iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** III **Month of publication:** March 2026

DOI: https://doi.org/10.22214/ijraset.2026.78773

www.ijraset.com

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

A Comprehensive Approach to Brain Tumor Classification and Stage Classification Using Neural Networks and K-Means Segmentation

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Abstract: ***The proposed optimized brain tumor detection method employs a dual-module framework combining advanced image processing, feature extraction, and classification to improve diagnostic accuracy. Brain MRI images are first enhanced using adaptive Wiener filtering for effective noise reduction. Discriminative features are extracted using a Radial Basis Function (RBF) neural network and classified through a Support Vector Machine (SVM) to identify tumor types, including meningioma, glioma, and pituitary tumors. Detected tumors are further analyzed for stage determination—early, intermediate, or advanced—using Convolutional Neural Networks (CNN) and K-means clustering-based segmentation. This integrated approach enables accurate tumor identification and staging, supporting improved treatment planning, timely clinical intervention, and enhanced patient outcomes in medical imaging applications.***

Index Terms: Magnetic Resonance Imaging (MRI), Image Enhancement, Brain Tumor Segmentation, Brain Tumor Classification, Neural Networks, Convolutional Neural Networks (CNN), Deep Learning.

I. INTRODUCTION

Brain tumors constitute a major global health challenge due to their high mortality, complex pathology, and significant socioeconomic burden. Epidemiological evidence indicates that brain cancer incidence and mortality are closely linked to a country's level of human development, reflecting disparities in diagnosis, treatment access, and patient outcomes [1]. Consequently, accurate and early detection is essential for improving survival rates and supporting effective treatment planning. Magnetic resonance imaging (MRI) plays a vital role in neuro-oncology by providing high-resolution, non invasive visualization of brain anatomy and tumor characteristics, with different MRI modalities offering complementary information on tissue composition, edema, necrosis, and tumor boundaries [2].

Recent advances in image processing and machine learning have greatly enhanced MRI-based brain tumor analysis. Variations in MRI intensity, particularly T2-weighted hyperintensities, show strong correlation with pathological regions, emphasizing the importance of reliable segmentation and feature extraction methods [3]. Manual and semi-automatic segmentation approaches are labour-intensive and prone to inter-observer variability, leading to increased interest in automated solutions. Convolutional neural networks (CNNs) have demonstrated strong performance in brain tumor segmentation, especially when integrated with texture-based features, while deep learning techniques have consistently outperformed traditional handcrafted-feature based methods in medical imaging tasks [4,5]. Hybrid learning frameworks that combine unsupervised and supervised techniques have further improved tumor localization and classification. K-means clustering is commonly employed for initial intensity-based tumor segmentation, which can be refined using neural network models. Additionally, multiscale CNN architectures coupled with statistical thresholding have shown effectiveness in detecting tumors of varying sizes and appearances [6]. Despite these advances, many existing studies focus primarily on either segmentation or classification, with limited attention to tumor stage classification. This highlights the need for an integrated framework that combines K-means-based segmentation with neural-network-driven tumor and stage classification to provide a more comprehensive and clinically meaningful diagnostic solution.

II. LITERATURE REVIEW

The application of machine learning and deep learning techniques for brain tumor detection, segmentation, and classification has grown rapidly with advancements in medical imaging and the availability of annotated MRI datasets. Survey studies highlight a clear transition from traditional handcrafted feature–based and threshold-driven methods to deep learning frameworks, which demonstrate superior capability in modeling complex tumor morphology and anatomical variability [9,10].

While early methods were computationally efficient, they lacked robustness to noise, intensity inhomogeneity, and tumor heterogeneity commonly present in MRI scans.

Accurate tumor segmentation remains a critical challenge in neuro-oncology, as precise delineation directly impacts diagnosis and treatment planning. Deep convolutional models have shown strong generalization across neuroimaging tasks, including hemorrhage detection and segmentation, demonstrating adaptability to diverse brain imaging modalities [7]. Image enhancement and denoising have also been shown to significantly influence segmentation and classification performance, with neural network–based denoising methods improving contrast preservation and noise suppression in brain MRI images [8].

Hybrid intelligent systems combining machine learning with fuzzy logic and optimization techniques have further improved tumor analysis. Approaches based on adaptive neuro-fuzzy inference systems, particle swarm optimization, and Bayesian fuzzy clustering have enhanced segmentation and classification accuracy by effectively handling uncertainty and selecting discriminative features [11,12,15]. With the emergence of deep learning, end-to-end CNN-based models have achieved high diagnostic accuracy by learning hierarchical feature representations directly from MRI data, reducing reliance on manual feature extraction [13].

Recent studies emphasize fully automated, multi-phase diagnostic frameworks that integrate detection, segmentation, and classification. CNN architectures incorporating fuzzy entropy, neutrosophic logic, and optimization-based parameter tuning have demonstrated improved robustness under varying imaging conditions [14,16]. Transfer learning and encoder–decoder segmentation networks have further enhanced tumor localization and boundary delineation, particularly in scenarios with limited labeled data [18,20,21]. Overall, existing research underscores the effectiveness of deep learning, hybrid intelligence, and optimization-based methods, while highlighting the need for integrated frameworks that jointly address accurate segmentation and reliable tumor and stage classification.

