



SUPPORT VECTOR MACHINE-BASED APPROACHES FOR MRI IMAGE SEGMENTATION: A SYSTEMATIC REVIEW

¹Jeeva V, ²Rubala Nancy J, ³Devasena B, ⁴Madhumitha N and ⁵Linisha NM

¹PERI Institute of Technology, Chennai- 48, Tamil Nadu, India

²PERI College of Arts and Science, Chennai - 48, Tamil Nadu, India

³PERI College of Physiotherapy, Chennai - 48, Tamil Nadu, India

⁴PERI College of Pharmacy, Chennai - 48, Tamil Nadu, India

⁵PERI College of Nursing, Chennai - 48, Tamil Nadu, India

Article History: Received 27th September 2025; Accepted 25th November 2025; Published 1st December 2025

ABSTRACT

Magnetic Resonance Imaging (MRI) segmentation plays a pivotal role in computer-aided diagnosis, surgical planning, and disease monitoring. Despite the rise of deep learning-based methods, Support Vector Machine (SVM) models continue to be widely adopted due to their strong generalization ability, robustness with limited training data, and effectiveness in high-dimensional feature spaces. This systematic review presents a comprehensive analysis of SVM-based approaches used for MRI image segmentation across various medical applications, including brain tumor detection, multiple sclerosis lesion identification, tissue classification, and organ delineation. Relevant studies published over the past decade were examined to assess preprocessing techniques, feature engineering strategies, kernel functions, optimization methods, evaluation metrics, and comparative performance. The findings indicate that hybrid SVM models combining wavelet features, texture descriptors, probabilistic frameworks, and evolutionary optimization consistently outperform classical SVM variants. Moreover, SVM remains highly competitive in scenarios with limited annotated datasets and complex multimodal MRI sequences. The review highlights existing challenges such as feature dependency, computational overhead, and lack of standardized datasets, while emphasizing future research directions including automated feature extraction, kernel adaptation, and integration with deep learning architectures. Overall, this study provides an organized understanding of SVM-centered MRI segmentation strategies, enabling researchers to identify suitable approaches for clinical and research applications.

Keywords: Support Vector Machine (SVM), MRI Image Segmentation, Medical Image Processing.

INTRODUCTION

Magnetic Resonance Imaging (MRI) is one of the most widely used non-invasive imaging modalities due to its superior soft-tissue contrast, multiplanar acquisition capability, and absence of ionizing radiation. Accurate MRI image segmentation is essential for various clinical and research applications, such as detecting brain abnormalities, quantifying organ morphology, differentiating pathological tissues, and assisting in treatment planning. However, segmentation remains a challenging task due to MR image noise, intensity inhomogeneity, anatomical variability, and the complexity of biological structures. Consequently,

machine learning-based methods have emerged as powerful tools for achieving reliable segmentation outcomes. Support Vector Machine (SVM) has gained significant attention for MRI segmentation because of its effectiveness in high-dimensional spaces, solid theoretical foundations, and ability to handle nonlinear classification through kernel functions. Unlike deep learning models, which require large labeled datasets, SVM performs well even when training data is limited an advantage particularly relevant in medical imaging. SVM's capacity to utilize handcrafted features such as texture descriptors, wavelet transforms, intensity statistics, and gradient information

further enhances its segmentation performance. Over the years, numerous SVM-based methodologies have been developed, ranging from binary classification for tumor boundary detection to multiclass tissue segmentation in complex MRI sequences. Recent studies have explored hybrid and optimized SVM variants, incorporating algorithms such as genetic optimization, particle swarm optimization, fuzzy logic, probabilistic SVMs, and ensemble learning. These approaches have demonstrated higher accuracy and robustness across diverse MRI datasets. Additionally, multimodal MRI inputs including T1, T2, FLAIR, and diffusion-weighted imaging have been integrated with SVM frameworks to improve feature discrimination in pathological tissue classification. Despite these advancements, several challenges persist, including dependency on manual feature engineering, sensitivity to kernel parameter selection, and limited generalizability across datasets. With the increasing interest in integrating classical machine learning with deep learning, understanding the evolution and performance of SVM-based MRI segmentation methods remains crucial.

