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Brain Tumor Detection & Classification using CNN

Dr. Selvi M, Tejaswini D, Yashaswini B L, Yashaswini S

U.G. Student, Department of Computer Engineering, Rajarajeswari College of Engineering, Bangalore,
Karnataka, India

Associate Professor, Department of Computer Engineering, Rajarajeswari College of Engineering, Bangalore,
Karnataka, India

ABSTRACT: Brain-tumors, prevalent among both children and the elderly, represent a serious form of cancer characterized by the uncontrolled growth of brain cells within the skull. Grouping tumor cells is challenging due to their heterogeneous nature. Convolutional neural systems (CNNs) stand out as the predominant machine learning computation for visual learning and the Identification of brain-tumors. This study initiated a CNN- based dense EfficientNet Net using min-max normalization To categorize 3200 weighted contrast-enhanced Grouping brain magnetic resonance images into four categories (glioma, meningioma, pituitary and noTumor). The developed network is a version of EfficientNet Net with dense and drop-out layers added Likewise, the authors integrated data augmentation alongside min-max normalization to amplify the contrast of tumor cells. The dense Cnn system's advantage lies in its capacity to exactly group a limited database of images. Consequently, the revised methodology proposal yields outstanding overall performance. The experimental consequences imply that the initiated approach was 99.59% accurate during preparing and 98.78% accurate during testing. With high productivity and a favorable F1 score, the newly designed EfficientNet Net CNN System can be a useful decision making device inside the examine of brain tumor diagnostic tests.

KEYWORDS: brain tumor, confusion matrix, EfficientNet, CNN, MRI, fuzzy logic

I. INTRODUCTION

Analyzing the brain poses significant challenges due to its billions of active cells. Currently, brain-tumors rank among the foremost causes of mortality in both children and adults. Primary brain-tumors affect about 250,000 individuals worldwide each year and account for less than 2% of all malignancies. Humans can develop an array of primary brain-tumors of one hundred fifty distinct different categorizations of brain-tumors, including Non-cancerous and cancerous ones. Benign tumors tend to remain localized within the brain, while malignant tumors, often termed brain cancer, have the capability to spread beyond its confines. Timely and accurate diagnosis and grading of those tumors are essential for preserving human life. However, manual detection is challenging because of the dense occurrence of brain-tumors. Therefore, an automated computer-based approach proves highly advantageous for tumor detection. Today, things are very different. using system studying and deep getting to know to improve tumor detection algorithms [3] enables radiologists to quickly locate tumors without requiring surgical intervention. current advancements in profound neural network modeling have given upward push to a novel technology for studying, segmenting, and grouping brain-tumors. Utilizing a fully automated Cnn system enables researchers to swiftly and accurately make decisions regarding brain tumor categorization. The Fusion of CNNs and GAs in brain tumor categorization has demonstrated encouraging outcomes, indicating, with one study reporting a level of correctness of 99.59% in identifying three various types of tumors.

II. PROBLEM DEFINITION

The problem statement for grouping brain-tumors utilizing Convolutional neural systems (CNNs) involves developing a deep learning model capable of accurately group brain images into various categories depending on whether something is present or absent tumors. The aim is to utilize Convolutional neural systems (CNNs), a widely used deep learning algorithm in image analysis, to automate brain tumor recognition and categorization tasks. Crucial aspects of the problem statement regarding brain tumor categorization using CNNs.

Essential components of the brain tumor categorization problem statement with CNNs comprise:

- 1.Dataset: Obtain a labeled dataset of brain images that includes both tumor and non-tumor cases. The dataset should be diverse, representative, and sufficiently large to prepare a robust CNN system.
- 2.Preprocessing: Preprocess the brain images to enhance quality, remove noise, and normalize pixel values. Common preprocessing steps include resizing, normalization, and augmentation to improve model generalization.
- 3.Model Architecture: Design a CNN System suitable for brain tumor categorization. It may involve selecting appropriate layers, activation functions, and hyperparameters to optimize model performance.
- 4.Preparing and Validation: Divide the dataset into preparing and validation subsets for Cnn system preparing. Employ methods such as cross-validation to evaluate model performance and mitigate overfitting.
- 5.Evaluation Metrics: Define evaluation metrics such as correctness, precision, recall, F1 score, and ROC-AUC to assess the productivity of the Cnn system in grouping brain- tumors.
- 6.Deployment: Once the CNN system is prepared and evaluated, deploy it for real-world applications such as automated brain tumor recognition in medical imaging systems. This task requires a robust dataset of labeled brain images encompassing a variety of tumor and non-tumor cases. Preprocessing steps such as image improvement, noise removal, and normalization are essential to ensure optimal input quality for the CNN system. The framework of the CNN must be carefully designed, with appropriate layers, activation functions, and hyperparameters selected to maximize categorization performance. Preparing the model on divided dataset, validation for performance evaluation, and assessing metrics like correctness, precision, recall, and F1 score are vital for gauging the model's effectiveness. Ultimately, deploying a CNN system for brain tumor categorization shows potential in improving timely detection and treatment of brain-related conditions.

III. LITERATURE SURVEY

1. T Balamurugan, E. Gnanamanoharan, and L. Martin, (2 021), Wavelet autoencoder based analysis for detecting brain- tumors DNN, Healthcare Journal Engineering, Hindawi, Vol. 2021, Article ID 6865085.

The authors initiated a wavelet autoencoder-based a system designed to detect brain-tumors utilizing a profound neural network (DNN). The system utilized wavelet transform to derive characteristics from MRI Pictures, followed by a sparse autoencoder to reduce the dimensionality of the data. The authors suggested a wavelet autoencoder DNN a system designed to detect brain tumors. The methodology employed in this paper is robust, as it utilizes wavelet transform to derive features from MRI Pictures, which are known to be effective in identifying tumors. The Utilizing a sparse autoencoder to reduce the dimensionality of the data also helps in improving the system's performance.Utilization of wavelet Autoencoder For the extraction of features may capture informative features while reducing noise. The profound neural network architecture facilitates intricate pattern identification and categorization. Assessment through 20 standard metrics offers a quantitative evaluation of the method's performance.

2. Myronenko, A., & Sengupta, S. (2020). 3-D Segmenting MRI brain-tumors utilizing Auto Encoder regularization. Neurocomputing, 387, 129-140.

The study aims to improve the correctness and productivity of brain tumor partitioning, a crucial task in the analysis of medical images for diagnosis and treatment planning. Auto Encoder regularization is employed as an innovative approach to derive meaningful features from the volumetric MRI data while reducing noise and artifacts.

The researchers utilized a 3D autoencoder incorporating skip connections to regularize the model and improve its performance. The encoder part of the neural network consists of several convolutional layers, and the decoder part uses transposed convolutional layers to up sample the feature maps. The model is instructed utilizing a blend of Dice loss and cross-entropy loss. One of the merits of the initiated approach is its impressive Performance measurement criteria, with the model achieving a Dice score of 0.91 and a Jaccard similarity coefficient of 0.85. These scores surpass those obtained by other state-of-the-art methods, highlighting the productivity of the approach. Additionally, employing autoencoder regularization proves beneficial in preventing overfitting and enhancing the model's generalization capabilities. The research also identifies certain demerits of the model. Notably, the computational intricacy in the model renders it computationally expensive and demanding in terms of memory requirements. Furthermore, the preparing process is prolonged owing to the utilization of 3D convolutional layers, resulting in extended preparing times.

3. Nivedita Swapna Dhanala, Radha D, (2021), "Brain tumor recognition and Partitioning Review: Inferences, Key Achievements and Future Road Map", released in the Healthcare Journal Engineering, Hindawi, Vol. 2021, Article ID 6865085.