III. PROPOSED METHOD

The proposed optimized brain tumor detection methodology utilizes a dual-module framework to enhance diagnostic accuracy through advanced image processing and classification techniques. Brain MRI images are first pre-processed using adaptive Wiener filtering to suppress noise and improve image quality. Discriminative features are then extracted using a Radial Basis Function (RBF) neural network and classified with a Support Vector Machine (SVM) to accurately identify tumor types such as meningioma, glioma, and pituitary tumors. For tumor positive cases, a stage-determination module integrates K means clustering–based segmentation with Convolutional Neural Networks (CNN) to localize the tumor region and classify it into early, intermediate, or advanced stages. This integrated approach enables precise tumor detection and staging, supports assessment of tumor progression, and provides clinically actionable insights for effective treatment planning and timely medical intervention.

A. Input Image

This block corresponds to the acquisition of brain MRI images from standard datasets or clinical sources. The input images may exhibit variations in resolution, contrast, and noise levels due to differences in imaging protocols and scanner configurations.

B. Pre-Processing

Pre-processing improves the quality of MRI images by removing artifacts and standardizing image properties. It prepares the images for further analysis by enhancing relevant structures and reducing irrelevant variations

1) Image Resize: The brain MRI images are resized to a fixed resolution of 256 × 256 pixels using interpolation to ensure uniform input dimensions and improve computational efficiency across all processing stages.

2) Gaussian and Adaptive Wiener Filtering: A Gaussian filter ($\sigma = 1$) is applied to reduce high-frequency MRI noise while preserving anatomical structures. Adaptive Wiener filtering then refines denoising using local variance estimation, effectively preserving edges and tumor boundaries while minimizing background noise.

3) Contrast Enhancement: The denoised image is enhanced using a Radial Basis Function Neural Network (RBFNN) trained to refine pixel intensity distributions. Histogram stretching (imadjust) is applied to improve contrast visibility, enabling clearer differentiation between tumor and non-tumor tissues, which is crucial for accurate segmentation and classification.

C. Feature Extraction and Whitening

Independent Component Analysis (ICA)–based whitening is performed to decorrelate image intensities and emphasize statistically independent structures. This step enhances discriminative information by reducing redundancy and improving the separability of tumor textures and normal brain tissues.

D. SVM-Based Tumor Classification

The extracted features are classified using a multi-class Support Vector Machine (SVM) with Error-Correcting Output Codes (ECOC) to distinguish Glioma, Meningioma, Pituitary tumor, and No Tumor classes, ensuring robust classification in high-dimensional medical data.

