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Article Title: Mobilenet and Streamlit Applications for Classification and Prediction of MRI-Based Types of Brain Tumo

MobileNet and Streamlit Applications for Classification and Prediction of MRI-Based Types of Brain Tumor

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ABSTRACT

The rapid proliferation of abnormal cells within the cerebrum and its surrounding areas leads to the formation of tumor cells with intricate and challenging patterns. Consequently, relying solely on magnetic resonance imaging (MRI) for brain tumor detection presents complexities due to the need for precise identification amidst normal anatomical structures and potentially anomalous tissues. Recognizing the urgency of early and precise diagnosis in combating brain cancers, this paper proposes a methodology for classifying and predicting MRI-based brain tumor types using MobileNet through a Streamlit application. Initially, the input image dataset undergoes preprocessing to enhance image quality, facilitated by a Gaussian filter. Subsequently, the FCM segmentation technique is employed to accurately delineate tumors' size, location, and morphology. Finally, feature extraction and classification are performed utilizing the MobileNet framework, a deep learning method known for its accuracy and efficiency, particularly in medical image segmentation. Performance evaluation metrics such as precision, recall, and accuracy are computed, culminating in the calculation of the F-score to assess the model's effectiveness. This work leverages the Streamlit environment, a Python platform for developing web-based interactive applications, to facilitate seamless user interaction. Ultimately, the predicted output images depicting various brain tumor types glioma, meningioma, pituitary, and absence of tumor are displayed within the Streamlit software interface. By offering a swift and precise means of disease classification, this approach aids healthcare professionals in promptly identifying tumor-afflicted patients while streamlining computational overhead. The proposed classifier shows the highest specificity of 94.5 % and sensitivity of 97.6%.

Keywords: Brain tumour, MRI, Guassian filter, FCM Segmentation, Streamlit.

1 Introduction

The technological advancement empowers radiologists to provide timely and precise diagnoses, crucial for early detection and treatment planning. According to the World Health Organization (WHO), over 100 different grades of brain tumors exist in humans, with meningiomas being among the most common types [1,2].

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MRI technology stands out as a precise method for scanning the human body, enabling detailed feature extraction for further investigation by radiologists. Deep learning methodologies play a pivotal role in accurately pinpointing tumor locations, leading to improved outcomes in treatment planning. Presently, efforts are underway to predict brain tumors more accurately and develop web-based applications based on trained models for wider accessibility and validation [3-7].

Numerous studies have explored brain tumor identification and classification using deep learning techniques. Another study in 2021 employed pre-trained CNN models such as VGG19, and InceptionV3, achieving the highest accuracy of 92% with Kaggle dataset [8-11]. Overall, these studies showcase the effectiveness of deep learning techniques in accurately identifying and classifying brain tumors, offering promising solutions for enhanced diagnosis and treatment planning. The literature review reveals that existing approaches predominantly leverage MRI brain image datasets accessible online for brain tumor classification. Machine learning and deep learning techniques are commonly employed with these online datasets. However, many of these methods exhibit high computational complexity, rendering them unsuitable for small-scale real-world applications [12-15]. To address this is guassian filter is utilized after pre-processing, accommodating both large and small online datasets.

This work leverages the Streamlit environment, a Python platform for developing web-based interactive applications, to facilitate seamless user interaction. Ultimately, the predicted output images depicting various brain tumor types glioma, meningioma, pituitary, and absence of tumor are displayed within the Streamlit software interface.

2 Related Works

Ayesha Jabbar et al (2023) have introduced the Caps-VGGNet hybrid model, amalgamating CapsNet with VGGNet by incorporating VGGNet layers. This fusion facilitates automatic extraction and classification of features, mitigating the need for extensive datasets. The hybrid model's enhanced detection speed and superior classification performance contribute to more accurate diagnoses of various brain tumor types. Experiment results demonstrate improved accuracy in picture segmentation, attributed to heightened recognition and generalization capabilities. However, limitations include the complexity of VGGNet and CapsNet structures, potentially hindering interpretability. Moreover, the model's performance across diverse datasets and medical scenarios remains unexplored, as does its evaluation on larger datasets to ascertain applicability and robustness [16].

Surendran Rajendran et al (2023) proposed feature extraction techniques employed by GLCM and VPT networks, alongside an ensemble approach combining both networks. While CNN outperforms in tumor segmentation, U-Net exhibits superior accuracy in this regard. Overfitting, a common concern with DNN-based methods, is addressed through variable assembly, optimizing model outputs. The ensemble technique offers a therapeutically

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beneficial and automated approach to brain tumor segmentation, facilitating disease management and patient care [17].

Andres Anaya-Isaza et al (2022) highlighted the exponential growth of deep learning networks, enabling complex tasks even in intricate fields like medicine. Data scarcity in medical contexts necessitates data augmentation techniques, as evidenced in brain tumor identification using ResNet50. Principal component analysis-based augmentation and transfer learning with ImageNet dataset yielded promising results, enhancing ResNet50's F1 detection score. Additionally, the study underscored methodological distinctiveness and significance compared to conventional approaches [18].