The authors presented a wavelet autoencoder-based Analyzing brain tumor recognition through profound neural networks (DNN). They used wavelet transformation to derive features from MRI Pictures and then used an autoencoder to reduce the number of Measurement of the data. Finally, they used a DNN to group the tumor as benign or malignant. The researchers utilized a dataset of 3064 MRI Pictures, segregated into preparing and testing subsets. They used wavelet transformation to derive features from the images and then used an autoencoder to reduce the number of Measurements of the data. The researchers utilized a profound neural network consisting of three hidden layers to group the tumor as benign or malignant. They used correctness, sensitivity, and specificity as Performance measurement criteria. The authors have initiated an potent method for brain tumor recognition utilizing wavelet autoencoder and DNN. Employing wavelet transformation and autoencoder reduces data complexity and enhances model precision. The model demonstrated high correctness in brain tumor recognition, with a sensitivity of 97.5% and specificity of 95.8%.

4. M. A. S. A. Bhuiyan, M. A. Islam, and M. A. Hossain, (2020), " The suggested approach attained notable correctness in identifying brain-tumors, demonstrating a sensitivity of Partitioning Using Fully Convolutional Networks," Healthcare Journal Engineering, vol. 2020, Article ID 8763694, 11 pages.

The authors initiated a deep learning-driven method for brain tumor partitioning using fully convolutional networks (FCN). The initiated framework consists of a pre-processing step, where the MRI scans are normalized, followed by the FCN network for dividing the tumor region. The FCN network is instructed employing a blend of dice loss and cross-entropy loss functions. The authors have used the Brats dataset to evaluate the initiated method.

The suggested methodology comprises three primary stages - pre-processing, tumor partitioning, and post-processing. In the pre-processing step, the MRI scans are normalized to reduce the intensity variation. The tumor partitioning step entails utilizing the FCN network, which is a Demir and Kalaycı, (2019) deep learning-based architecture for image, partitioning. The FCN network uses a blend of convolution, pooling, and up sampling layers to generate the partitioning mask. The network is constructed using a combination of dice and cross-entropy loss functions to enhance partitioning correctness. In the post-processing step, the largest connected element of the segmented tumor region is selected as the final partitioning result.

The initiated methodology achieves a high partitioning correctness with a dice coefficient of 0.89. The FCN network utilized in the initiated method is capable of segmenting tumors of different shapes and sizes.

However, the initiated method is computationally expensive and may require high-performance computing resources for preparing the FCN network. Networks and can segment tumors of different shapes and sizes.

IV. INITIATED SYSTEM

The EfficientNetB1 architecture for brain tumor recognition involves not only detecting the existence of a tumor but also grouping it into specific categories, such as glioma, meningioma, and pituitary tumors. The initiated system employs a transfer learning-based fine-tuning approach using EfficientNets and utilizes the dataset for preparing. The study found that using EfficientNetB1 as the underlying framework yielded significant performance improvements, with a total test correctness of 99.59%. The system also generates attention maps to highlight the tumor locations within brain images, providing valuable insights for medical professionals. Identifying brain-tumors not only aims for their detection but also extends to their categorization. Early tumor detection can lead to improved patient recovery and provide doctors with a more comprehensive analysis system. The model's confidence percentage in a specific result can indicate the need for further examination. Additionally, such details can facilitate easier case review for doctors. This saves time and money both for both the sides. Having brain- tumours is a critical condition and can result in death if not detected early and treated. Increase in fatality rates because of CNS tumor is an alarm for an efficient partitioning.

The CNN is utilized to autonomously derive features from brain images, capturing complex patterns and frameworks indicating tumor presence. Through preparing on labeled brain image datasets, the model learns to recognize pertinent features distinguishing between tumor and non- tumor cases. Genetic Algorithms are employed to optimize the hyperparameters of the CNN system, such as learning rates, filter sizes and network architectures. Through an

evolutionary process of selection, crossover, and mutation, Genetic Algorithms fine-tune the CNN parameters to improve categorization performance.