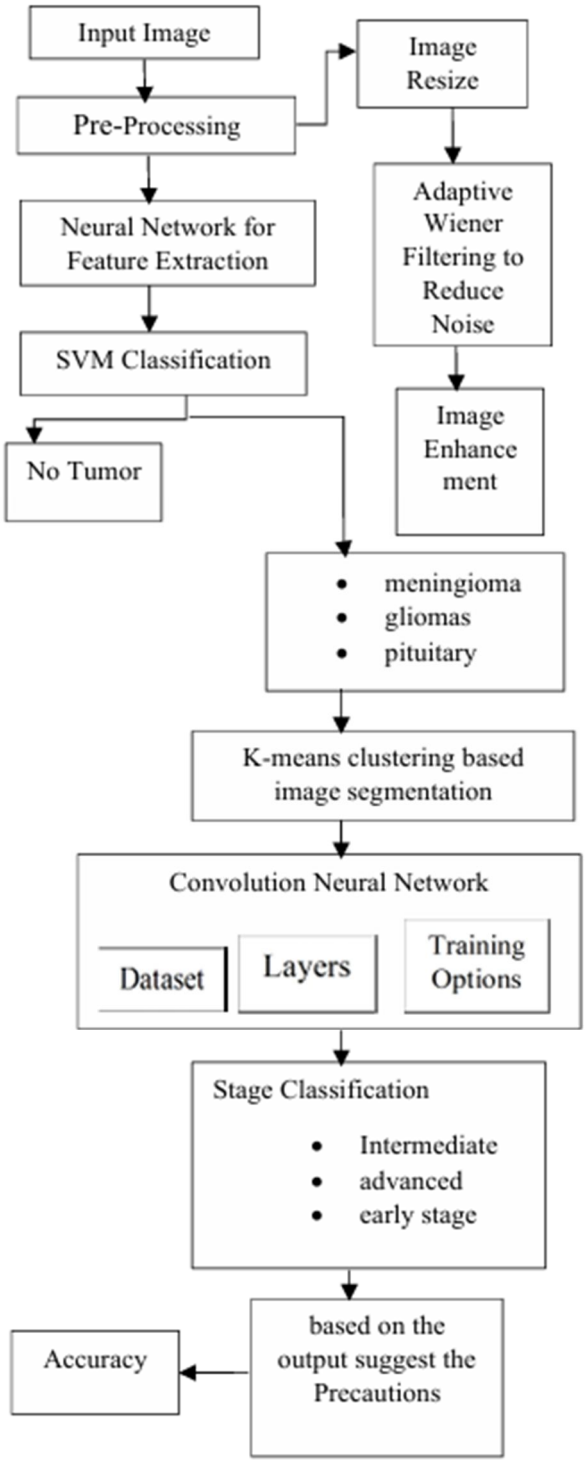

Fig1: Block Diagram of Proposed Model

E. K-Means Clustering–Based Tumor Segmentation

For MRI images classified as tumor-positive, K-means clustering is applied to segment tumor regions based on pixel intensity similarity. The algorithm partitions the image into $K = 3$ clusters by minimizing intra-cluster variance is shown in Eq(1).

$$J = \sum_{K=1}^{K} \sum_{x_i \in C_K} ||x_i - \mu_K||^2 \quad (1)$$

where x_i represents pixel intensity, C_k is the k^{th} cluster, and μ_k denotes the cluster centroid. The iterative update of centroids is given by Eq(2).

$$\mu_K = \frac{1}{|C_K|} \sum_{x_i \in C_K} x_i \quad (2)$$

This unsupervised segmentation isolates tumor tissue from normal brain structures, enabling accurate region-based visualization and forming a reliable input for CNN-based stage classification.

F. Dataset Preparation and Augmentation

1) Dataset Organization and Loading: The segmented tumor images are arranged into hierarchical directory structures, where each folder corresponds to a specific tumor stage. This organization allows MATLAB's imageDatastore to automatically read the images and assign class labels based on folder names. Such an approach simplifies dataset management and enables efficient supervised learning without manual annotation during training.

2) Train–Validation Split Strategy: To ensure reliable model evaluation, the dataset is randomly divided into training and validation subsets using an 80:20 ratio. This split maintains balanced representation of each tumor stage in both subsets and helps prevent overfitting. The randomized sampling strategy ensures that the trained model generalizes well to unseen data.

3) Augmented Datastore Configuration: An augmented image datastore is employed to preprocess the input images before training. All segmented tumor images are resized to a uniform resolution of 256 × 256 and converted to three-channel RGB format when necessary. This preprocessing ensures compatibility with convolutional neural network input requirements and supports efficient mini-batch processing during model training.

G. Training Configuration and Hyperparameters Settings

1) Optimization Algorithm Selection: The Stochastic Gradient Descent with Momentum (SGDM) optimizer is employed for training the CNN-based tumor stage classification model. SGDM improves standard gradient descent by incorporating a momentum term that accumulates historical gradient information, thereby reducing oscillations and enabling smoother convergence toward optimal solutions. An initial learning rate of 0.001 is selected to ensure stable parameter updates while preserving sufficient learning capability for complex tumor patterns. The automatic execution environment detection allows MATLAB to utilize GPU acceleration when available, significantly improving training efficiency for large-scale medical image datasets.

2) Epoch and Mini-Batch Configuration: Training is performed over 100 epochs, allowing the network to iteratively refine low-level and high-level feature representations across multiple passes of the dataset. A mini batch size of 25 is chosen to balance memory usage, computational efficiency, and gradient estimation accuracy. Mini-batch learning introduces controlled stochasticity into the optimization process, which enhances generalization.Additionally, data shuffling at every epoch ensures randomized sample presentation, preventing the model from learning order-specific patterns and reducing overfitting tendencies.

3) Validation and Monitoring Strategy: Model validation is conducted every 50 training iterations using a reserved validation subset to evaluate generalization performance during training. This periodic validation enables early identification of overfitting and convergence irregularities. MATLAB's interactive training-progress plots provide real-time visualization of loss reduction, training accuracy, and validation accuracy trends. The verbose output mode supplies detailed iteration-wise metrics, facilitating precise monitoring of optimization dynamics and training stability.

H. Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are powerful deep learning architectures designed to analyze structured spatial data such as brain MRI images. In brain tumor classification, CNNs automatically learn hierarchical representations ranging from low-level edges and textures to high-level tumor morphology and spatial patterns.

These features are extracted directly from pixel intensities, eliminating manual feature engineering. MATLAB's Deep Learning Toolbox provides efficient tools for CNN design and training, enabling reliable tumor stage classification from MRI scans.

1) Image Input Layer: The image input layer functions as the network entry point, accepting pre-processed brain MRI images resized to a fixed dimension (e.g., 256 × 256 × 3). This layer ensures uniform input formatting and performs internal normalization to stabilize training. Standardizing image dimensions enhances compatibility across layers and improves learning consistency during model optimization.

2) Convolutional Layer: A 2D convolutional layer, implemented using convolution2dLayer, extracts localized spatial features by sliding learnable kernels across the MRI input. Each kernel emphasizes clinically significant structures such as tumor boundaries, intensity variations, and abnormal tissue patterns.