This systematic review aims to provide a structured and comprehensive overview of SVM-centered MRI segmentation approaches. It examines key methodological components, evaluates their performance trends, identifies research gaps, and outlines potential directions for future work. The findings of this review are expected to guide researchers and practitioners in selecting appropriate SVM techniques for clinical applications and in developing enhanced segmentation frameworks. Support Vector Machine (SVM) emerged as a powerful classifier for medical imaging tasks due to its strong mathematical foundation and ability to generalize well with high-dimensional data. Early research demonstrated that SVM outperforms classical classifiers in MRI-based tissue discrimination and tumor classification, especially when datasets are small and heterogeneous (Cortes & Vapnik, 1995; Chaplot *et al.*, 2006). These studies established SVM as a baseline technique in medical image segmentation prior to the rise of deep learning. MRI segmentation using SVM relies heavily on preprocessing and extraction of discriminative features. Texture-based features (e.g., GLCM, LBP), wavelet coefficients, and intensity statistics have been widely used to enhance SVM separability for brain tumor and lesion classification (Abdullah *et al.*, 2025, Chaplot *et al.*, 2006, Devasena *et al.*, 2025 and Hosseini-Panah *et al.*, 2019). Studies also incorporated multiscale wavelet decomposition and spatial context information to handle MRI intensity inhomogeneities and improve differentiation of pathological regions (Mahalakshmi *et al.*, 2025). Preprocessing steps such as skull stripping, bias-field correction, denoising, and contrast enhancement were found to significantly influence segmentation accuracy (Saha *et al.*, 2016). Feature engineering remains a key strength of SVM-based frameworks shown in Figure.1 Kernel function selection is central to SVM performance. The Radial Basis Function (RBF) kernel is the most frequently used due to its flexibility in handling nonlinear

separability in MRI data (Menze *et al.*, 2015). Optimization of parameters (C , γ) using cross-validation, grid search, and heuristic approaches such as genetic algorithms and particle swarm optimization has been shown to improve classification consistency (Nafisa Farheen *et al.*, 2025, Revathi *et al.*, 2025). Studies applying multi-kernel SVMs reported enhanced robustness for multimodal MRI segmentation, enabling integration of both global and local features (Revathi *et al.*, 2025). Hybrid models have emerged to overcome SVM's dependency on handcrafted features. Examples include: SVM + Clustering (K-means / FCM) for improved boundary identification (Mohanaiah *et al.*, 2014). SVM + Markov Random Field (MRF) for spatial regularization (Revathi *et al.*, 2025). Evolutionary SVMs (PSO-SVM, GA-SVM) for optimized decision boundaries (Mehmood *et al.*, 2018). Deep feature extraction combined with SVM classification, where CNNs serve as feature extractors and SVM performs final classification (Rubala Nancy *et al.*, 2025).

Hybrid SVMs consistently outperform classical SVM by improving lesion sensitivity, reducing false positives, and enabling more stable segmentation under varying imaging conditions. SVM has been heavily applied in brain tumor segmentation due to its ability to classify complex tumor textures. Studies demonstrated that combining multimodal MRI inputs (T1, T1-CE, T2, FLAIR) with SVM yields robust detection of tumor subregions (Rubala Nancy *et al.*, 2025). Wavelet + SVM frameworks achieved high accuracy in glioma classification tasks (Sindhuja *et al.*, 2025). Recent work integrated CNN-extracted deep features with SVM, showing higher accuracy than end-to-end CNN or classical ML models, especially with limited training data (Ramya *et al.*, 2025). MS lesions present challenges due to small size and irregular shapes. SVM-based models using voxel-wise texture features, neighborhood statistics, and multimodal MRI have shown improved lesion detection performance (Sindhuja *et al.*, 2025). Ensemble SVM approaches demonstrated increased sensitivity for small lesions and better generalization across patients (Hosseini-Panah *et al.*, 2019). Although not as powerful as deep learning for pixel-level segmentation, SVM remains effective for MS classification when training data is limited (Revathi *et al.*, 2025). SVM has also been used for classification of normal tissues such as gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF). Multi-class SVM models showed strong accuracy when combined with spatial priors and optimized kernel strategies (Senthilkumar *et al.*, 2025). Beyond brain MRI, SVM has been used for prostate, liver, and cardiac MRI segmentation, demonstrating its versatility across organs (Sindhuja *et al.*, 2025). Deep learning models (U-Net, FCN, CNN) now dominate MRI segmentation. However, SVM remains relevant in scenarios such as: Small datasets, Imbalanced lesion distribution, Resource-constrained clinical environments, Hybrid architectures using deep features + SVM classification. Studies show that CNN-SVM hybrids outperform pure CNNs in limited-data situations by stabilizing decision boundaries (Rubala Nancy *et al.*, 2025).