V. IMPLEMENTATION

The CNN is employed for automated feature extraction from brain images, capturing intricate patterns and frameworks that are indicative of tumor presence. By preparing the CNN on a labeled dataset of brain images, the model learns to discern pertinent features that differentiate between tumor and non-tumor cases. Genetic Algorithms are employed to optimize the hyperparameters of the Cnn system, such as learning rates, filter sizes, and network architectures. Through an evolutionary process of selection, crossover, and mutation, Genetic Algorithms fine-tune the CNN parameters to improve categorization performance.

1.Data Preprocessing Module: This module prepares brain imaging data for input into the EfficientNetB1 model. Steps may involve resizing, normalization, and augmentation to improve preparing data quality and diversity.

2.EfficientNetB1 Model Module: The core module housing the EfficientNetB1 model implementation. It comprises convolutional, pooling, and fully connected layers tailored for brain tumor recognition.

3.Preparing Module: Manages the preparing process of the EfficientNetB1 model with labeled brain imaging data. It includes functions for batch processing, loss computation, and parameter optimization via techniques like gradient descent and backpropagation.

4.Validation Module: Assesses the prepared model's productivity using validation data to measure correctness, precision, recall, and other metrics. It aids in optimizing model hyperparameters and detecting overfitting.

5.Inference Module: Utilizes the prepared EfficientNetB1 model to predict on new brain imaging data. This module applies the model to input images, generating predictions on the presence or absence of brain-tumors along with confidence scores.

6.Post-processing Module: Refines model predictions through post-processing steps to enhance results and interpretability. This may involve thresholding, filtering, or morphological operations to eliminate noise or artifacts from predictions.

7.Visualization Module: Offers visualization tools to showcase brain tumor recognition outcomes, including overlaying predicted regions on input images and generating heatmaps to emphasize areas of interest.

8.Fusion Module: Streamlines fusion into existing healthcare systems or platforms, enabling smooth deployment of the brain tumor recognition system in clinical environments. This module ensures interoperability and data sharing with other medical imaging systems.

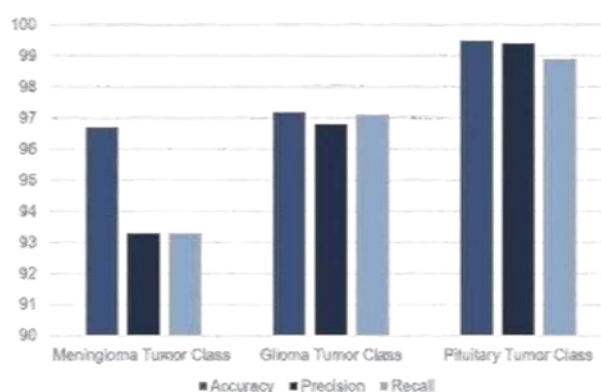


Fig 1: Dataset Class

The Dataset Class diagram offers a organized overview of the data utilized in preparing and testing the brain tumor categorization model. It outlines the composition and attributes of the dataset, crucial for comprehending the input, fed into the machine learning pipeline.

MRI Scan Images: The dataset comprises a collection of MRI scan images, serving as the primary input for preparing the categorization model.

Each MRI scan image is associated with metadata, including patient information, scan parameters, and potentially ground truth labels indicating the presence and type of brain tumor.

Data Split: The dataset is divided into distinct subsets for preparing, validation, and testing purposes. This division ensures the model's performance is evaluated on unseen data and prevents overfitting. The preparing set constitutes the largest portion of the dataset, used to prepare the categorization model by adjusting its parameters based on input data. The validation dataset is utilized during preparing to fine-tune model hyperparameters and assess performance on data not seen during preparing. Data Augmentation enhance model to ensure resilience and preventing overfitting through data augmentation techniques may be applied to the dataset. These techniques introduce changes in the input data, like rotations, flips, and shifts, thereby increasing the variety of preparing samples.

