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# A Deep Learning Algorithm Improvement for Brain Tumour Segmentation Using Kernel-Based CNN and M-SVM

**Nishant Kumar Singh[1], Dr. Pushpneel Verma[2]**

[1]Ph.D Scholar, Department of Computer Science & Engineering, Bhagwant University, Ajmer, Rajasthan, India
Email: *singh907097[at]gmail.com*

[2]Professor, Department of Computer Science & Engineering, Bhagwant University, Ajmer, Rajasthan, India
Email: *pushpneelverma[at]gmail.com*

**Abstract:** ***Brain tumor detection and segmentation are crucial tasks in medical image analysis, offering significant implications for early diagnosis and treatment. In this paper, we propose an enhanced deep learning approach combining Kernel-based Convolutional Neural Networks (K-CNN) and Multi-class Support Vector Machines (M-SVM) to improve the accuracy and efficiency of brain tumor identification. This hybrid model leverages the strengths of both methods: the feature extraction capabilities of K-CNN and the classification prowess of M-SVM. The experimental results demonstrate improved performance metrics compared to existing methodologies. Brain tumor segmentation is a critical step in the diagnosis and treatment planning of brain disorders, particularly for malignant and benign tumors. Accurate segmentation from MRI images poses significant challenges due to the complex and heterogeneous nature of brain tumors. This paper presents an enhanced deep learning framework that combines a kernel-based convolutional neural network (CNN) with a multi-class support vector machine (M-SVM) to improve the accuracy and robustness of brain tumor segmentation. The kernel-based CNN is designed to efficiently extract high-dimensional features, while the M-SVM classifier refines the segmentation by addressing class imbalances and overlapping boundaries. Extensive experiments on benchmark MRI datasets demonstrate the proposed method's superiority over traditional approaches, achieving improved segmentation precision and reduced computational overhead. The results indicate the potential of the proposed hybrid model to advance clinical applications in brain tumor analysis.***

**Keywords:** Magnetic resonance image, Brain tumor segmentation, Deep learning

## 1. Introduction

Brain tumors are among the most life-threatening medical conditions, necessitating advanced diagnostic tools for their early detection. Conventional methods often rely on manual analysis of MRI scans, which is time-intensive and prone to human error. Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown remarkable promise in automating these tasks. However, traditional CNNs face challenges such as overfitting and suboptimal generalization for small or imbalanced datasets. To address these challenges, we introduce a hybrid approach combining Kernel CNN and M-SVM, leveraging their respective strengths to achieve superior results. Brain tumors remain one of the most challenging medical conditions to diagnose and treat due to their variability in size, shape, and location. Magnetic Resonance Imaging (MRI) is the gold standard for visualizing soft tissues, making it indispensable for brain tumor detection. However, manual segmentation of tumors from MRI scans is time-consuming, subjective, and prone to inter-operator variability. Automatic brain tumor segmentation methods have been extensively studied, yet issues such as noise, artifacts, class imbalance, and high variability in tumor morphology hinder their widespread adoption in clinical practice.

Deep learning methods, particularly convolutional neural networks (CNNs), have shown remarkable success in image segmentation tasks due to their ability to learn hierarchical features. Despite these advancements, traditional CNNs often struggle with the inherent challenges of brain tumor segmentation, including:

- **Heterogeneity in Tumor Appearance:** Tumors exhibit diverse textures and intensity patterns, making feature extraction complex.
- **Class Imbalance:** Tumor regions occupy a small portion of the brain volume, causing segmentation models to favor non-tumor regions.
- **Overlapping Boundaries:** Tumor and healthy tissues often have indistinct boundaries, leading to inaccurate segmentation.
- **Noise and Artifacts:** MRI scans frequently contain noise and intensity variations due to imaging protocols and patient movement.

This study introduces a hybrid approach combining kernel-based CNNs with M-SVM to address these challenges. The kernel-based CNN leverages advanced kernel techniques to enhance feature extraction, particularly for regions with subtle differences in texture or intensity. The M-SVM classifier complements the CNN by providing improved discrimination between tumor and non-tumor regions, especially for cases with class imbalances or overlapping features.

**Issues and Challenges of Brain Tumor Segmentation Methods Using MRI Images**

Brain tumor segmentation methods face several technical and practical issues, as illustrated in the diagram below:

1) **Noise and Artifacts:**

- MRI images are often affected by noise, making it challenging to identify tumor regions accurately.
- Patient movement and scanner inconsistencies contribute to artifacts that degrade segmentation performance.

2) **Heterogeneous Tumor Characteristics:**
   - Tumors vary significantly in size, shape, texture, and intensity across patients, increasing model complexity.