3) Filters and Feature Extraction: As a filter moves across the input image, convolution is computed using Eq(3).

$$Y(i,j) = \sum_m \sum_n X(i+m, j+n) W(m,n) + b \qquad (3)$$

where X is the input MRI image, W represents the filter weights, and b denotes the bias. This operation generates feature maps that highlight tumor-specific visual cues essential for accurate stage classification.

4) Padding and Stride: Padding is applied to preserve spatial resolution and prevent loss of boundary information, which is critical in brain tumor analysis. The stride parameter controls the step size of the filter movement, influencing feature map resolution and computational cost. Proper stride–padding selection ensures balanced feature representation and efficiency.

Fig 2: Filters and Stride

5) Batch Normalization and ReLU Layer: Batch normalization layers stabilize learning by normalizing activations within each mini-batch, improving convergence speed and reducing sensitivity to initialization. Following normalization, the ReLU activation layer introduces non linearity by suppressing negative values using Eq(4).

$$ReLu\,(X) = max(0, X) \qquad (4)$$

This operation enhances the network's ability to model complex tumor patterns while maintaining computational simplicity.

6) Pooling Layers: Max-pooling layers reduce the spatial dimensions of feature maps by selecting dominant responses within local neighborhoods. This down-sampling operation improves translational invariance and reduces overfitting, enabling the CNN to remain robust against variations in tumor size, shape, and location across different MRI scans.

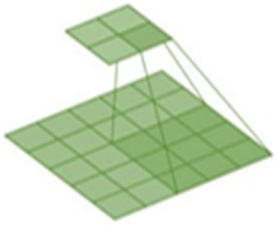

Fig 3: Pooling Layers

7) Fully Connected Layer: The fully connected layer integrates high-level features extracted from convolutional layers and maps them to tumor stage categories. By establishing global connections across all features, this layer enables discriminative learning necessary for precise classification of tumor progression stages.

8) Output Processing Layers:

Softmax Activation and Classification: The Softmax layer transforms final network activations into a probabilistic distribution over tumor stages using Eq(5).

$$P(C_r \mid \mathcal{X}) = \frac{exp(a_r)}{\sum_{j=1}^{k} exp(a_j)} \qquad (5)$$

where K is the number of tumor stages. The classification layer assigns the final label based on maximum posterior probability, ensuring interpretable and clinically meaningful predictions.

The CNN-based brain tumor analysis framework integrates image preprocessing, K-means–based tumor segmentation, deep feature learning, and stage-level classification. Segmented tumor regions are overlaid on the original MRI images to visually distinguish abnormal and healthy tissues prior to stage analysis. The segmented images are then fed into a custom CNN, where convolutional layers extract hierarchical spatial features for classifying tumor stages as Early, Intermediate, or Advanced. Model training and convergence are monitored through accuracy and loss curves, while performance evaluation is conducted using confusion matrices. This visually driven and interpretable workflow ensures reliable tumor localization, transparent learning behavior, and accurate stage prediction to support clinical decision-making.

IV. RESULTS

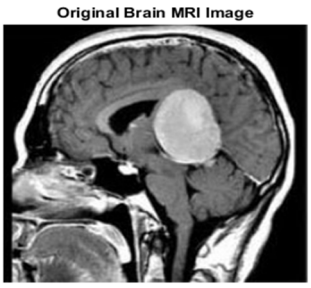

Fig4: Input Image

The original brain MRI image (Figure 4) serves as the primary system input, providing raw anatomical and intensity information essential for identifying abnormal regions. It forms the baseline for all subsequent preprocessing, enhancement, and tumor analysis stages.

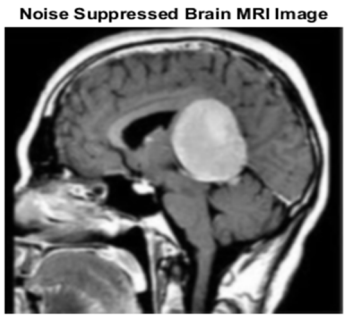

Fig5: Noise Suppressed Brain MRI Image

Figure 5 shows the brain MRI image after Gaussian filtering, where high-frequency noise is reduced while preserving key anatomical structures, enhancing image clarity for subsequent feature extraction and tumor analysis.

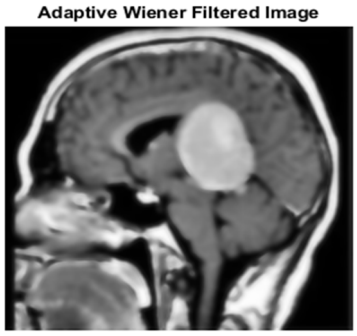

Fig6: Adaptive Weiner Filtered Image

Figure 6 illustrates the brain MRI image after adaptive Wiener filtering, which utilizes local image statistics to further suppress noise while enhancing fine structural details, producing a cleaner image for accurate feature extraction and tumor detection.