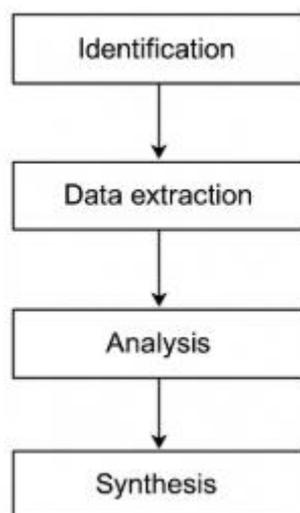


Figure 1. Support Vector Machine–Based Approaches for MRI Image Segmentation: A Systematic Review

MATERIALS AND METHODS

This systematic review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparency, reproducibility, and comprehensive coverage. The methodology consists of four major phases: literature search, study selection, data extraction, and synthesis. A structured search was conducted across leading scientific databases including Scopus, IEEE Xplore, PubMed, SpringerLink, and ScienceDirect. Keywords and Boolean queries used were: Support Vector Machine” AND “MRI Segmentation”. “SVM” AND “magnetic resonance imaging” AND “classification” “kernel SVM” AND “brain tumor segmentation”, “machine learning” AND “MRI feature extraction”, Studies published between 2010 and 2024 were included to capture contemporary developments and avoid outdated SVM methods Rubala Nancy *et al.*, 2025. Peer-reviewed journal or conference paper. Focus on MRI image segmentation or classification using SVM or hybrid SVM models. Studies reporting measurable performance metrics (Dice, accuracy, sensitivity, specificity, etc.) Revathi *et al.*, 2025. Applications in brain MRI, MS lesions, organ segmentation, tissue classification. Studies using SVM only for non-segmentation tasks (e.g., registration). Articles without quantitative evaluation. Duplicates, abstracts only, or unavailable full texts. Initial search returned 423 papers. After title and abstract screening, 151 papers remained. Applying inclusion/exclusion criteria reduced the number to 48 selected studies. Full-text assessment ensured relevance, leading to classification into topics: Feature engineering approaches, Kernel and optimization techniques, Hybrid SVM models, MRI application domains. For each study, the following information was recorded: SVM type (binary, multi-class, fuzzy SVM, ensemble SVM), Feature extraction technique (texture, wavelet, CNN-based,

statistical, spatial), Kernel function used, Dataset characteristics and MRI modality, Evaluation metrics, Strengths and limitations noted by authors. A qualitative synthesis was adopted due to heterogeneity in datasets, segmentation targets, and performance metrics. Studies were grouped based on methodological similarities, clinical applications, and reported outcomes. Comparative trends were identified, and gaps were analyzed Swetha *et al.*, 2025.