Ahmed S. Musallam et al (2022) emphasized the challenge of accurate diagnosis in brain diseases, particularly malignant brain cancer, necessitating a Computer-Aided Diagnosis (CAD) system. A three-step preprocessing method enhances MRI image quality, complemented by a novel Deep Convolutional Neural Network (DCNN) architecture for glioma, meningioma, and pituitary diagnosis. This architecture prioritizes batch normalization for accelerated training and utilizes a lightweight model with minimal convolutional layers and iterations [19].

Ankit Vidyarthi et al (2022) presented the global use of computer-aided diagnosis systems for brain tumor classification. The work focuses on multiclass classification of high-grade malignant brain tumors, employing a vast feature set across six domains and a Cumulative Variance method for feature selection. K-Nearest Neighbour (KNN), multi-class Support Vector Machine (mSVM), and Neural Network (NN) are utilized for predictive accuracy. Future directions entail extending the methodology to incorporate deep learning models for enhanced multiclass classification of brain tumor types [20].

3 Proposed Work

In this system, the input dataset undergoes preprocessing initially, wherein a Gaussian filter is applied to eliminate noise and enhance image quality. Subsequently, in the FCM segmentation stage, the observed data is thoroughly analyzed to accurately delineate tumor size, location, and shape variations. Following segmentation, the classification step employs MobileNet, a convolutional neural network renowned for its deep learning capabilities. MobileNet, initially trained on the ImageNet dataset, is repurposed to extract image features from brain MRIs instead of performing classification directly. Furthermore, a performance matrix module computes metrics including accuracy, precision, F1-score, and recall value to assess the model's effectiveness. The methodology utilizes the MobileNet model for network construction, distinguishing between tumor and non-tumor classes, and integrates the Streamlit framework for tumor prediction. This prototype is developed within the Streamlit environment, an open-source Python platform tailored for building web-based interactive applications. Ultimately, the predicted output is presented to the user through a web interface facilitated by the Streamlit software, offering seamless accessibility and interpretation of results.

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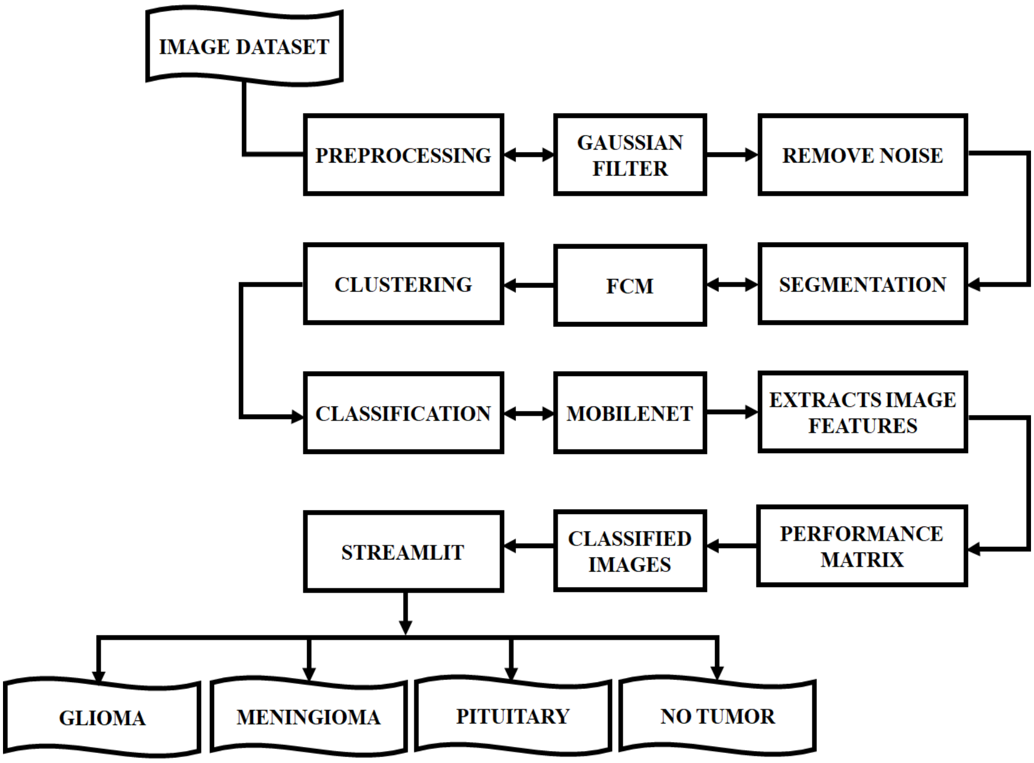

Figure 1: *Block Diagram for Proposed System*

3.1 Image Preprocessing By Guassian Filter

Detecting brain tumors in different stages presents a significant challenge due to overlapping symptoms. Symptoms observed in milder stages may persist or intensify in moderate stages, accompanied by additional, stage-specific symptoms. This overlap complicates classification, particularly in advanced stages. Preprocessing plays a crucial role in enhancing image data, aiming to minimize unwanted distortions and highlight essential elements for subsequent processing, including geometric alterations. Utilizing the Gaussian filter, the input dataset undergoes preprocessing to refine image quality.

Image processing entails the application of algorithms or quantitative analysis to digital image data, with the primary objective of improving the identification of abnormal brain tissue in neuroimaging. Common techniques in image processing encompass segmentation, noise reduction, edge sharpening, edge detection, and contrast enhancement. These methods streamline or partially automate the manual disease detection process, contributing to more efficient diagnosis. Noise removal, a fundamental aspect of image processing, is often achieved through techniques such as the Gaussian filter. Image processing finds applications across various domains, including remote sensing via satellite, medical imaging, radar and sonar image processing, and robotics. Advances in technology have enabled the manipulation of multi-dimensional signals, broadening the scope and efficacy of image processing techniques.