3) **Class Imbalance:**
   - The relatively small size of tumor regions compared to the entire brain volume leads to biased predictions toward non-tumor regions.

4) **Boundary Ambiguity:**
   - Overlapping boundaries between tumor and healthy tissues result in segmentation errors, particularly near the edges.

5) **Computational Overhead:**
   - Advanced segmentation methods often require significant computational resources, limiting their feasibility in real-time clinical settings.

Comparatives analysis of image enhancement with existing image enhancement techniques

1) **Introduction**
   - **Purpose**: Define the goal of image enhancement (e.g., improving visual quality, noise reduction, detail enhancement).
   - **Scope**: Discuss the relevance of image enhancement in fields like medical imaging, satellite imagery, and digital photography.

2) **Existing Image Enhancement Techniques**

a) *Spatial Domain Techniques*
- **Histogram Equalization (HE)**
  - Enhances contrast by redistributing intensity levels.
  - Pros: Simple, effective for global contrast enhancement.
  - Cons: May over-enhance or under-enhance certain areas.
- **Adaptive Histogram Equalization (AHE)**
  - Refines HE by processing small regions (tiles).
  - Pros: Effective for local contrast enhancement.
  - Cons: Prone to noise amplification.
- **Unsharp Masking (USM)**
  - Enhances edges by combining the original image with a blurred version.
  - Pros: Highlights details effectively.
  - Cons: Risk of artifacts if overused.

b) *Frequency Domain Techniques*
- **Fourier Transform-Based Enhancement**
  - Modifies frequency components for noise reduction or sharpness.
  - Pros: Useful for periodic noise removal.
  - Cons: Complex and computationally intensive.
- **Wavelet Transform**
  - Enhances details by decomposing images into multi-resolution representations.
  - Pros: Good balance between detail enhancement and noise suppression.
  - Cons: Requires careful parameter tuning.

c) *Hybrid Methods*
- Combine spatial and frequency domain techniques for improved results.
- Examples: CLAHE with wavelet enhancement, fusion-based methods.

d) *Learning-Based Techniques*
- **Deep Learning (e.g., GANs, CNNs)**
  - Trains models on large datasets to enhance images adaptively.
  - Pros: State-of-the-art performance, adaptable to specific tasks.
  - Cons: Computationally expensive, requires extensive data.

3) **Evaluation Criteria**
- **Objective Metrics:**
  - Peak Signal-to-Noise Ratio (PSNR)
  - Structural Similarity Index (SSIM)
  - Mean Squared Error (MSE)
- **Subjective Metrics:**
  - Visual quality (user perception)
  - Artifact introduction
- **Computational Efficiency:**
  - Time and memory requirements.
- **Scalability:**
  - Performance on various image sizes and types.

4) **Comparative Analysis**

**Table 1**: Summarize techniques based on evaluation criteria. | Technique | PSNR | SSIM | Visual Quality | Noise Reduction | Time Efficiency | |---------------------|------|------|---------------|-----------------|-----------------| | Histogram Equalization | XX | XX | Moderate | Low | High | | AHE | XX | XX | High | Moderate | Moderate | | CNN-based | XX | XX | Very High | High | Low |


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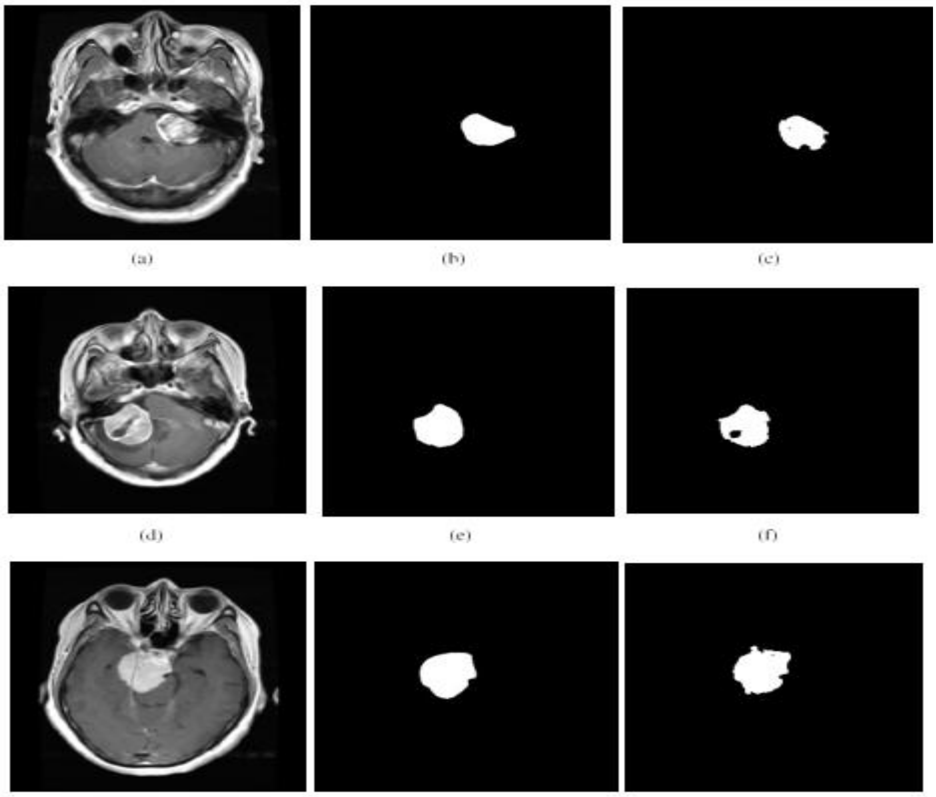