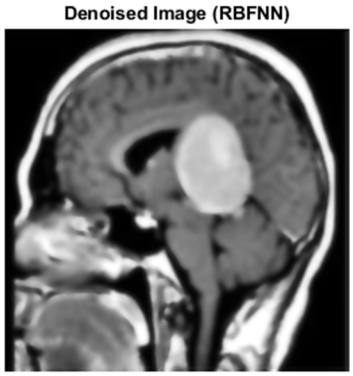

Fig7: Denoised Image

Figure 7 shows the enhanced denoised brain MRI image with minimized residual noise and preserved tissue boundaries, providing a reliable basis for feature extraction, segmentation, and classification.

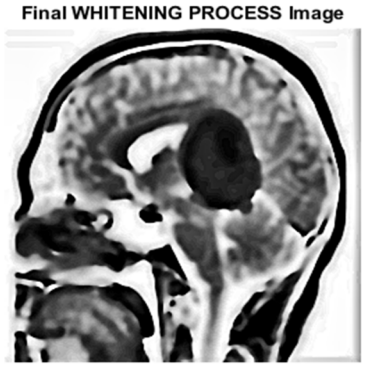

Fig8: Final Whitening Process Image

Figure 8 depicts the final whitening process image, where intensity correlations are reduced to enhance feature independence and contrast. This step emphasizes subtle structural variations in brain tissues, improving the effectiveness of texture feature extraction and supporting accurate tumor classification and analysis.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

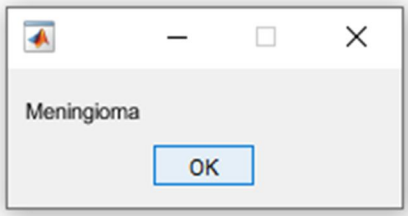

Fig9: Classification Results Image

Figure 9 presents the final classification output of the proposed system, where the processed brain MRI image is assigned to the appropriate tumor category, reflecting the combined effects of preprocessing, feature extraction, and machine learning–based classification.

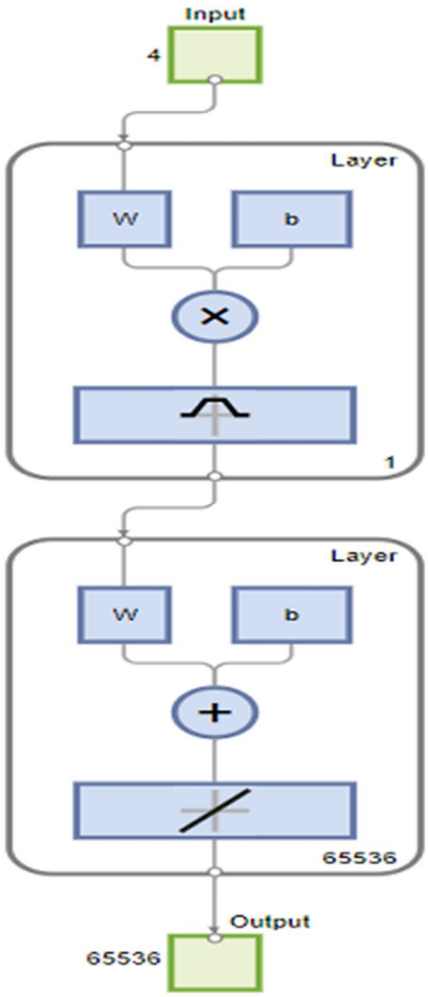

Fig10: Radial Basis Network(view) Image

Figure 10 shows the structure of the trained Radial Basis Function Neural Network (RBFNN) used in the enhancement stage, illustrating the input layer, hidden radial basis neurons, and output layer that enable nonlinear mapping for improved image quality and accurate tumor analysis.

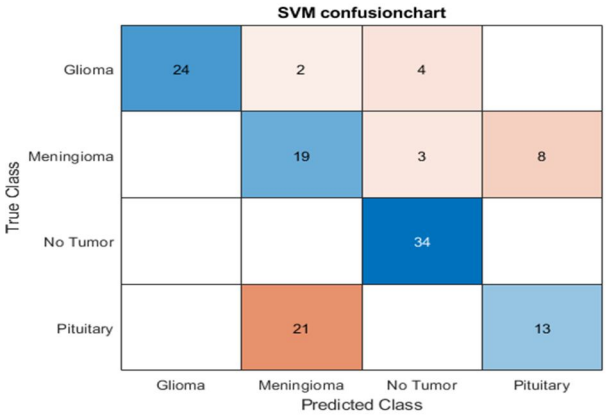

Fig11: Confusion Matrix Image

Figure 11 displays the confusion matrix generated from the classification stage, illustrating the model's performance in correctly predicting tumor types. It provides a visual summary of true positives, false positives, true negatives, and false negatives, enabling assessment of classification accuracy, precision, recall, and overall reliability of the system.