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Gaussian filters represent one of the most commonly utilized smoothing techniques. These filters serve not only as effective edge and line detectors but also play a significant role in edge detection within the human visual system. Functioning as a low-pass filter, the Gaussian filter effectively blurs specific regions of an image, thereby reducing noise or high-frequency components. Constructed as an Odd-sized Symmetric Kernel, a digital representation akin to a matrix, the filter traverses each pixel within the Region of Interest, imparting the desired effect. Gaussian filters find application in various domains, including ultrasound imaging, where they are employed to mitigate speckle noise. This noise, resulting from external influences and variations in light intensity, can compromise image clarity, particularly when captured under low-light conditions using handheld cameras. Image restoration techniques aim to rectify such noise-induced distortions, restoring images to their original quality by recalculating pixel values. Restoration processes operate in opposition to image degradation, following a paradigm of linear degradation.

Mathematically principled restoration techniques leverage principles of goodness to achieve optimal estimation of the desired outcome. By restoring pixel values, these techniques play a pivotal role in preserving image quality, effectively countering the effects of noise and blur to enhance visual clarity and fidelity.

3.2 Segmentation by FCM

Image segmentation, a fundamental technique in digital image processing and analysis, involves partitioning an image into distinct regions or segments based on pixel properties. This process aims to identify and delineate pixel-rich areas, often represented through a labeled image or a mask. Common segmentation methods rely on detecting abrupt changes in pixel values, indicating edges that delineate regions, or identifying similarities among image regions. Techniques such as region growing, clustering, and thresholding exemplify approaches that leverage similarity detection to segment images. Region growing, for instance, iteratively merges neighboring pixels with similar properties to form coherent regions. Clustering algorithms group pixels into clusters based on feature similarity, facilitating segmentation. Thresholding involves separating pixels based on intensity values exceeding a predefined threshold. Over the years, various domain-specific segmentation approaches have emerged, tailored to address segmentation challenges in specific application areas. These methods leverage domain knowledge to enhance segmentation accuracy and efficiency.

One prominent clustering-based approach to image segmentation is Fuzzy C-Means (FCM) segmentation. This method assigns pixels to clusters based on their degree of membership, allowing for soft boundaries between segments. FCM segmentation is particularly useful in scenarios where pixel properties exhibit degrees of ambiguity or uncertainty, offering robust segmentation performance across diverse image datasets.

Segmentation, the process of partitioning an image into distinct subgroups or pixels known as picture objects, is integral to many image processing systems. In this particular system,

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segmentation is facilitated using the Fuzzy C-Means (FCM) method, effectively reducing the image's complexity. The initial step involves analyzing the input picture to discern whether the mole is malignant, followed by transforming the image to the HSV format for further processing. Utilizing the Fuzzy C-Means technique for segmentation and grouping, the image is automatically partitioned into multiple colors, with specific emphasis on regions corresponding to darker lesions against lighter surroundings.

Fuzzy C-Means clustering is a widely employed model for clustering, particularly in pattern recognition tasks. This algorithm assigns data points to clusters based on their proximity to cluster centers, with each data point having a degree of membership indicating its affiliation with each cluster. FCM optimally partitions a collection of vectors into fuzzy groups, minimizing a cost function based on distance measures. This approach allows for partial membership of data points to multiple clusters, accommodating cluster overlap and providing a degree of participation ranging from zero to one.

The FCM algorithm operates iteratively to minimize the weighted within-group sum of squared error objective function, resulting in an optimal partition of the data into clusters. The outcome of fuzzy clustering is a fuzzy c-partition, represented mathematically through the iterative optimization process aimed at achieving an optimal clustering solution.

$$J_{FCM} = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik})^q \, d^2(x_k, v_i) \tag{1}$$

A refined algorithm has been devised to iteratively optimize solutions within the Fuzzy C-Means (FCM) framework. Operating within the fuzzy clustering paradigm, the FCM algorithm iteratively adjusts membership degrees to minimize fuzziness within cluster variations. FCM stands as a cornerstone technique for assigning multiclass membership values to pixels in image processing applications. Once the membership values for each class (or cluster) are determined for data points such as pixels, the assignment of pixels to the class with the highest membership becomes straightforward.

A notable advantage of the fuzzy c-means approach is its unsupervised nature, eliminating the need for an initial set of training data. This characteristic allows for the generation of membership functions post-processing, enabling efficient and adaptable processing without the constraints of predefined training datasets.

3.3 Classification by Mobilenet

Classification, the process of categorizing data into distinct classes and assigning labels accordingly, is a fundamental task in supervised learning. Various classification techniques exist, each with its strengths and weaknesses. The Random Forest classifier, for instance, remains robust in the presence of missing data but may suffer from computational complexity and slow real-time predictions. Decision Trees offer simplicity and ease of interpretation, yet they are prone to overfitting and may perform poorly on certain datasets.