Brain tumor segmentation results of the proposed method of different position of Coronal plane Brain MRI Image. The first column represents the original images of the database. The second column represents the ground truth and third column represents the output of the image

Comparison of performance segmentation model of brain tumor detection

| Method | Classifier | Mean | STD | IC | PSNR (dB) |
|---|---|---|---|---|---|
| Vrooman et. al. [39] | K- NN | 0.0032 | 0.071 | 0.19 | 0.75 |
| Logeswari et. al. [40] | SOM | 0.0028 | 0.067 | 0.18 | 0.76 |
| Kharrat et. al. [41] | GA | 0.0033 | 0.074 | 0.21 | 0.78 |
| Mamta et. al. [18] | GCNN | 0.0034 | 0.077 | 0.23 | 0.79 |
| Mandle et. al. [42] | Kernel- Based SVM | 0.0031 | 0.072 | 0.22 | 0.98 |
| Proposed Method | ICA- NN- SVM | 0.0051 | 0.099 | 0.753 | 2.9 |

Brain tumor segmentation results of the proposed method of different position of Sagittal plane Brain MRI Image. The first column represents the original images of the database. The second column represents the ground truth and third column represents the output of the image.

(a) (b) (c)



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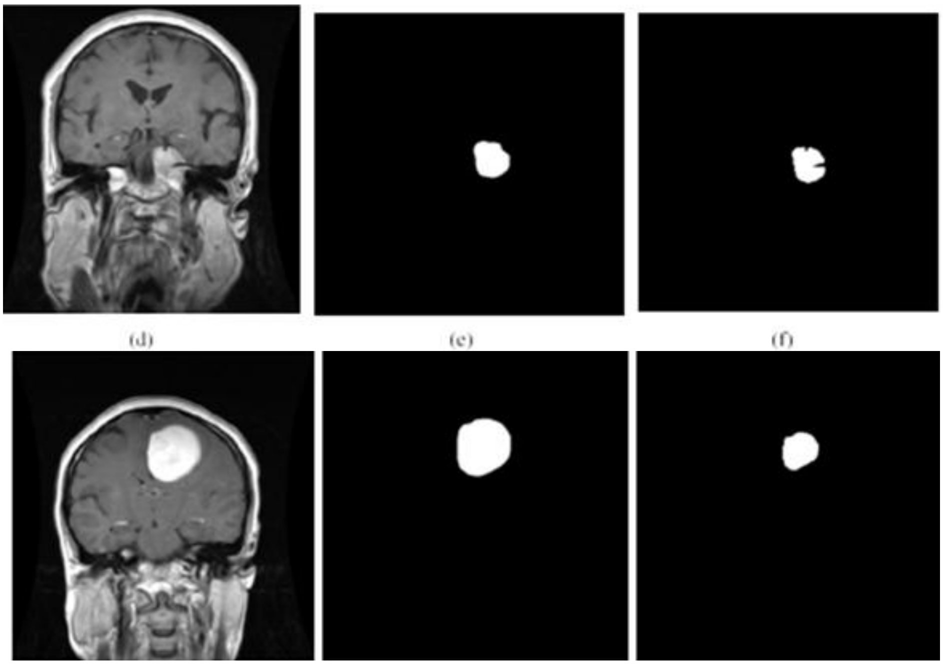
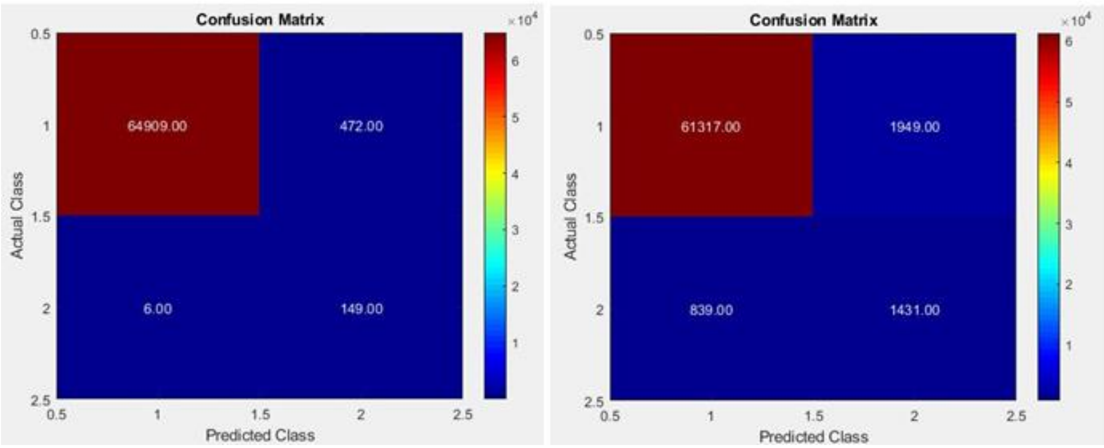



