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Research Paper

Analysis of the Effect of Principal Component Analysis on Brain Tumor Classification Performance in MRI Images Based on Texture and Deep Features Using Subspace K-Nearest Neighbour

Fitriyani Mus Mulyadi, Pandji Triadyaksa, Qidir Maulana Binu Soesanto

Department of Physics,
Faculty of Science and Mathematics (FSM), Diponegoro University, Semarang, Indonesia.

Corresponding Author: Pandji Triadyaksa

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ABSTRACT

Advancements in deep learning and computer vision have improved the accuracy of MRI-based brain tumor classification. Yet, manual analysis still faces limitations such as subjectivity and long processing times. This study compares classical texture features (LBP, HOG, GLCM), feature combinations, and deep features from MobileNet for brain tumor classification using the Subspace K-Nearest Neighbour method. All MRI images were preprocessed, including grayscale conversion, resizing, CLAHE, and intensity normalization. Classical features were extracted with optimized parameters, while MobileNet was employed as a pre-trained feature extractor without full fine-tuning. Dimensionality reduction was performed using Principal Component Analysis (PCA) to improve computational efficiency. Experimental results show that HOG achieved the highest accuracy among classical features (0.967), while the LBP_HOG combination slightly improved performance (0.969). Deep features from MobileNet achieved the highest accuracy (0.974) with lower computational time compared to end-to-end training. PCA reduced the number of features by 42–46% for high-dimensional features without significant accuracy loss, whereas low-dimensional features were sensitive to reduction. The optimal configuration was identified as the MobileNet_Features + PCA + Subspace KNN pipeline, which maintained high accuracy (0.972) while minimizing computational complexity. These findings highlight the effectiveness of combining deep features, dimensionality reduction, and ensemble KNN in MRI-based brain tumor classification, offering an optimal balance between performance and computational efficiency.

Keywords: Brain tumor classification, MRI, Texture features, Deep features, Principal Component Analysis, Subspace K-Nearest Neighbor

INTRODUCTION

Brain tumors represent one of the most critical neurological disorders, characterized by considerable morbidity and mortality rates. Consequently, accurate and timely diagnosis plays a crucial role in determining appropriate clinical treatment strategies [1]. Magnetic Resonance Imaging (MRI) serves as the primary imaging modality for brain tumor identification and characterization due to its ability to provide detailed visualization of soft tissue structures in a non-invasive manner [2]. Nevertheless, manual interpretation of MRI scans heavily relies on radiologists' expertise, may introduce subjectivity, and often requires substantial analysis time. These limitations have motivated the development of automated computer-based classification systems to enhance diagnostic accuracy and efficiency in clinical decision-making [3].

In medical image classification systems, feature extraction constitutes a fundamental stage, as it directly influences the quality of image representation. Traditional handcrafted feature approaches such as Local Binary Pattern (LBP), Histogram of Oriented Gradients (HOG), and Grey Level Co-occurrence Matrix (GLCM) have been widely utilized to capture texture characteristics and spatial patterns in MRI images [4]. These methods are computationally efficient and effective in modeling local image information. However, the complex morphology of brain tumors and the high variability in MRI intensity patterns often cannot be fully represented by conventional texture-based features.

Advancements in deep learning, particularly through Convolutional Neural Network (CNN) architectures, provide a more adaptive approach for automatic feature representation learning. Lightweight architectures such as MobileNet are capable of producing discriminative features with improved computational efficiency through depthwise separable convolutions. Despite these advantages, deep learning-derived features are typically high-dimensional and may contain redundant information, potentially increasing model complexity and computational time without guaranteeing proportional performance improvement [5].

Several studies have indicated that increasing the number of features does not necessarily result in improved classification accuracy. Therefore, dimensionality reduction techniques such as Principal Component Analysis (PCA) have become essential strategies to preserve the most informative variance components while reducing computational complexity [6]. Furthermore, ensemble-based approaches such as bagging-based Subspace K-Nearest Neighbour (KNN) enhance model generalization by constructing multiple classifiers on different feature subsets, thereby improving robustness when handling high-dimensional feature spaces [7,8].

Although numerous approaches have been proposed, a comprehensive evaluation comparing classical texture features, deep learning features, and their combinations within a multiclass MRI-based brain tumor classification framework remains limited. Additionally, the integrated impact of normalization, dimensionality reduction, and ensemble strategies on both classification performance and computational efficiency has not been systematically analyzed within a unified experimental framework.

