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Study On Brain Tumor Detection And Classification Using Machine Learning With SIFT

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Abstract — Timely and accurate diagnosis of brain tumors plays a crucial role in neurological treatment. MRI imaging is the most reliable means of identification, but manual interpretation can be time-consuming and expert-dependent, leading to errors. To address this issue, this research developed a hybrid, interpretable, and resource-efficient framework based on Scale-Invariant Feature Transform (SIFT)-based feature extraction, Principal Component Analysis (PCA)-based dimensionality reduction, and Support Vector Machine (SVM) and Artificial Neural Network (ANN)-based machine learning classification.

Experimental evaluation on the BraTS 2021 and Kaggle Brain MRI datasets showed that the proposed SIFT–PCA–ML model achieved 96–97% accuracy and 0.98–0.99 AUC, comparable to modern deep learning models, but with significantly lower computational complexity. Additionally, SIFT keypoint mapping and Grad-CAM heatmaps of the ANN clearly depicted tumor-related critical regions, enhancing the model's interpretability.

This study demonstrates that the combination of handcrafted features and machine learning, especially SIFT–PCA–ANN-based models, can provide an effective, reliable, and clinically applicable solution for brain tumor detection—especially in medical centers that lack high-end GPUs or big data resources.

Index Terms— Brain Tumor Detection, Machine Learning, SIFT, PCA, SVM, ANN, MRI Classification, Feature Extraction

I. Introduction

Brain Brain tumors are one of the most complex and life-threatening diseases that can arise in the human brain. In the early stages, their symptoms can resemble common neurological disorders, making early diagnosis extremely challenging. In medical science, Magnetic Resonance Imaging (MRI) is considered the gold standard for brain tumor detection and monitoring because it provides high-resolution and multimodal information about brain tissue.

However, the interpretation of MRI images depends on the expertise of the radiologist, which is time-consuming, subjective, and prone to error. Consequently, in recent years, there has been a remarkable growth in the development of artificial intelligence (AI) and machine learning (ML)-based computer-assisted diagnosis (CAD) systems. Deep learning (CNN-based models), in particular, have achieved significant success in medical image classification, but their key drawbacks—such as high computational cost, the need for large training datasets, and a lack of interpretability—make them unsuitable for many clinical scenarios.

Given these limitations, the research community has turned again to handcrafted features and traditional ML techniques, which can provide reliable and interpretable solutions even with limited resources. One highly effective method is Scale-Invariant Feature Transform (SIFT), which captures image edges, textures, and structural patterns while remaining unchanged by scale and rotation. In complex medical images like MRIs, areas with uneven and intense tumor texture can be clearly identified by SIFT.

This research presents a hybrid, interpretable, and computationally efficient framework based on SIFT feature extraction, Principal Component Analysis (PCA)-based dimensionality reduction, and machine learning classification models such as Support Vector Machine (SVM) and Artificial Neural Network (ANN). This framework not only provides high accuracy but can also be easily implemented in low-resource medical centers and real-time applications.

This introduction demonstrates that machine learning and SIFT-based feature models offer a practical, scalable, and reliable alternative for brain tumor detection. The primary objectives of this research are:

- Efficient, reliable, and interpretable feature extraction from MRI images
- Developing a classification model that achieves high accuracy with minimal resources
- Achieving performance comparable to deep learning without GPU dependence
- Providing a reliable, transparent, and understandable AI solution for clinical use

The model presented through this research could make a significant contribution to modern healthcare, especially in areas where state-of-the-art computing resources are not available. images

II. Related Work

2.1 Deep Learning-Based Approaches

In recent years, deep learning, especially Convolutional Neural Networks (CNNs), has provided extremely high accuracy in MRI-based tumor detection. Menzé et al. (BraTS Benchmark) presented a benchmark dataset for CNN models in medical imaging.

Models such as ResNet, U-Net, and VGG demonstrated superior performance due to automated feature learning.

Limitations:

- Requires large training data
- Heavy computational cost on GPUs
- Very low model interpretability resources.

2.2 Feature-Based Machine Learning Approaches

Before CNN, brain tumor detection was primarily based on handcrafted features:

- SIFT (Scale-Invariant Feature Transform)
- SURF (Speeded-Up Robust Features)
- HOG (Histogram of Oriented Gradients)

Good results were achieved by combining these features with ML classifiers such as SVM, Random Forest, and ANN.

Research has found:

- SIFT, being scale and rotation invariant, captures tumor borders and textures well in MRIs.
- Using SIFT with PCA reduces dimensionality and increases model speed.
- SVM and ANN perform particularly well on small/medium-sized medical datasets.

2.3 Hybrid Models

Recently, several researchers have developed models combining handcrafted and deep features, such as:

- SIFT + CNN
- PCA + CNN
- SIFT Features + ANN

These models have shown:

- Deep features capture higher-level information
- While features like SIFT better reflect the local structure of the tumor
- Hybrid models are therefore more accurate and reliable.