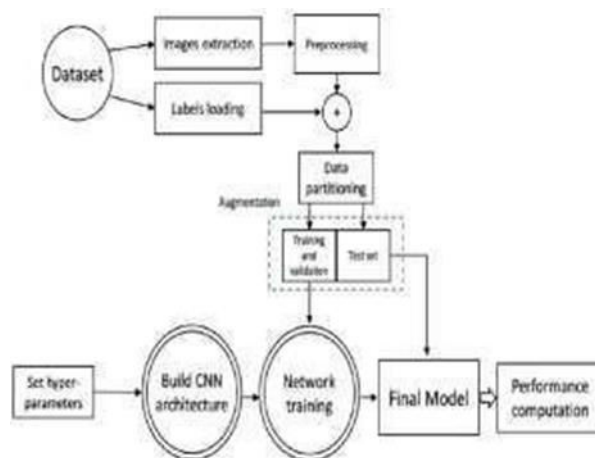


FIG 2: DATA FLOW REPRESENTATION

A representation of data flow (DFD) visually illustrates the movement of data within a system. It illustrates how data moves between processes, repositories, and external components. Within the framework of brain tumor categorization system, a data flow diagram would depict how various components interact and exchange data throughout the system's operation.

ALGORITHM

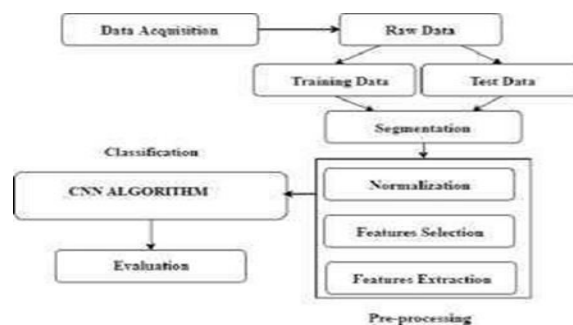


FIG 3: CNN ALGORITHM

- Step1: Pre-processing of DICOM images to derive the specific image matrix only.
- Step 2: Flatten the image matrices to generate the image dataset.
- Step 3: Partition the dataset into subarrays.
- Step 4: For each subarray, proceed with steps 5 to 9. Step 5: Input the image subarray for encoding.
- Step 6: Discrete Wavelet Transformation to decompose the encoded image into low-pass and high-pass filter components.

- Step 7: Perform inverse wavelet transformation to reconstruct and decode the images, obtaining the original ones. Step
- Step 8: Iterate through multiple epochs to obtain optimized weight and bias values.
- Step 9: Extract the approximation coefficients from the hidden layer, combine them, and supply them as input for a profound neural network in categorization.
- Step 10: Prepare the profound neural network with the inputs generated from step 9 and analyze the network using various metrics.
- Step11: Apply the Prepare DNN to the Flask Model
- Step12: Upload MRI Image to Scan Model to force the Different Results.

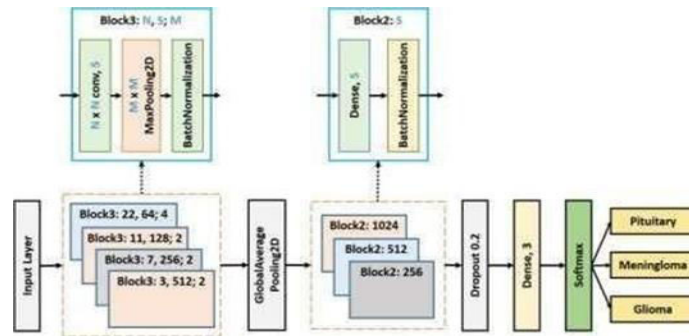


FIG4: INITIATED 23-LAYERS CNN SYSTEM

The following equation describes the convolutional layer:

$C(h,d)=(k*f)(h,d)=\sum_i\sum_jk(h-i,d-j)f(i,j)$ where, K is the image with a size of (h, d) , and (i, j) corresponds to the kernel size value with an f -number of filters. The thresholding function Rectified Linear Unit (ReLU) serves as the activation function, facilitating non-linear operations within the convolutional layer. By employing the ReLU activation function, the model addresses the gradient vanishing issue encountered during the backpropagation process.