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MobileNet stands out as a Convolutional Neural Network (CNN) architecture tailored for Image Classification and Mobile Vision applications. While numerous models exist, MobileNet distinguishes itself by its exceptionally low computational requirements, making it ideal for deployment on mobile devices, embedded systems, and computers lacking GPU support or possessing limited computational resources, all without compromising significantly on accuracy. Developed and open-sourced by Google, MobileNet is specifically designed for training classifiers, offering a lightweight alternative in the realm of computer vision models.

A key feature of MobileNet is its utilization of Depthwise separable convolutions, which markedly reduce the number of parameters compared to traditional convolutional networks while maintaining depth in the network. This innovative approach results in lightweight deep neural networks, well-suited for resource-constrained environments. Tensorflow's pioneering mobile computer vision model, MobileNet employs a total of 27 convolution layers, comprising 13 depthwise convolutions, 1 Average Pool layer, 1 Fully Connected layer, and 1 Softmax Layer, further enhancing its efficiency and applicability in various contexts.

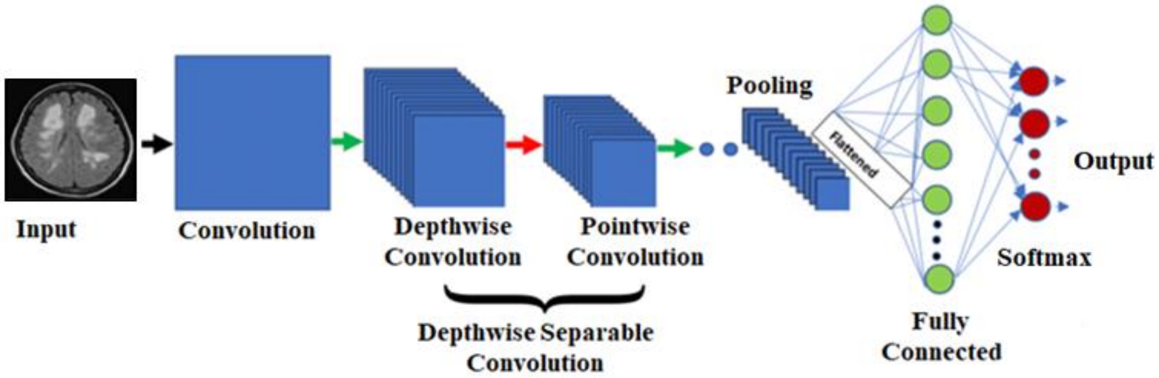

Figure 2: *Mobilenet Architecture*

In MobileNet, the depthwise layer differs from standard convolution by utilizing a single filter for each input channel, instead of applying one filter to inputs with channel dimensions. Following the depthwise layer, the pointwise layer conducts a 1x1 filter multiplication operation to merge the feature map outputs. The MobileNet architecture leverages pre-trained weights from ImageNet, enhancing its effectiveness in various tasks. The output of these layers is then fed into the Average Pooling layer. Subsequently, the results undergo finalization via fully connected layers comprising 1024, 1024, and 512 neurons, each activated by ReLU. Finally, the Softmax function is applied to the output of the fully connected layers. Softmax serves to transform vector input into a probability distribution, thereby providing the final classification probabilities.

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Convolution Layer

The first convolution layer in MobileNet employs a standard convolution method with 32 filters and a kernel size of 3x3. Each filter processes the input from the preceding layer to generate output features for subsequent layers.

MobileNet Depthwise Separable Convolution

The Depthwise Separable Convolution consists of two layers: the depthwise convolution and the pointwise convolution. The depthwise convolution filters input channels, while the pointwise convolution combines them to create new features.

Depthwise Convolution

Originating from the concept of separating a filter's depth and spatial dimensions, the depthwise convolution performs a single convolution on each input channel separately. This approach significantly reduces parameters compared to traditional convolutions, enhancing computational efficiency.

Pointwise Convolution

The pointwise convolution combines features generated by the depthwise convolution using a 1x1 convolution. This step further refines the features, facilitating effective feature extraction.

MaxPool

The MaxPool layer, with a 2x2 kernel, reduces overfitting and computational burden by selecting the maximum value from filtered feature sections of the previous layer.

AveragePool Layer

Following MaxPool, the AveragePool layer processes the output from MobileNet, reducing data size and preparing for subsequent layers by calculating average outputs.

Fully Connected Layer

In the fully connected layer, model outputs are flattened into a one- vector. Neurons in this layer, typically numbering 1024, are interconnected with the next layers, enhancing training time and accuracy.

Softmax

The Softmax function normalizes input values into a probability distribution, facilitating classification. This layer consists of 17 neurons corresponding to output classes, producing probability values for predictions.
MobileNet employs Depthwise and Pointwise convolutions, distinct from traditional CNNs, to enhance efficiency in image prediction. These convolution methods optimize comparison and

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recognition time, making MobileNet suitable for real-world applications such as object detection, fine-grained classifications, and facial attribute localization in mobile systems.

3.4 Predicted Performance Matrix

In the subsequent experimental evaluation, various fundamental indicators are taken into account, including TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative). TP signifies the number of correctly predicted attack flows, TN represents the number of correctly predicted normal flows, FP indicates the number of incorrectly predicted attack flows, and FN denotes the number of incorrectly predicted normal flows.