Based on these research gaps, this study aims to conduct a comparative analysis of LBP, HOG, GLCM, feature combinations, and MobileNet features for MRI-based brain tumor classification. The study further evaluates the effects of normalization, PCA-based dimensionality reduction, and Subspace KNN on accuracy, confusion matrix performance, and computational time to identify an optimal and efficient classification model.

MATERIALS & METHODS

a. Research Design

This study employs a quantitative experimental approach to evaluate the performance of various feature-extraction and dimensionality-reduction methods for brain tumour image classification. The experiments are designed comparatively, contrasting classical texture features with deep learning features, both with and without PCA-based dimensionality reduction, using separate training and testing schemes

b. Dataset and Data Splitting

The dataset consists of brain MRI images categorized into four classes: glioma, meningioma, pituitary, and no tumor. The data are organized into separate directories for training and testing. A hold-out approach is applied to ensure objective model evaluation, with 80% of the data used for training and 20% for testing. The dataset is sourced from a publicly available Kaggle dataset that can be downloaded for free [9].

c. Image Preprocessing

All images undergo preprocessing to enhance data quality and consistency. The preprocessing steps include conversion to grayscale (for classical texture features), resizing images to 224 × 224 pixels [5], contrast enhancement using Contrast Limited Adaptive Histogram Equalization (CLAHE) with a clip limit of 2.0 and an 8 × 8 grid, and normalization of pixel intensity to the 0–255 range. These steps aim to reduce lighting variations and improve the visibility of texture patterns [10].

d. Feature Extraction

- Classical Texture Features

The LBP, HOG, and GLCM methods follow the basic principles outlined in [11], with parameters such as the number of LBP neighbours, HOG cell size, and GLCM angles/distances adjusted to optimize performance on this dataset. LBP captures local texture patterns with parameters P = 8 and R = 1 using the uniform method; the resulting histogram is normalized to form a feature vector. HOG encodes gradient and object shape information, with a pixel resolution of 16 × 16 and a cell resolution of 1 × 1. GLCM extracts statistical texture features by computing co-occurrence matrices at four orientations (0°, 45°, 90°, 135°) with a pixel distance of 1; features extracted include contrast, correlation, energy, and homogeneity, which are then averaged. In addition to individual features, feature fusion is performed by combining LBP + HOG, LBP + GLCM, and HOG + GLCM, as employed in previous studies [4,6].

- Deep Learning Features

The deep learning feature extraction approach follows principles from prior studies, but instead of using ResNet or EfficientNet, this study employs MobileNet as the feature extractor. MobileNet was chosen based on several studies demonstrating superior performance in brain tumor detection, particularly in computational efficiency and the ability to capture key features in medium-sized datasets [5,12,13]. A pretrained MobileNet model (ImageNet) is used with the classification layers removed (include_top = False), and global average pooling is applied to produce fixed-length feature vectors. Each image is converted to RGB and preprocessed using the preprocess_input function before feature extraction.

e. Normalization and Dimensionality Reduction

Before classification, all features are normalized using StandardScaler to ensure a zero mean and unit variance. Optional dimensionality reduction is performed using Principal Component Analysis (PCA), retaining 95% of the cumulative variance. The number of principal components is automatically determined based on this variance threshold. Evaluations are conducted under two scenarios: feature extraction without PCA and with PCA. The application of PCA in this study follows the approach used in previous research [6].

f. Classification Using Subspace KNN

The classification method employed is an ensemble-based Subspace K-Nearest Neighbour (KNN). This approach is implemented using a BaggingClassifier with KNN as the base learner (k = 1). Key characteristics of the method include: 30 estimators, random selection of feature subsets (random subspace), no bootstrap sampling, and Euclidean distance as the metric. The method aims to improve model stability for high-dimensional features and reduce overfitting. The working principle of this approach has been described in several studies [7,14–16]

g. Performance Evaluation.

The model's performance is assessed on the test dataset using the following metrics: accuracy, confusion matrix, training time, and testing time. Accuracy is calculated as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

where TP denotes true positives, TN true negatives, FP false positives, and FN false negatives

h. Experimental Implementation

All experiments are implemented in Python using key libraries including OpenCV, scikit-image, scikit-learn, TensorFlow/Keras, NumPy, Pandas, and Matplotlib. Computations are performed on a system with an Intel Core i9 processor, 64GB RAM, and an NVIDIA RTX 5060 GPU to ensure consistent measurement of training and testing times. Evaluation results for each feature combination and PCA scenario are recorded in Excel for further analysis.

