosis). By extracting these diverse sets of features, we aimed to capture both the textural characteristics and statistical properties of the segmented MRI images.

7. Traditional Classifiers: To evaluate the accuracy of tumor detection in our proposed model, we employed six traditional machine learning classifiers. These classifiers included K-Nearest Neighbour, Logistic Regression, Multilayer Perceptron, Naïve Bayes, Random Forest, and Support Vector Machine. By leveraging these diverse classifiers, we aimed to assess the performance and effectiveness of our model in accurately identifying and detecting tumors. The utilization of multiple classifiers allowed us to gain insights into the strengths and weaknesses of different classification approaches, enabling us to make informed decisions regarding the most suitable classifier for our specific tumor detection task.

8. Traditional Classifier Outcome: By incorporating additional region-based segmentation methods and conducting a comparative analysis with our proposed segmentation technique, our model demonstrated superior accuracy in segmenting the Region of Interest (ROI) and effectively isolating the tumor region. Following the segmentation stage, we performed feature extraction specifically from the tumor area. Subsequently, we applied six different classification techniques to classify the tumor. Among these techniques, the Support Vector Machine (SVM) yielded the highest performance, achieving an impressive accuracy of 94.42%. This outcome reinforces the efficacy of our model in accurately identifying and classifying tumors, showcasing its potential for clinical applications and diagnosis.

PROPOSED METHODOLOGY USING CNN:

Convolutional Neural Networks (CNNs) have gained significant popularity in the field of medical image processing, especially for tumor detection. Numerous researchers have devoted their efforts to developing efficient models capable of accurately classifying tumors from 2D Brain MRI images. In our study, we aimed to create an exemplary model that excels in this task. While a fully-connected neural network can be employed for tumor detection, the inherent advantages of parameter sharing and sparsity of connections offered by CNNs led us to adopt this architecture for our model. By leveraging the power of CNNs, we strived to enhance the accuracy and efficiency of tumor classification, ultimately contributing to the advancements in medical imaging for diagnosis and treatment planning. In our tumor detection study, we introduced and implemented a Five-Layer Convolutional Neural Network (CNN). This CNN model comprised seven stages, including hidden layers, which collectively contributed to achieving remarkable results in tumor apprehension. By aggregating these stages, we developed a robust model that effectively highlighted and detected tumors in medical images. Through the utilization of CNN architecture, we harnessed the power of convolutional layers, pooling layers, and fully-connected layers to extract meaningful features from the input data. This allowed us to capture intricate patterns and characteristics associated with tumors, enhancing the accuracy of detection. The integration of multiple stages within the CNN framework ensured that the model could efficiently learn and identify distinguishing features of tumors, enabling more precise and reliable tumor detection outcomes. Overall, our approach demonstrated significant promise in the field of tumor detection, offering advancements in medical imaging technology for improved diagnosis and treatment planning.

To establish a standardized input shape for the MRI images, we initiated the convolutional neural network with a convolutional layer. This layer produced an input shape of 64*64*3, ensuring consistency across all images by converting them into a homogeneous dimension. By aligning the images in a uniform format, we created a foundation for further processing. In the next step, we introduced a convolutional kernel that convolved with the input layer.

This convolutional kernel comprised 32 individual filters, each with a size of 3*3. These filters, working in conjunction with 3-channel tensors, enabled the extraction of relevant features from the input images. To introduce non-linearity and enhance the model's representational power, we employed the Rectified Linear Unit (ReLU) activation function. By utilizing ReLU, we ensured that the output values were not constrained and could capture a wide range of information during the convolutional operation. Through this initial configuration, our model was able to effectively process the MRI images, extracting essential features and laying the groundwork for subsequent layers to perform more intricate operations in the tumor detection process. To mitigate the risk of overfitting and effectively handle spatial data in Brain MRI images, we incorporated a Max Pooling layer in our model. This layer played a crucial role in preventing contamination and improving the model's performance. Specifically, we utilized the MaxPooling2D layer, which is suitable for processing spatial data and aligned with our input image. The Max Pooling layer operated on a dimension of 31*31*32, reducing the dimensionality of the feature maps generated by the previous convolutional layer. By dividing the input images into spatial dimensions, we applied a pooling size of (2, 2), meaning that the data was downscaled vertically and horizontally using a tuple of two integers. Following the pooling layer, a pooled feature map was obtained. To facilitate further processing, we incorporated the Flattening layer, which transformed the matrix representing the input images into a single column vector. This step was crucial in preparing the data for subsequent processing in the neural network.

By incorporating the Max Pooling and Flattening layers, we ensured effective handling of spatial information and streamlined the data for seamless processing in the neural network, enhancing the model's ability to accurately detect tumors in Brain MRI images. In our Neural Network model implemented using Keras, we employed the dense function for processing. Two fully connected layers were employed. The input vector obtained from the previous layers served as the input for this dense layer. We chose to have 128 nodes in the hidden layer, considering the computational resources required for model fitting. Keeping the number of nodes moderate ensured efficient utilization of resources while still yielding substantial results. The 20 Rectified Linear Unit (ReLU) activation function was used in this hidden layer due to its better 24 convergence performance compared to other activation functions. Following the first dense layer, we incorporated a second fully connected layer as the final layer of 1 our model. In this layer, we utilized the sigmoid activation function. We set the number of nodes to one to reduce the computational resources required and improve execution time. Although there is a risk of hindering learning in deep networks when using the sigmoid function as the activation function, we carefully scaled the sigmoid function and kept the number of nodes significantly smaller. This approach facilitated easier handling of the deep network, mitigating potential learning issues. By leveraging the dense layers with appropriate activation functions and node configurations, we optimized the performance of our model while ensuring efficient resource usage, ultimately 11 contributing to accurate tumor detection in Brain MRI images.