3.4.1 Accuracy

It refers to the ratio of correct predictions to all the predictions, a higher accuracy indicates a more accurate prediction by the learning model it is denoted by

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{2}$$

3.4.2 Precision

The capacity to avoid mislabeling negative records as positive; a high precision rate equates to a low rate of false positives. It refers to the ratio of correctly predicted attacks to the total predicted attacks, denoted by

$$\text{Precision} = \frac{TP}{TP + FP} \tag{3}$$

3.4.3 Recall

Recall also called True Positive Rate, refers to the ratio of correctly predicted attacks to the actual attacks, denoted by

$$\text{Recall} == \frac{TP}{TP + FN} \tag{4}$$

3.4.4 F1 score

F1 score is the weighted average of Precision and Recall, denoted by

$$F1 = \frac{2 \cdot (\text{Recall} \cdot \text{Precision})}{\text{Recall} + \text{Precision}} \tag{5}$$

3.4.5 AUC

AUC stands for Area under the ROC Curve which plots Recall against False Positive Rate at different classification thresholds.

$$(FPR = \frac{FP}{FP+TN}) \tag{6}$$

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The module predicts the classified datasets and evaluates the values of accuracy, recall, time, F1 score, precision, and confusion matrix. Finally, the performance of the classification technique is achieved.

3.5 Streamlit

Streamlit, an open-source Python library, facilitates the creation of interactive web applications tailored for machine learning and data science tasks. Its user-friendly design allows for the rapid development of applications through simple Python scripting. With Streamlit, creating a user interface for web-based applications becomes accessible, enabling broader accessibility to the models developed. Streamlit's compatibility with major Python libraries such as scikit-learn, Keras, PyTorch, SymPy (latex), NumPy, pandas, and Matplotlib further enhances its appeal. Compared to other frameworks, Streamlit offers simplicity and requires minimal code, making it an attractive choice for deploying machine learning models as web apps. As Streamlit continues to evolve with new features in subsequent releases, it provides users with expanded capabilities for building and deploying applications. Model selection typically follows completion of model training and testing, with considerations such as accuracy, sensitivity, specificity, recall, and F1 score influencing the choice of optimal deep learning architecture. Utilizing Streamlit's open-source platform, developers can create web applications spanning machine learning, deep learning, and data science domains. Streamlit code, written in Python, can be easily shared through GitHub repositories, leveraging Streamlit's free sharing service. During the development process, challenges such as data loading issues and long dashboard load times were encountered. However, leveraging resources such as Europe PMC's listserv for developers and implementing Streamlit's built-in caching feature helped overcome these obstacles effectively. Streamlit seamlessly integrates with primary Python libraries for data visualization and analysis in machine learning, enhancing the overall user experience and productivity in application development.

4 Results and Discussions

The implementation of this paper relies on Python software. Anaconda serves as a valuable tool, enabling the creation of environments housing various Python and package versions. Within these environments, Anaconda facilitates tasks such as package installation, removal, and upgrades. Additionally, Anaconda simplifies the process of launching required projects with just a few clicks. The Jupyter Notebook program is utilized to create and edit pages showcasing the input and output of Python or R language scripts. Once saved, these files can be easily shared with others.

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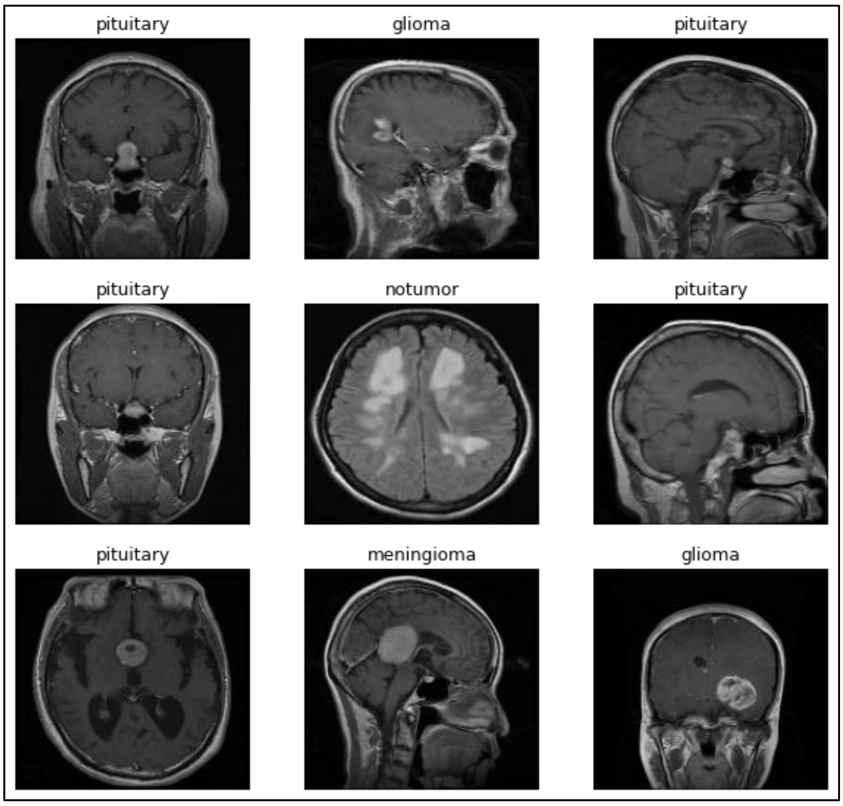

Figure 3: *Input Image Dataset*

In Figures 3, the input image dataset illustrates both the absence of tumors (no-tumor) and the presence of brain tumors, respectively. MR images are utilized as input due to their high resolution, offering detailed insights into brain structures. Additionally, the input images are grayscale, further simplifying the processing pipeline. The database comprises a collection of both normal and abnormal brain tumor images, with each image serving as a single input for analysis.