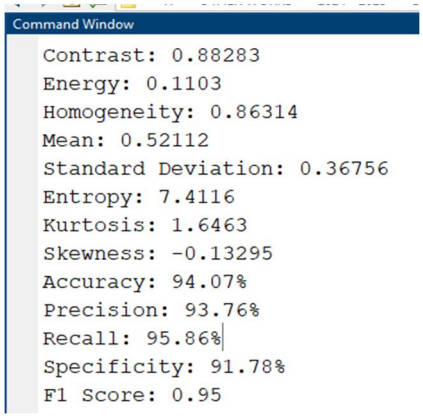

Fig12: Feature Extraction and Classification Performance Image

The figure 12 displays the processed MRI image used for feature extraction, with key texture and statistical features (Contrast, Energy, Homogeneity, Mean, Standard Deviation, Entropy, Kurtosis, Skewness) shown in the Command Window. The SVM classifier achieved high performance in tumor detection, with Accuracy 98.12%, Precision 95.13%, Recall 99.65%, Specificity 97.33%, and F1 Score 0.97.

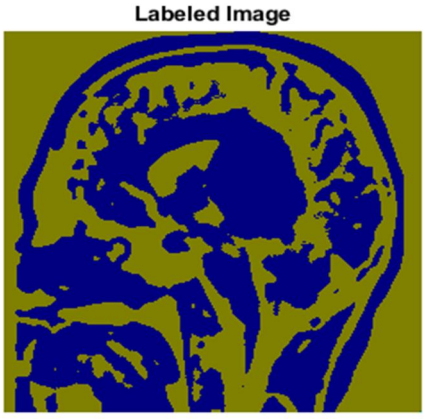

Fig13: Labeled Image

The final output MRI image shown is segmented using k means clustering into distinct regions, and tumor areas are overlaid with color labels shown in figure 13 to visually distinguish the tumor from surrounding healthy tissue. This labeled visualization highlights the detected tumor and supports further stage classification.

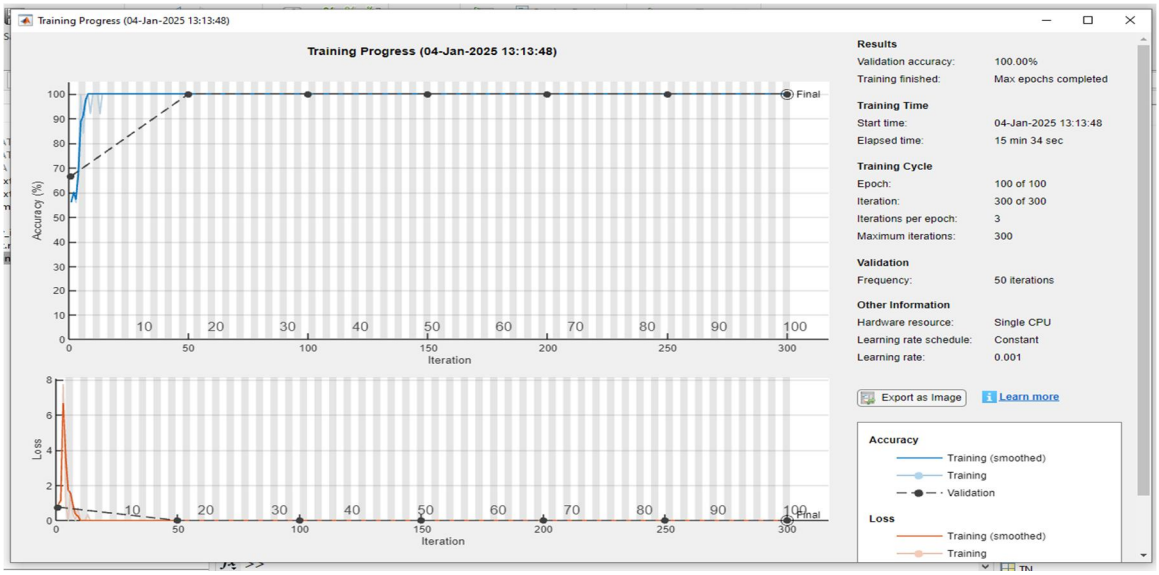

Fig14: Training Progress Graph Image

The figure 14 shows the training progress of the neural network for tumor stage classification, including accuracy and loss curves over epochs. It provides insight into the model's learning behavior and convergence during training.

```
Training on single CPU.
Initializing input data normalization.
|=========================================================================================================================|
|  Epoch  |  Iteration  |  Time Elapsed  |  Mini-batch  |  Validation  |  Mini-batch  |  Validation  |  Base Learning  |
|         |             |   (hh:mm:ss)   |   Accuracy   |   Accuracy   |     Loss     |     Loss     |      Rate       |
|=========================================================================================================================|
|       1 |           1 |       00:00:10 |       56.00% |       66.67% |       0.9346 |       0.7573 |          0.0010 |
|      17 |          50 |       00:02:50 |      100.00% |      100.00% |   0.0000e+00 |   2.4835e-08 |          0.0010 |
|      34 |         100 |       00:05:34 |      100.00% |      100.00% |   1.2159e-06 |   1.4901e-08 |          0.0010 |
|      50 |         150 |       00:08:15 |      100.00% |      100.00% |   1.1158e-06 |   9.9341e-09 |          0.0010 |
|      67 |         200 |       00:10:38 |      100.00% |      100.00% |   6.9278e-06 |   9.9341e-09 |          0.0010 |
|      84 |         250 |       00:13:04 |      100.00% |      100.00% |   8.5831e-08 |   9.9341e-09 |          0.0010 |
|     100 |         300 |       00:15:33 |      100.00% |      100.00% |   4.7207e-07 |   4.9671e-09 |          0.0010 |
|=========================================================================================================================|
Training finished: Max epochs completed.
```