RESULT

Table 1. Comparison of Classification Performance for Various Feature Extraction Methods

Feature Type	Feature Type	Accuracy	TrainTime (s)	TestTime (s)
Single	LBP	0.893	0.084	0.085
	HOG	**0.967**	1.913	4.191
	GLCM	0.374	0.057	0.026
Combination	LBP+HOG	**0.969**	1.915	2.894
	LBP+GLCM	0.919	0.142	0.102
	HOG+GLCM	0.968	1.943	2.876
Deep Learning	MobileNet_Features	0.974	1.321	3.477
	Full_MobileNet	0.935	510.972	5.185

Table 1 presents the comparison of classification performance across single handcrafted features, feature combinations, and deep learning approaches in terms of accuracy, training time, and testing time. Among single features, HOG achieved high accuracy (0.967), outperforming LBP (0.893) and GLCM (0.374), although it required longer computational time due to higher feature dimensionality. Feature combinations slightly improved performance, with LBP+HOG achieving 0.969 accuracy and HOG+GLCM reaching 0.968, indicating that combining gradient and texture information enhances discriminative capability. MobileNet feature extraction produced the highest overall accuracy (0.974) with moderate training and testing time, whereas the full end-to-end MobileNet model achieved lower accuracy (0.935) and required substantially longer training time (510.972 seconds), demonstrating lower computational efficiency.

Table 2. Comparison of Classification Performance for Various Feature Extraction Methods Using Principal Component Analysis

Feature Extraction	Accuracy	Training Time (s)	Testing Time (s)	Num Features Before PCA	Num Features After PCA	Reduction (%)
LBP	0.605	0.040	0.022	9	3	66.7%
HOG	0.968	1.547	2.558	1764	960	45.6%
GLCM	0.374	0.032	0.019	1	1	0.0%
LBP_HOG	0.968	1.388	2.616	1773	959	45.9%
LBP_GLCM	0.618	0.043	0.024	10	3	70.0%
HOG_GLCM	0.968	1.547	2.612	1765	960	45.6%
MobileNet_Features	0.972	0.477	2.571	1024	590	42.4%

Table 2 summarizes the impact of applying Principal Component Analysis (PCA) on feature dimensionality and classification performance. High-dimensional features such as HOG, LBP_HOG, HOG_GLCM, and MobileNet_Features experienced significant dimensional reduction of approximately 42–46% while maintaining nearly identical accuracy. For instance, MobileNet features were reduced from 1024 to 590 dimensions with only a slight decrease in accuracy (0.974 to 0.972) and a notable reduction in training time. In contrast, aggressive reduction on low-dimensional features such as LBP and LBP_GLCM led to substantial accuracy decreases (0.605 and 0.618, respectively), indicating information loss. GLCM remained unchanged due to its single-feature representation and continued to show low classification performance. Overall, PCA effectively reduced redundancy in high-dimensional features without significantly affecting accuracy.

DISCUSSION

This study aims to analyze the impact of using single versus combined features on brain tumour classification performance in MRI images, using the Subspace K-Nearest Neighbour (Subspace KNN) method. Evaluation was conducted on three classical texture feature extraction methods: LBP, HOG, and GLCM, as well as one deep feature approach based on MobileNet. Observed parameters include accuracy, training time, testing time, and total computational time (training + testing).

Based on Table 1, single-feature methods exhibit substantial performance variation. Among them, HOG achieved the highest accuracy of 0.967, surpassing LBP (0.893) and, in particular, GLCM, which reached only 0.374. This indicates that gradient-based representations in HOG are more effective at capturing texture and edge patterns in MRI images than statistical texture features such as GLCM. However, the higher accuracy of HOG comes at a higher computational cost, especially during testing.

In the feature combination category, performance generally improved compared to most single features. The LBP + HOG combination achieved the highest accuracy at 0.969, followed by HOG + GLCM (0.968) and LBP + GLCM (0.919). These results suggest that feature fusion enriches image representation by combining local texture and edge information. Nevertheless, the accuracy gain is relatively modest compared to single HOG, making HOG still competitive in terms of computational efficiency.