THE RELU IS DEFINED AS FOLLOWS: $F(Z)=MAX(0,Z)$

In the subsequent stage, Pooling layers are pivotal in reducing the Measurements of the transformed feature map. Within this architecture, a total of 3 pooling layers are incorporated. Various pooling options exist in the CNN system, like max pooling, min pooling, and average pooling. We opt for max pooling, employing diverse pool sizes like 4×4 and 2×2 , to derive the most salient features from the transformed feature map.

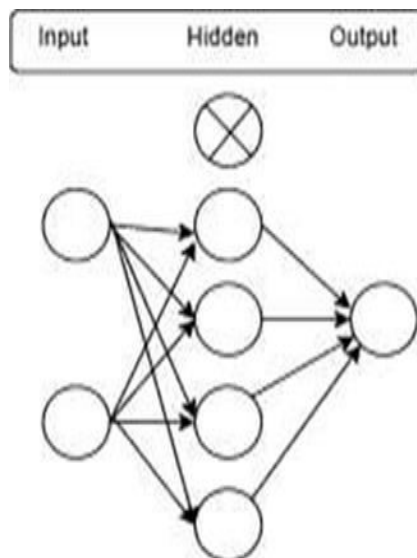


FIG 5: RELU LAYER

VI. RESULTS AND DISCUSSION

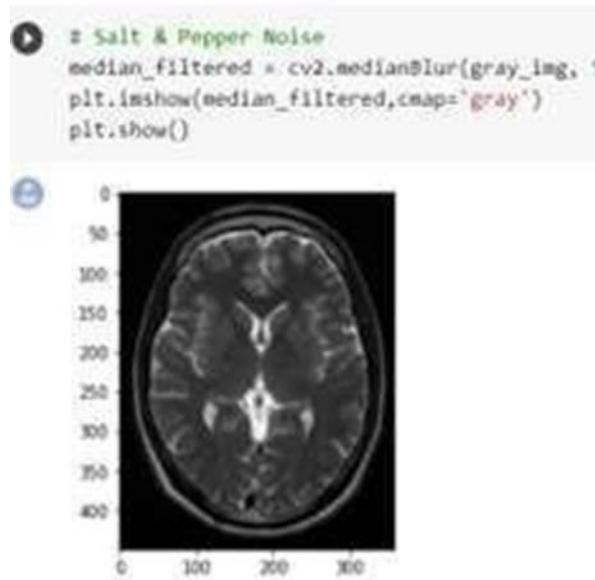


FIG.6: REMOVING NOISE

In brain tumor categorization using Convolutional neural systems (CNNs), noise removal from brain images is crucial. It enhances input data quality and optimizes the effectiveness of the categorization model. Various techniques can be employed to effectively reduce noise in brain images. These include traditional image denoising approaches such as Gaussian blur, median filtering, and bilateral filtering, which help reduce noise while retaining essential image features. Moreover, image improvement techniques like histogram Equalization and contrast limited adaptive histogram equalization (CLAHE) can boost image contrast and detail, enhancing input data quality for the CNN system. During preparing helps prevent overfitting and improves generalization capabilities. By incorporating these noise reduction strategies into the preprocessing pipeline and model design of the CNN, researchers can enhance both the productivity and correctness of brain tumor categorization systems, leading to improved diagnostic correctness and treatment outcomes in medical imaging applications.