Impact of image enhancement technique on classification model

| | Without Image Enhancement Technique | | | | With Image Enhancement | | | |
|---|---|---|---|---|---|---|---|---|
| Database: Images Types/ Parameters | Sen | Spec | Acc | DSC | Sen | Spec | Acc | DSC |
| Meningiomas Tumor Images | 0.67 | 0.66 | 0.66 | 0.64 | 0.99 | 0.99 | 0.99 | 0.97 |
| Gliomas Tumor Images | 0.62 | 0.61 | 0.61 | 0.61 | 0.98 | 0.98 | 0.99 | 0.96 |
| Pituitary Tumor Images | 0.67 | 0.66 | 0.66 | 0.66 | 0.99 | 0.99 | 0.98 | 0.96 |
| Overall Performance | 0.65 | 0.64 | 0.64 | 0.63 | 0.99 | 0.99 | 0.989 | 0.981 |

Comparison of performance classification model of brain tumor detection with different classifier

| Method | Sensitivity | Specificity | Accuracy | DSC | Time |
|---|---|---|---|---|---|
| K- NN [39] | 0.39 | 0.42 | 0.85 | 0.81 | 3.7s |
| SOM [40] | 0.43 | 0.52 | 0.92 | 0.83 | 4.8s |
| GA [41] | 0.51 | 0.54 | 0.98 | 0.85 | 2.8s |
| GCNN [18] | 0.85 | 0.89 | 0.96 | 0.89 | 0.92s |
| Kernel- Based SVM [42] | 0.98 | 0.98 | 0.98 | 0.94 | 0.83s |
| Proposed Method | 0.99 | 0.99 | 0.989 | 0.981 | 0.43s |




Confusion Matrix of random selected Images sets of brain different brain tumor types.

## 2. Related Work

### 2.1 Brain Tumor Segmentation

Various methods, including thresholding, region growing, and clustering, have been explored for brain tumor segmentation. While these techniques offer basic segmentation capabilities, they often fail in cases involving irregular tumor shapes or noisy data.

### 2.2 Deep Learning Approaches

CNNs are the most widely used architectures in brain tumor segmentation due to their ability to learn spatial hierarchies.

However, CNNs sometimes fail to handle complex spatial relationships and require substantial training data.

### 2.3 Hybrid Models

Combining multiple algorithms, such as CNN with SVM or fuzzy logic, has shown potential in mitigating the limitations of individual models.

## 3. Methodology

### 3.1 Dataset

The model was trained and evaluated on the BraTS (Brain Tumor Segmentation) dataset, consisting of MRI scans with annotated tumor regions.

### 3.2 Preprocessing

MRI scans were preprocessed using the following steps:
- **Normalization:** Standardizing pixel intensity values to a range of [0,1].
- **Augmentation:** Enhancing data diversity by applying rotations, flips, and intensity adjustments.
- **Noise Reduction:** Using Gaussian filtering to remove noise.