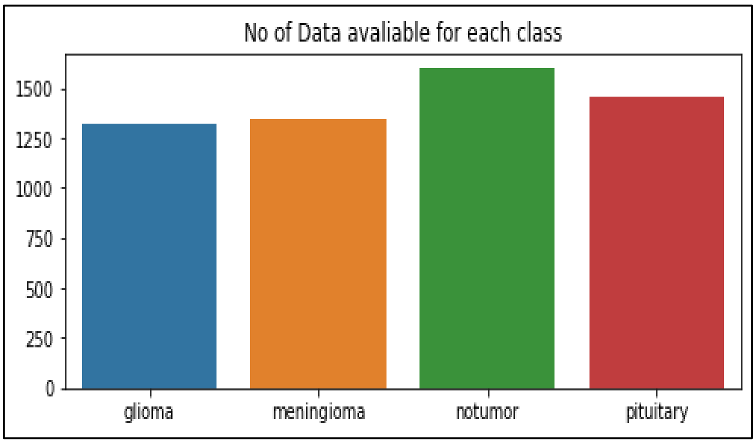

Figure 4: *Data distributions for each class*

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In Figure 4, the data distribution is depicted for three distinct types of tumors as well as the no-tumor category. Notably, each dataset surpasses the current availability of 1250 datasets for a specific type of brain tumor.

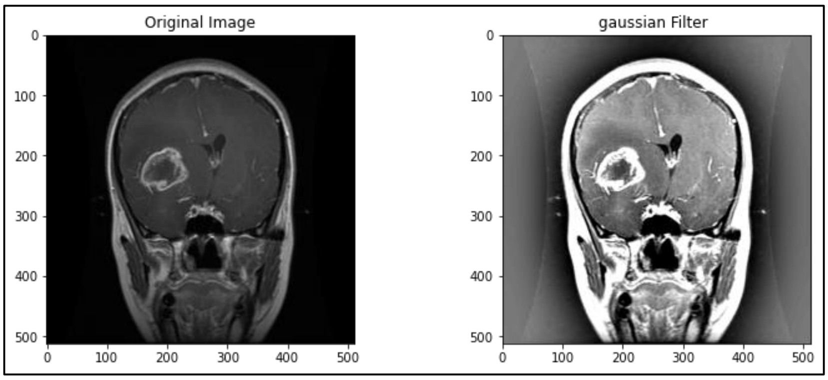

Figure 5: *Preprocessed Image for Gaussian filter*

Figure 5 showcases a preprocessed, filtered image. Prior to proceeding with the main procedure, each image undergoes essential preprocessing to ensure its suitability for further analysis. In this instance, the preprocessing involves applying a Gaussian filter to the image. This step serves two purposes: noise removal and image enhancement. The Gaussian filter is instrumental in refining the image's precision and interpretability, thereby optimizing its suitability for subsequent processing stages.

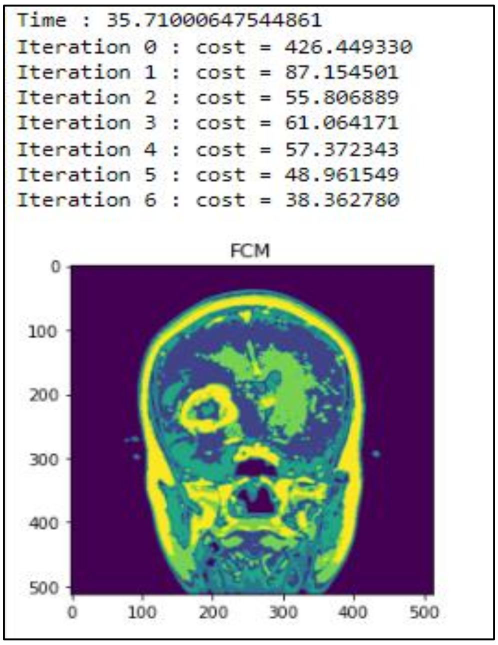

Figure 6: *Segmented Image*

Picture segmentation is employed to delineate between tumor and non-tumor regions within the image. Segmentation refers to the process of dividing a digital image into distinct segments

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or regions. In this context, segmentation is achieved using the Fuzzy C-means (FCM) algorithm. The initial step in segmentation involves normalizing the intensity across the pixel range to effectively differentiate between tumor and non-tumor areas.