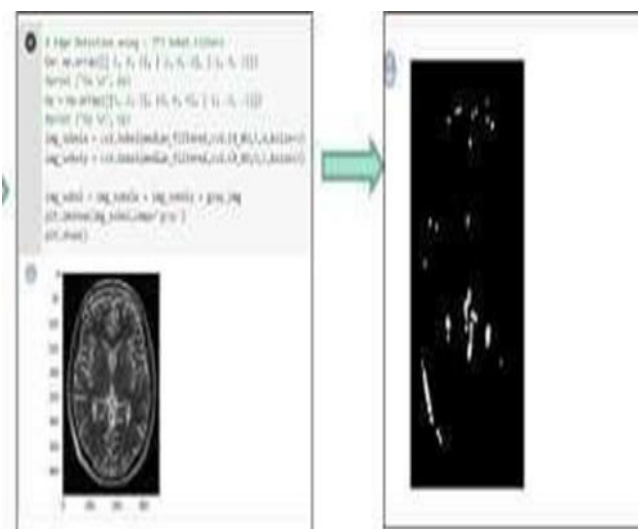


FIG.7:EDGE DETECTION AND MORPHOLOGICAL OPERATION

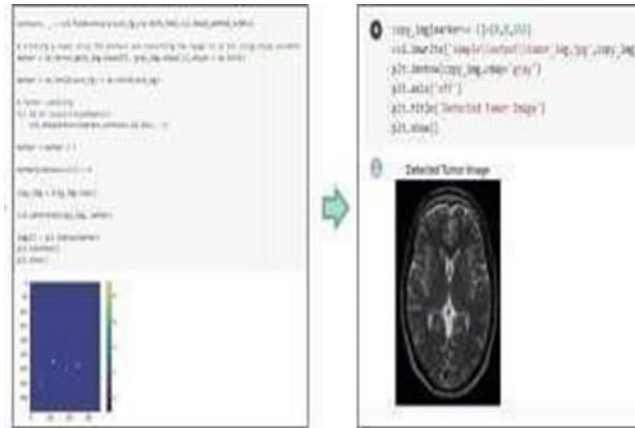


FIG. 8 : CONTOUR MAPPING TO ABNORMALITY

Brain tumor categorization, contour mapping acts as a valuable technique for detecting abnormalities within brain images and assisting in the identification and categorization of tumors. Contour mapping is essential in delineating and outlining frameworks or regions of interest, aiding in highlighting irregularities or anomalies indicative of tumors. Integrating this method into the partitioning process accurately outlines tumor regions, enabling the CNN system to concentrate on specific areas for categorization. Additionally, contour mapping facilitates the extraction of shape-based features like area, perimeter, and shape descriptors, providing valuable insights into the morphology and spatial characteristics of tumors, thereby enriching the CNN system's understanding. The contrast of extracted contours with reference templates or healthy brain contours, by exposing it to diverse data variations. Additionally, integrating regularization techniques include dropout, batch normalization, and normalization techniques normalization in the model architecture methods enables the CNN to effectively group noisy image, augmenting the dataset with noise reduction contour mapping facilitates the identification of deviations from normal brain frameworks, indicating abnormal tissue growth associated with tumors. By combining contour-based features with pixel intensity information in the CNN can enhance the differentiation between normal brain frameworks.

VII. CONCLUSION

The project has made significant strides in developing a robust brain tumor categorization system, CNN's and EfficientNetB1 architecture. Through rigorous experimentation and optimization, the system has demonstrated high correctness levels on the testing dataset, showcasing its productivity in accurately identifying and categorizing brain-tumors. Furthermore, the fusion of key features like EfficientNetB1 For the extraction of features, coupled with a compact Cnn system for categorization, underscores the productivity and effectiveness of the initiated approach. The system was devised to preprocess MRI Pictures, extract features using EfficientNetB1, and group the tumors as benign or malignant using a CNN. The system attained a level of correctness of 99.59% on the testing dataset, indicating its level of productivity in categorizing brain-tumors. The key features of the project include the use of EfficientNetB1 For the extraction of features, which significantly reduced the complexity of the data while preserving the important features. The Cnn system was designed with the less number of layers to prevent overfitting and improve generalization. The system incorporated data augmentation techniques to broaden the preparing dataset and boost the model's productivity. In essence, the project signifies a notable advancement in medical imaging analysis, particularly in brain tumor categorization. By harnessing state-of-the-art deep learning methods and integrating essential features, the system shows potential for enhancing diagnostic correctness and ultimately improving patient outcomes. many images and found that it successfully detect the text region.

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