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ORB-SVM: An Innovative Hybrid Framework for Efficient Brain Tumor Detection from MRI Scans

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Abstract

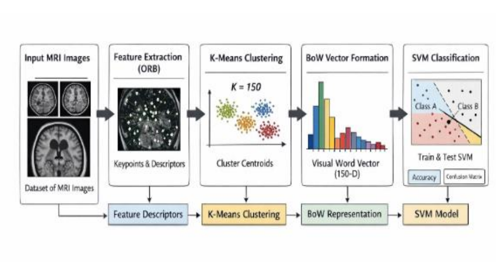
Brain cancer diagnosis remains challenging due to the complexity of MRI scans and the limitations of traditional methods. This paper introduces ORB-SVM, a hybrid framework combining ORB feature extraction with a Support Vector Machine classifier for efficient brain tumor detection. ORB identifies distinctive keypoints in MRI images, compressing data by approximately 99.5% while preserving critical structural information. These features are encoded into compact vectors using a Bag of Words model and classified by an SVM with an RBF kernel. Tested on 3000 MRI scans (Br35H dataset), the proposed method achieves 97.5% classification accuracy. This approach offers significant computational efficiency compared to deep learning models, presenting a viable tool for clinical decision support without requiring high-end infrastructure.

The purpose of the research

The primary objective of this research is to develop a lightweight yet highly accurate computer-aided diagnosis system for brain tumor detection from MRI scans. The aim is to overcome the limitations of traditional diagnostic methods and computationally intensive deep learning models. By leveraging ORB's capability for rapid and distinctive feature extraction, and SVM's strength in handling non-linear separations, the goal is to create a tool that assists clinicians by providing fast, reliable, and objective second opinions. This approach seeks to reduce diagnostic ambiguity, minimize computational costs, and pave the way for integration into clinical environments where resources and time are often constrained.

Research method

The methodology follows a four-stage pipeline. First, the ORB algorithm detects feature points in MRI scans using the FAST method, enhanced with a Gaussian image pyramid for scale invariance and a gray centroid method for rotation invariance. Second, ORB computes descriptors for these points using a steered BRIEF algorithm, creating binary feature vectors. Third, to manage dimensionality, a Bag of Words (BoW) model with K-Means clustering (k=150) groups similar descriptors into a visual vocabulary. Each MRI scan is then represented as a frequency histogram of these visual words, reducing data size by 99.5%. Finally, these compact 150-dimensional vectors are normalized and fed into a Support Vector Machine (SVM) classifier with a Radial Basis Function (RBF) kernel to distinguish between healthy and cancerous scans.



Practical or simulation results

The ORB-SVM model was evaluated on a dataset of 3000 MRI scans (Br35H), with a 70/10/20 split for training, validation, and testing. The framework achieved outstanding performance metrics: an overall accuracy of 97.5%, precision of 97%, and recall of 98%. The confusion matrix shows 291 True Negatives and 294 True Positives, with only 6 False Positives and 9 False Negatives. Crucially, the ORB feature extraction and BoW encoding compressed the input data by 99.5%, drastically reducing computational load and processing time compared to conventional CNNs, while maintaining superior sensitivity to subtle malignant patterns.

EVALUATION METRICS

Metric	Formula	Calculation	Value
Accuracy	$\frac{TP+TN}{\text{Total}}$	$\frac{291+294}{600}$	97.50%
Precision	$\frac{TP}{TP+FP}$	$\frac{291}{300}$	97.00%
Recall (Sensitivity)	$\frac{TP}{TP+FN}$	$\frac{291}{297}$	$\approx$ 98%

Model	Architecture	Parameters	Accuracy
Proposed ORB-SVM	ORB + BoW + SVM	**12,349**	**97.50%**
Custom CNN	3× Conv2D + 2× Dense	3,284,159	~97.16%
Xception	Depthwise Separable Conv	20,863,529	~98.0%
DenseNet169	Dense Connections	12,642,880	~96.0%
InceptionResNetV2	Inception + Residual	54,338,273	~66.0%
ResUNet	Encoder-Decoder + Attention	31,575,649	~93.8%

conclusion

The proposed ORB-SVM framework successfully balances high diagnostic accuracy with computational efficiency. By reducing data dimensions by 99.5%, the model achieves 97.5% accuracy without the need for high-end infrastructure, making it suitable for real-world clinical settings. While results are promising, future work should focus on expanding the dataset to include more tumor types and stages, and exploring hybrid models that combine ORB-SVM with deep learning architectures to potentially capture even more nuanced features.

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