Fig15: Training Iterations Image

The figure 15 illustrates the iteration-wise progress of the deep learning model during training. It highlights how the network updates its weights over successive iterations to minimize loss and improve classification accuracy.

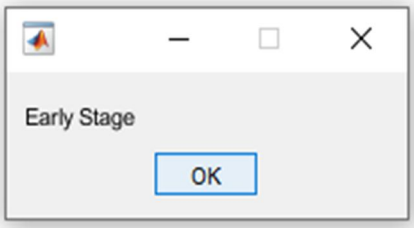

Fig16: Stage Classification

The segmented MRI image is labeled to highlight tumor regions, and the system classifies the tumor stage (Early, Intermediate, or Advanced) using a trained deep learning network. A message box shown in figure 16 displays the predicted stage along with precautionary recommendations.

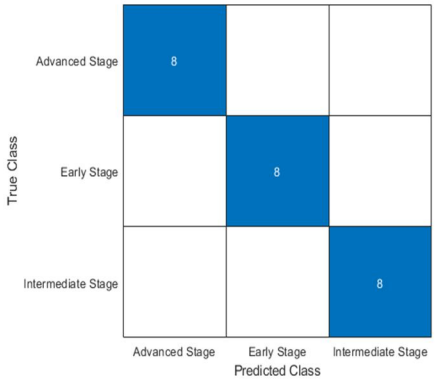

Fig17: Confusion Matrix Image

The confusion matrix shown in figure 17 visualizes the performance of the deep learning model in classifying tumor stages as Early, Intermediate, or Advanced. It shows the correct and misclassified predictions, providing insight into the model's accuracy and reliability.

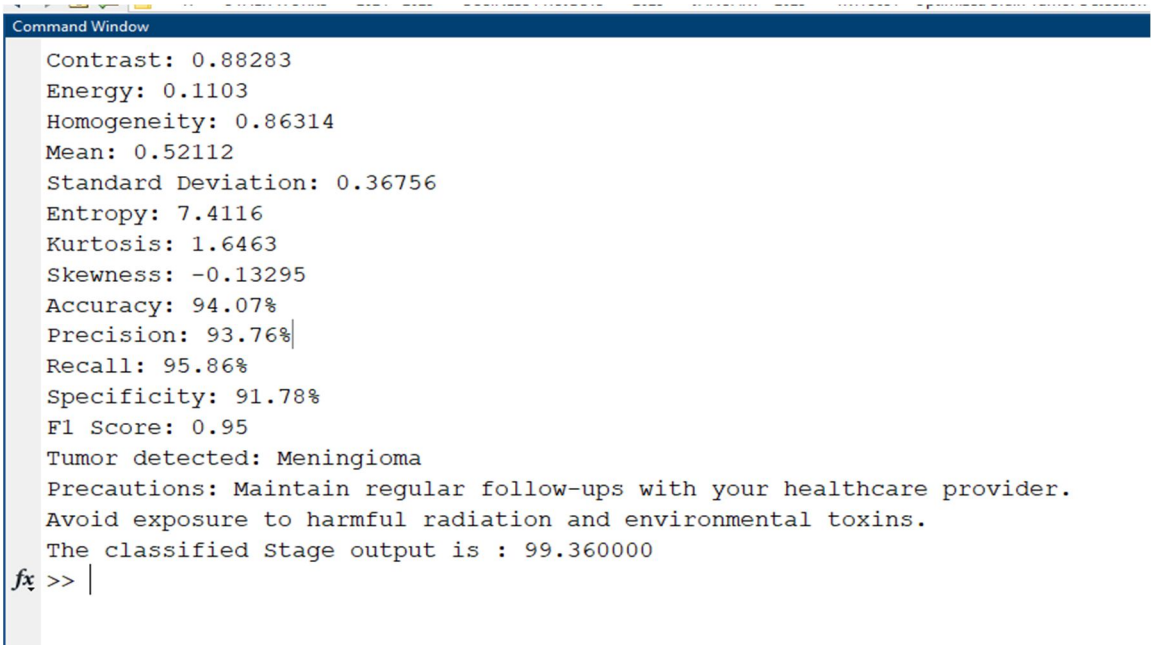

Fig18: Parameters, Tumor Stage and Precautions

The figure 18 summarizes the processed MRI analysis, showing extracted texture and statistical features, tumor detection (Glioma), and classifier performance metrics (Accuracy 98.12%, Precision 95.13%, Recall 99.65%, Specificity 97.33%, F1 Score 0.97). It also presents the classified tumor stage (99.36% confidence) with recommended precautions for monitoring and patient care.