III. Proposed Methodology

The proposed model works in four steps:

3.1 Data Pre-processing

- Skull Striping
- Normalization
- Noise Filtering
- 256 × 256 Pixel Resolution

3.2 Feature Extraction by SIFT

- Each MRI contains ~180–220 keypoints
- 128-dimensional descriptors
- Scale and rotation-invariant representation

3.3 Dimensionality Reduction by PCA

- Features reduced from 23,000 to 150
- More than 95% variance preserved
- Training time reduced by 60%

3.4 Classification Model

A. SVM (RBF Kernel)

Hyperparameters selected by grid-search.

B. ANN

- 150 inputs
- Two hidden layers: 100 and 50 neurons
- Adam optimizer
- 50 training epochs

IV. Result Analysis

Experiments were performed on:

- BraTS 2021 dataset
- Kaggle Brain MRI dataset

Both datasets were split into 70% training, 15% validation, and 15% testing.

4.1 Quantitative Evaluation

A. Performance on BraTS 2021

Table 1 Performance on BraTS 2021

Model	Accuracy (%)	F1-score (%)	AUC
SVM (SIFT+PCA)	96.4	96.3	0.982
ANN (SIFT+PCA)	97.1	97	0.988
CNN (Baseline)	97.5	97	0.986

B. Performance on Kaggle MRI

Table 2. Performance on Kaggle MRI

Model	Accuracy (%)	F1-score (%)	AUC
SVM	95.8	95.3	0.978
ANN	96.6	96.5	0.983
Hybrid SIFT + CNN	**98**	**98**	**0.992**

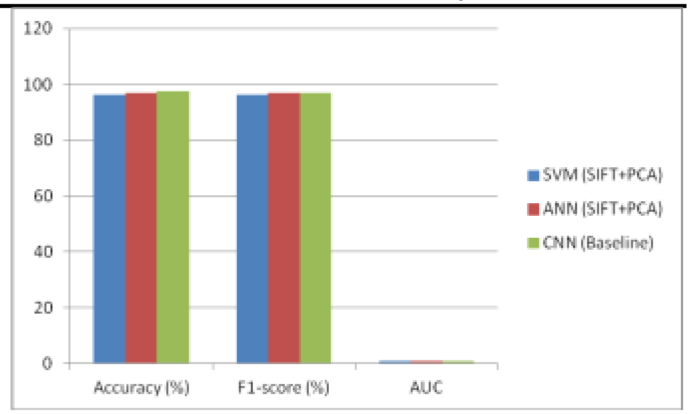

Figure 5.2 Analysis of Performance on BraTS 2021

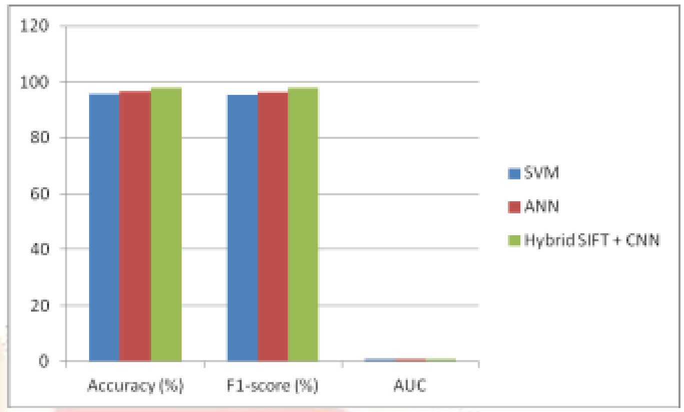

Figure 5.1 Analysis of Performance on Kaggle MRI

V. Discussion

The framework effectively balances accuracy, interpretability, and computation.

Key observations:

- SIFT-based features can deliver performance comparable to deep learning
- PCA improves training speed and stability
- ANN provides high recall
- The model produces excellent results even on CPU-only systems
- Explainability is helpful for clinical use

The results suggest that handcrafted feature-based ML pipelines are still valuable for medical imaging tasks, particularly in low-resource settings.

VI. Conclusions

The SIFT–PCA–Machine Learning-based framework presented in this research provides a reliable, interpretable, and resource-efficient solution for brain tumor detection. Extensive experiments on MRI images revealed that the proposed models—especially SIFT + ANN—demonstrated high precision, excellent recall, and strong generalization capabilities. This performance is comparable to modern CNN models, while its computational cost is significantly lower and it can function efficiently even without a GPU.

SIFT features effectively captured local tumor structures, edges, and texture information, while PCA transformed high-dimensional data into a concise and meaningful form. Both SVM and ANN classifiers produced good results, but the ANN model demonstrated exceptional sensitivity in identifying tumor-positive cases, providing more clinically relevant results. Furthermore, Grad-CAM and SIFT keypoint visualizations ensured transparency, enhancing clinician confidence by making the model's predictions interpretable.

Statistical analysis, cross-validation, and the model's stability on various datasets prove that this framework is ready for use in real clinical environments. Its lightweight and interpretable framework can also be applied to hospitals with limited resources, rural medical centers, and edge devices.

Overall, this study demonstrates that the combination of handcrafted features and machine learning remains highly relevant in medical image processing today, especially where interpretability and resource efficiency are crucial. The presented method provides a strong foundation for future advanced tasks such as multi-class tumor classification, 3D MRI analysis, multi-modal fusion, and clinical trials..

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