The deep feature approach using MobileNet Features demonstrated the best overall performance, achieving an accuracy of 0.974. This suggests that high-level feature representations learned through transfer learning are better at capturing complex patterns in brain tumour MRI images than manually engineered features. Moreover, the training time for MobileNet Features (1.321 s) remains far more efficient than full network training (Full MobileNet), which required 510.972 s. This highlights the advantage of deep feature extraction without full fine-tuning in terms of computational efficiency.

This efficiency is largely attributed to the use of depthwise separable convolutions, which reduce computational complexity and memory requirements. The compact architecture helps minimize overfitting while effectively extracting essential features, particularly for a moderately sized dataset (~4,500 images). Therefore, MobileNet is considered the most suitable for MRI-based brain tumor detection, especially in resource-constrained environments [5].

In contrast, Full MobileNet achieved lower accuracy (0.935) with substantially higher computational cost. This outcome likely results from the limited dataset size, making end-to-end training less generalizable and prone to overfitting. Consequently, in scenarios with limited data, deep feature extraction combined with a classical classifier, such as Subspace KNN, proves more effective.

Overall, the findings indicate that feature representation complexity significantly affects classification performance. Deep learning-based features achieve the highest accuracy, followed by combined classical features, and then single features. However, there is a trade-off between accuracy and computational efficiency. Therefore, the choice of the optimal method should consider application requirements, particularly the balance between diagnostic accuracy and system computational load.

The analysis presented in Table 2 evaluates the impact of applying Principal Component Analysis (PCA) on the performance of Subspace K-Nearest Neighbour for brain tumour classification across different feature extraction schemes. Performance was assessed in terms of accuracy, computational time, and the degree of dimensionality reduction before and after PCA.

In general, PCA successfully reduced the number of features for most methods. The greatest reductions were observed in LBP + GLCM (70.0%) and LBP (66.7%), while moderate reductions occurred in HOG, HOG + GLCM, LBP + HOG, and MobileNet Features (approximately 42–46%). No reduction occurred for GLCM, as it initially contained only one feature. These results indicate that PCA's effectiveness depends strongly on the initial feature dimensionality and the relative importance of the information encoded by each feature.

Regarding accuracy, the impact of PCA varies across methods. For low-dimensional features such as LBP, accuracy dropped sharply to 0.605 compared to the non-PCA scenario, suggesting that overly aggressive dimensionality reduction can remove important discriminative information. A similar pattern is observed for LBP + GLCM, which achieved an accuracy of only 0.618. This indicates that low-dimensional features are more sensitive to PCA reduction.

Conversely, for high-dimensional features such as HOG, LBP + HOG, and HOG + GLCM, PCA did not significantly reduce performance. These methods maintained high accuracy (0.968) despite a ~45% reduction in dimensionality. This demonstrates that PCA effectively eliminates redundancy in high-dimensional features without compromising discriminative power, while slightly improving training and testing times, indicating enhanced computational efficiency.

The deep feature approach using MobileNet Features continued to achieve the highest performance, with an accuracy of 0.972 after PCA. Reducing the feature set from 1024 to 590 (42.4%) did not result in a meaningful drop in accuracy. This reinforces that deep learning features provide a more robust representation against dimensionality reduction, as critical information is compactly encoded during feature extraction.

Interestingly, PCA offered no advantage for GLCM, either in terms of dimensionality reduction or accuracy, which is expected given the very limited initial feature count. This finding confirms that PCA is most relevant for medium- to high-dimensional features.

Overall, the results indicate that PCA effectively improves computational efficiency without significantly affecting accuracy for high-dimensional features, particularly HOG-based and deep features. However, for low-dimensional features such as LBP and GLCM, PCA may reduce classification performance. Therefore, PCA should be applied with consideration of the initial feature dimensionality to achieve an optimal balance between dimensionality reduction and classification accuracy.

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CONCLUSION

This study demonstrates that feature type strongly influences the performance of brain tumor classification in MRI images. Among classical features, HOG achieved the best results, while feature combinations provided only modest improvements in accuracy. Deep features extracted using MobileNet yielded the highest overall performance, highlighting the advantage of high-level representations obtained through transfer learning.

The application of PCA effectively reduced feature dimensionality and computational time without compromising accuracy for high-dimensional features, but it was less suitable for low-dimensional features. Considering both accuracy and efficiency, the configuration combining MobileNet Features with PCA and Subspace KNN proved to be the most optimal pipeline, maintaining high classification accuracy while minimizing computational complexity.

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