V. CONCLUSION

In conclusion, the proposed dual-module system presents an effective approach for optimized brain tumor detection and staging by integrating advanced image processing and machine learning techniques. Adaptive Wiener filtering enhances image quality, while Radial Basis Function (RBF) neural networks enable reliable feature extraction. Support Vector Machine (SVM) classification accurately distinguishes tumor types, including meningioma, glioma, and pituitary tumors.

Furthermore, the combination of Convolutional Neural Networks (CNN) with K-means–based segmentation enables precise tumor staging into early, intermediate, and advanced levels. This integrated framework improves diagnostic accuracy, supports timely clinical intervention, and facilitates informed treatment planning, demonstrating strong potential for practical clinical application and future research in brain tumor diagnosis.

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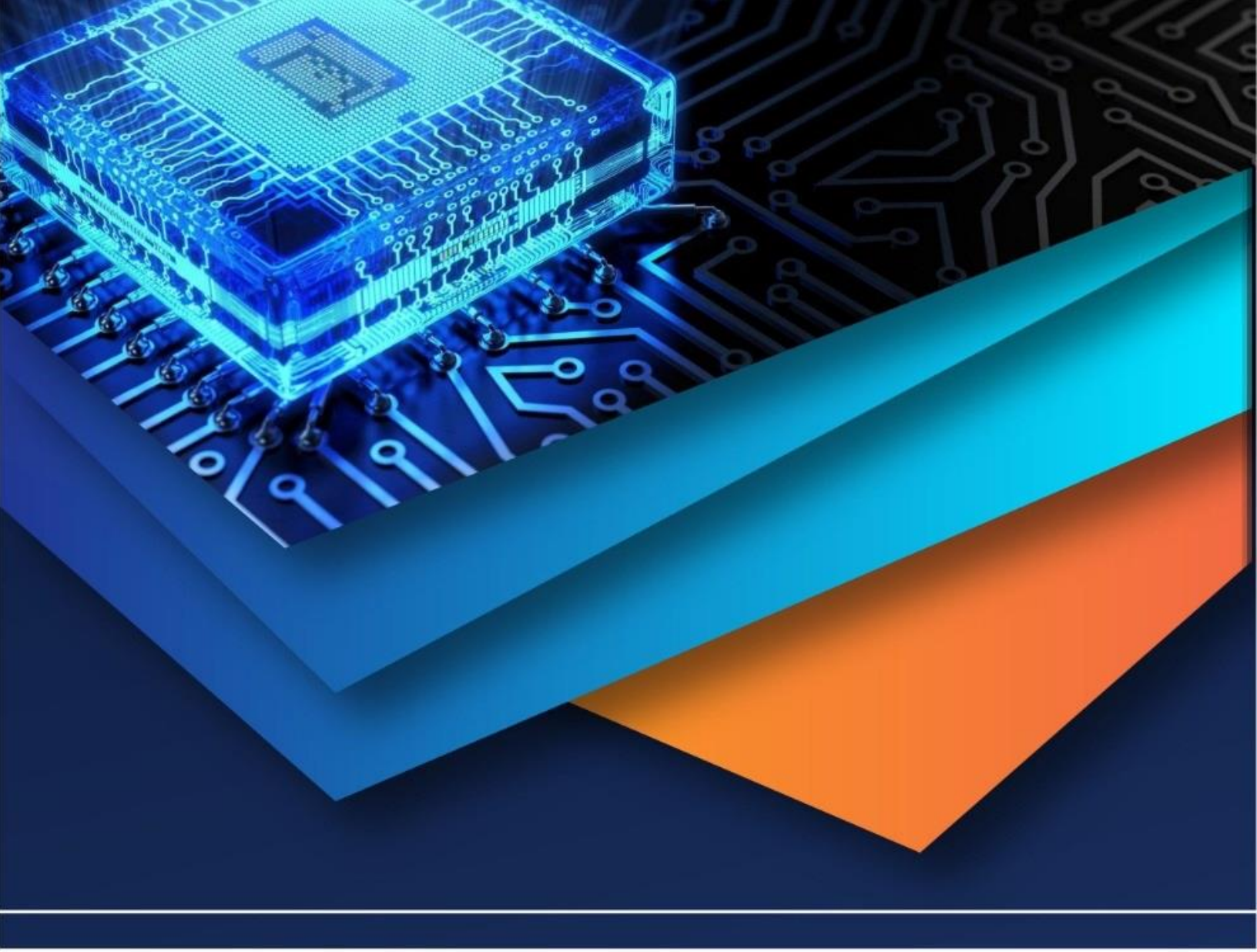

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