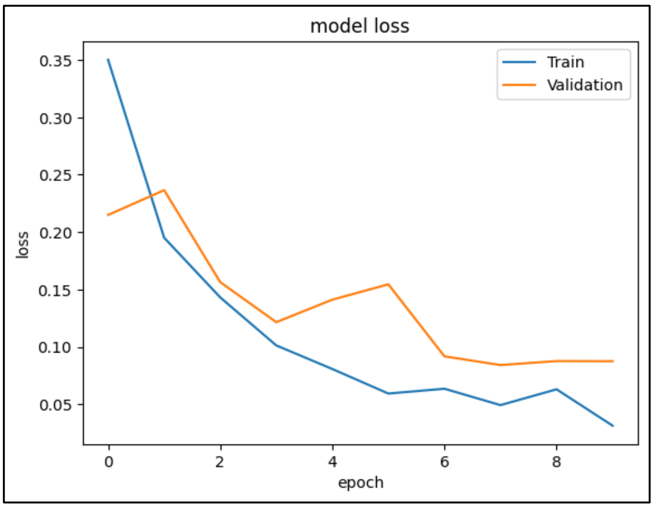

Figure 7: *Model Loss*

A loss metric quantifies the extent of error in a model's prediction for a single example. A perfect prediction results in a loss value of zero, while imperfect predictions yield higher loss values. During model training, the objective is to determine a set of weights and biases that minimize the average loss across all examples. Figure 7 illustrates demonstrations of the model's loss, showcasing variations in loss values across different examples.

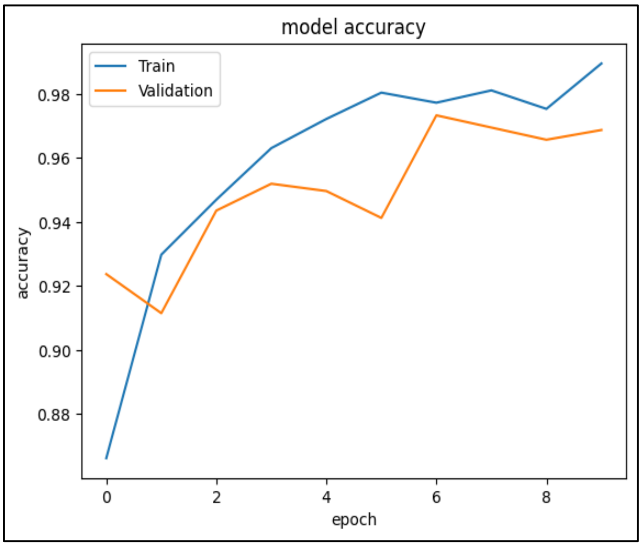

Figure 8: *Model Accuracy*

Model accuracy refers to the proportion of correct predictions made by a model out of the total number of predictions. While accuracy is a key metric for evaluating model performance, it is

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not the sole measure. Figure 8 provides visual representations of the model's accuracy, offering insights into the model's predictive capabilities.

```
30/30 [==============================] - 2s 44ms/step
              precision    recall  f1-score   support

           0       0.98      1.00      0.99       222
           1       0.99      0.98      0.98       215
           2       1.00      1.00      1.00       247
           3       1.00      0.99      1.00       259

    accuracy                           0.99       943
   macro avg       0.99      0.99      0.99       943
weighted avg       0.99      0.99      0.99       943

Specificity : 0.9953
Sensitivity : 98.22 %
Confusion Matrix:
[[221   1   0   0]
 [  4 211   0   0]
 [  0   0 247   0]
 [  0   2   0 257]]
```

Figure 9: *Performance of Mobilenet*

In Figure 9, the performance matrix of MobileNet is depicted. MobileNet, an open-source computer vision model developed by Google, is specifically designed for training classifiers. It leverages depthwise convolutions to substantially decrease the number of parameters in comparison to other networks, thereby creating a lightweight deep neural network.

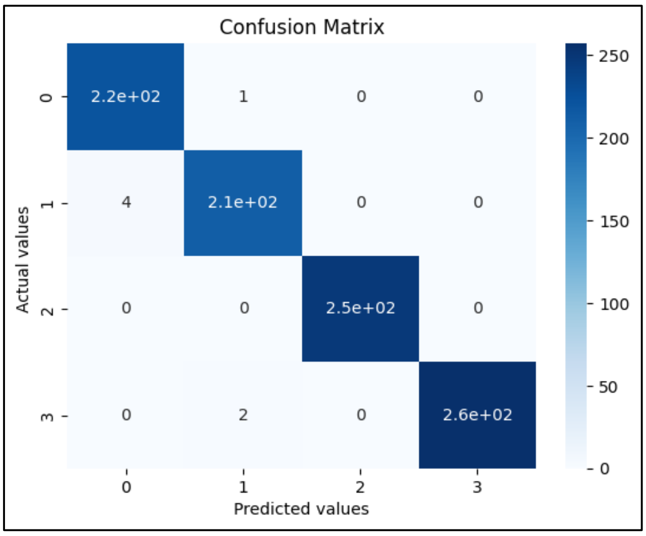

Figure 10: *Confusion matrix for MobileNet*

Figure 10 illustrates the confusion matrix for MobileNet. This matrix showcases the values for actual and predicted labels. Confusion matrices are commonly utilized to evaluate the performance of classification models, particularly those tasked with predicting categorical labels for input instances.

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Figure 11: *Outcome Page of Streamlit*

Figure 11 displays the outcome page of the Streamlit app. To replicate this setup, create a new folder named "pages" in the directory where the Python file is located. As depicted in the figure, users can upload an input image by clicking on the browse file icon. The uploaded image is then processed to determine whether it depicts a tumor or non-tumor image, and the outcome is presented to aid user comprehension.