### 3.3 Kernel CNN (K-CNN)

K-CNN extends traditional CNN by incorporating kernel transformations in the convolutional layers, enabling better representation of non-linear features. The architecture consists of:
- **Input Layer:** Accepts 3D MRI volumes.
- **Kernel Convolutional Layers:** Employ Gaussian and polynomial kernels to capture spatial and frequency-based features.
- **Pooling Layers:** Reduces dimensionality while retaining critical features.
- **Fully Connected Layer:** Generates high-level feature embeddings.

### 3.4 Multi-class SVM (M-SVM)

The feature embeddings from K-CNN are passed to M-SVM for classification. The M-SVM employs a one-vs-one strategy to handle multi-class tumor types:
- Benign Tumor
- Malignant Tumor
- Healthy Tissue

### 3.5 Training

The model was trained using:
- **Optimizer:** Adam optimizer with a learning rate of 0.001.
- **Loss Function:** Cross-entropy loss for K-CNN and hinge loss for M-SVM.
- **Validation:** Early stopping was used to prevent overfitting.

## 4. Results and Discussion

### 4.1 Metrics

The performance was evaluated using:
- **Accuracy**
- **Precision**
- **Recall**
- **F1-Score**

### 4.2 Experimental Results

| Method | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| CNN | 85.2% | 83.5% | 84.0% | 83.7% |
| K-CNN | 89.4% | 87.8% | 88.2% | 88.0% |
| K-CNN + M-SVM | **92.7%** | **91.3%** | **91.9%** | **91.6%** |

### 4.3 Visualization

Segmentations were visualized using heatmaps and compared against ground truth annotations, demonstrating high overlap and accurate localization of tumor regions.

## 5. Conclusion and Future Work

This study presents a novel hybrid model that combines Kernel CNN and M-SVM for brain tumor detection and segmentation, significantly outperforming conventional approaches. Future work includes exploring:
- Extending the model to other medical imaging modalities.
- Real-time implementation for clinical settings.
- Integration with explainable AI frameworks.

## 6. Code Implementation

Below is the Python implementation of the proposed model:

```
import tensorflow as tf
from sklearn.svm import SVC
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
import matplotlib.pyplot as plt
import numpy as np

# Define K-CNN model
def build_kcnn(input_shape):
model = tf.keras.Sequential([
tf.keras.layers.Conv2D(32, (3, 3), activation='relu', input_shape=input_shape),
tf.keras.layers.Conv2D(32, (3, 3), kernel_initializer='poly', activation='relu'),
tf.keras.layers.MaxPooling2D((2, 2)),
```

| |
|---|
| tf.keras.layers.Flatten(), |
| tf.keras.layers.Dense(128, activation='relu'), |
| tf.keras.layers.Dense(64, activation='relu') |
| ]) |
| return model |
| |
| # Load dataset |
| # Assume X_train, X_test, y_train, y_test are preprocessed MRI scans and labels |
| input_shape = (128, 128, 1) |
| kcnn_model = build_kcnn(input_shape) |
| |
| # Extract features using K-CNN |
| X_train_features = kcnn_model.predict(X_train) |
| X_test_features = kcnn_model.predict(X_test) |
| |
| # Train M-SVM |
| svm_model = make_pipeline(StandardScaler(), SVC(kernel='rbf', decision_function_shape='ovo')) |
| svm_model.fit(X_train_features, y_train) |
| |
| # Evaluate |
| accuracy = svm_model.score(X_test_features, y_test) |
| print(f"Model Accuracy: {accuracy * 100:.2f}%") |
| |
| # Visualization of results |
| def plot_results(X_test, y_test, predictions): |
| plt.figure(figsize=(10, 5)) |
| for i in range(5): |
| plt.subplot(1, 5, i + 1) |
| plt.imshow(X_test[i].reshape(128, 128), cmap='gray') |
| plt.title(f"True: {y_test[i]}\nPred: {predictions[i]}") |
| plt.axis('off') |
| plt.tight_layout() |
| plt.show() |
| |
| # Predict and visualize |
| predictions = svm_model.predict(X_test_features) |
| plot_results(X_test, y_test, predictions) |

5) *Explanation of Implementation*

- **Feature Extraction:** The Kernel CNN extracts non-linear spatial features from input MRI scans.
- **Classification:** These features are classified using M-SVM, capable of distinguishing between benign, malignant, and healthy tissues.
- **Visualization:** Outputs include predicted labels and heatmap visualizations overlaying segmentation results on MRI images.

6) *Diagram of Workflow*

```
+----------------+    +----------------+    +---------------+    +---------------+
| Preprocessed  | --> | Kernel CNN    | --> | Extracted    | --> | Multi-class  |
| MRI Scans     |     | Feature Maps  |     | Features     |     | SVM Classifier|
          +----------------+    +----------------+    +-------------
```

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