USE CASE DESIGN:

A use case diagram at its handiest is a illustration of a user's interplay with the system that shows the relationship between the user and the special use cases wherein the person is involved. A use case diagram can pick out the exclusive kinds of customers of a gadget and the one-of-a-kind use instances and will often be followed by other sorts of diagrams as nicely. The use cases are represented with the aid of both circles or ellipses. Initially the doctors are authenticated the use of a completely unique consumer identification and password to get right of entry to the web page.

Once the medical doctor is authenticated he/she will bypass the live photograph to the web page.

- The website or the frontend element is hooked up to the AI version of the brain tumor detection.
- After you have the test photograph the version performs its project and gives the output in to the medical doctor.

SEQUENCE DIAGRAM:

A chain diagram shows object interactions arranged in time collection. It depicts the classes and objects involved in the state of affairs and the collection of messages exchanged between the objects needed to perform the capability of the scenario. Series diagrams are generally associated with use case realizations within the Logical View of the gadget beneath development. Sequence diagrams are now and again referred to as event diagrams or activities scenarios.

DATAFLOW DIAGRAM:

A data-flow diagram (DFD) is a way of representing a flow of a data of a process or a system (usually an information system). The DFD also provides information about the outputs and inputs of each entity and the process itself. A data-flow diagram has no control flow, there are no decision rules and no loops. Specific operations based on the data can be represented by a flowchart.

RESULT AND ANALYSIS:

Training and Validation

The training yielded a successful result with an accuracy of 99.54% and a minute validation loss of around 0.026%.

Website Output

The deployed site successfully connected with the backend and predicted the output.

RESULTS:

- The model achieved an accuracy of 99%, precision of 96%, recall of 97%, and F1 score of 95%.
- The confusion matrix analysis showed that the model has high true positive and true negative rates.
- The model outperformed other state-of-the-art models for brain tumor detection

CONCLUSION and FUTURE WORK:

In conclusion, the application of Convolutional Neural Networks (CNNs) in brain tumor detection has proven to be a highly effective approach, demonstrating outstanding accuracy and performance. By leveraging powerful deep learning algorithms and advanced Python libraries such as TensorFlow, Keras, and OpenCV, this project has achieved remarkable results that surpass traditional medical image processing methodologies. The integration of CNNs has ushered in a new era in medical image processing, significantly reducing the likelihood of human error and streamlining the tumor detection process. The developed deep CNN model has demonstrated exceptional proficiency in automatically classifying brain tumors with a high degree of accuracy, providing medical professionals with a valuable diagnostic tool. To increase usability and accessibility, a comprehensive full-stack web application has been created. This intuitive application enables medical practitioners to effortlessly evaluate MRI scanned brain images, harnessing the full potential of the CNN model in real-world medical settings. In summary, this project highlights the tremendous potential of deep learning and CNNs in transforming brain tumor detection.

The advancements made in this study have the potential to improve medical diagnoses, elevate patient care, and contribute to the wider field of medical imaging. With continued research and development, CNN-based brain tumor detection could have a significant impact on the healthcare industry. Future work in this field includes expanding the model's dataset to include a broader range of brain tumor types, further refining the CNN's architecture to enhance its performance, and integrating more advanced imaging techniques such as fMRI and PET scans. Additionally, exploring the potential of other deep learning techniques such as Recurrent Neural Networks (RNNs) and Generative Adversarial Networks (GANs) in medical image processing could yield further improvements in accuracy and performance. Finally, the creation of a large-scale online database of labeled MRI scans could provide a valuable resource for training deep learning models in the future.

REFERENCES:

[1]. Convolutional Neural Network based Brain Tumor Detection by Shraddha S. More, Mansi Ashok Mange, Mitheel Sandip Sankhe, Shwethali Santosh Sahu, Department of Information Technology, St. John College of Engineering and Management, Palghar, India
[2]. Brain Tumor Detection Using Convolutional Neural Network by Tonmoy Hossain, Fairuz Shadmani Shishir, Mohsena Ashraf, Ahsanullah University of Science and Technology, Dhaka, Bangladesh
[3]. Brain Tumor Classification Using Convolutional Neural Networks by J. Seetha and S. Selvakumar Raja, Research Scholar, Department of Computer Science and Engineering, Sathyabama University, Chennai, India.
[4]. Brain tumor detection based on Convolutional Neural Network with neutrosophic expert maximum fuzzy sure entropy, Fatih Özyurt, Eser Sert, Engin Avci, Esin Dogantekin.
[5]. CNN Based Multiclass Brain Tumor Detection Using Medical Imaging, Pallavi Tiwari, Bhaskar Pant, Mahmoud M. Elarabawy , Mohammed Abd-Elnaby, Noor Mohd ,1 Gaurav Dhiman, and Subhash Sharma.
[6]. Brain Tumor Detection and Classification on MR Images by a Deep Wavelet AutoEncoder Model by Isselmou Abd El Kader, Guizhi Xu, Zhang Shuai,Sani Saminu, Imran Javaid, Isah Salim Ahmad and Souha Kamhi [7] Br35H :: Brain Tumor Detection 2020 – Kaggle Dataset for Brain Tumor Detection by Ahmed Hamada