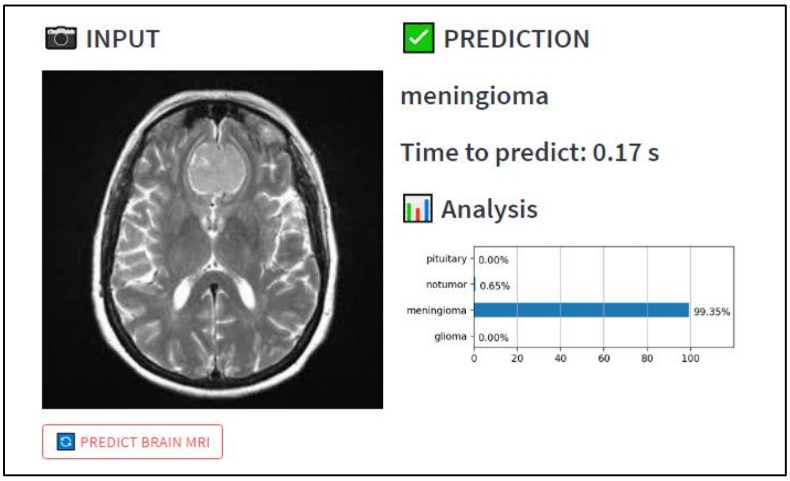

Figure 12: *Prediction of Meningioma Tumor*

In Figure 12, meningioma tumor images from four distinct datasets are showcased, each contributing to the identification of the tumor. The successful prediction yields a 99.35% accuracy in detecting meningioma tumors, with a prediction time of 0.17 seconds.

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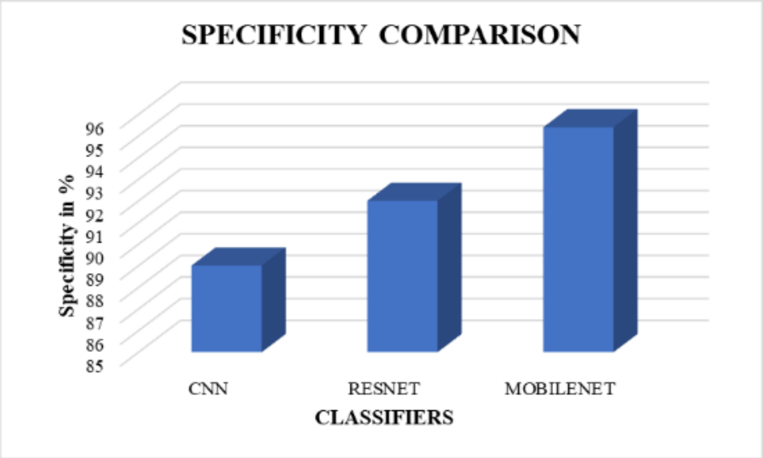

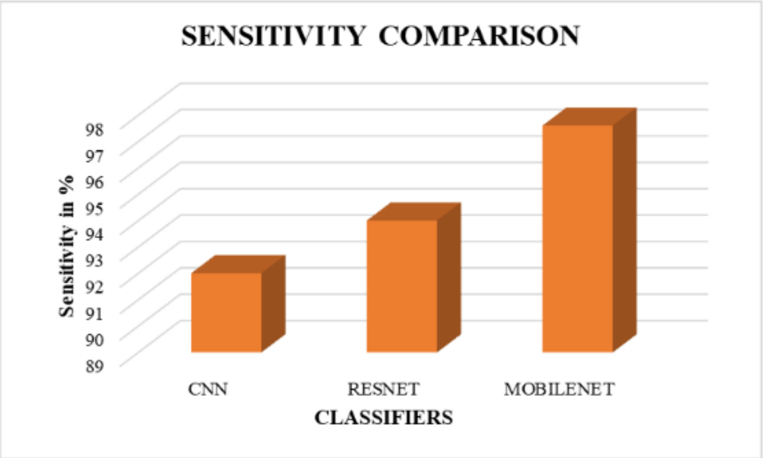

Figure 13: *Comparison of Sensitivity and Specificity*

Figure 13 shows the sensitivity and specificity of various classifiers in which the proposed classifier shows the highest specificity of 94.5 % and sensitivity of 97.6% than other conventional classifiers.

5 Conclusion

This paper introduces a Python software solution for classifying and predicting different kinds of MRI-based brain tumors using MobileNet, implemented through a Streamlit application. Pre-processing and segmentation play pivotal roles in enhancing the efficiency of tumor detection and classification when deploying the MobileNet classifier. Leveraging a pre-trained MobileNet model facilitates the generation of image representations, resulting in lower model loss and higher accuracy during training and testing phases. The proposed technique demonstrates superior performance in terms of accuracy, precision, and F1-score. Notably, the detection rate achieves an impressive F1-score of 99%, specificity of 99.53%, and sensitivity of 98.22%. MobileNet significantly improves overall prediction accuracy, achieving a peak

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accuracy of 99%. Ultimately, this work streamlines manual segmentation processes and enhances classification capabilities. This paper is deployed as a user-friendly web application using the Streamlit framework, providing medical professionals with an intuitive interface for accessing and utilizing the developed models. The chosen model is seamlessly integrated into the web application, leveraging the Streamlit framework's capabilities to provide an interactive platform for displaying concepts, code, and results. The proposed classifier shows the highest specificity of 94.5 % and sensitivity of 97.6%.

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