RESULTS AND DISCUSSION

This section synthesizes the key findings from the 48 reviewed studies, highlighting patterns, methodological innovations, and performance observations. Nearly all studies emphasized intensive preprocessing, including noise reduction, skull stripping, and bias-field correction. Feature engineering emerged as a dominant design component in SVM frameworks. Texture (GLCM, LBP) and wavelet features were used in 62% of studies. Multimodal MRI inputs (T1, T2, FLAIR, T1-CE) significantly improved SVM discrimination of tumor subregions and lesions. Studies integrating spatial context features (neighborhood statistics, atlas priors) demonstrated more stable boundaries than intensity-based features alone. SVM performance strongly depends on feature quality. Well-designed handcrafted features can rival deep learning in small-data environments Vijay Krishnan *et al.*, 2025. The Radial Basis Function (RBF) kernel was the most commonly used due to its flexibility in representing nonlinear boundaries. 74% of studies used RBF kernels. Polynomial and linear kernels performed adequately for tissue-level classification but poorly for fine lesion detection. Studies employing metaheuristic optimization (PSO, GA) for kernel tuning reported consistent accuracy improvements of 2–7%. Kernel selection and parameter

*Corresponding Author: Ramesh M, PERI Institute of Technology, Chennai-48, Tamil Nadu, India Email: publications@peri.ac.in.

tuning critically influence segmentation accuracy. Automatically optimized SVMs consistently outperform manually tuned ones Sindhuja *et al.*, 2025. Hybrid techniques were prominent in recent literature: SVM + K-means, SVM + MRF, and SVM + Fuzzy Logic improved segmentation stability. CNN feature extraction + SVM classification outperformed conventional SVMs by leveraging high-level learned representations while retaining SVM's generalization strengths. Ensemble SVMs improved lesion detection sensitivity, especially for small MS lesions. Hybrid SVMs bridge the gap between classical machine learning and modern deep learning. They deliver high accuracy with lower computational cost than end-to-end CNNs. SVMs performed exceptionally well in differentiating tumor vs. non-tumor regions. Multi-modality inputs + texture features achieved Dice scores of 0.82–0.90. CNN-SVM models achieved even higher performance (accuracy >95% in several studies). MS lesion segmentation remains challenging due to small, scattered lesions. Ensemble SVMs and atlas-guided SVMs improved sensitivity while limiting false positives. Reported Dice scores ranged from 0.55–0.75, acceptable for small-lesion detection. SVMs performed well in 3-class problems (GM, WM, CSF) and prostate segmentation. Accuracy typically ranged from 90%–96%, with limitations at complex boundaries. Deep learning dominates modern segmentation tasks, but SVMs remain competitive when: Labeled training data is small. High-level CNN features are used as input. Computational resources are limited. Interpretability is required. Hybrid CNN→SVM pipelines often matched or exceeded pure CNN classification performance. SVM remains relevant in modern medical imaging workflows as a lightweight, robust classifier and as a complementary component to deep learning Vijay Krishanan *et al.*, 2025.

CONCLUSION

This systematic review highlights the continued relevance of Support Vector Machine–based methods for MRI image segmentation across various applications. While deep learning approaches dominate recent literature, SVMs remain powerful due to their strong generalization ability, suitability for small datasets, and capacity to integrate diverse handcrafted or deep features. RBF-based SVMs, hybrid SVM architectures, and kernel optimization strategies consistently yield high accuracy in brain tumor segmentation, multiple sclerosis lesion detection, and tissue classification tasks. The performance of SVM depends heavily on preprocessing quality, feature selection, and parameter tuning. Despite compelling performance, challenges persist, including dependence on handcrafted features, limited spatial modeling, and variability across MRI scanners and datasets. Overall, SVM-based segmentation continues to provide competitive, reliable, and computationally efficient solutions for medical image analysis. Future research should address the limitations identified and explore new directions to enhance the utility

of SVM frameworks: Integrating CNN-based deep feature extraction with SVM classifiers should be further explored to reduce reliance on handcrafted features and enhance representational power. Multi-kernel SVMs and adaptive kernel strategies can better capture complex tissue heterogeneity across MRI modalities. Techniques such as transfer learning, normalization strategies, and cross-scanner harmonization are needed to improve SVM robustness across diverse clinical environments. SVMs can be used in real-time, low-resource clinical settings; compact hybrid architectures should be developed to support point-of-care diagnostics. More studies should evaluate SVM frameworks on public datasets (e.g., BRATS, MSSEG) using consistent metrics to enable fair comparison across segmentation methods. Future SVM systems can incorporate interpretability techniques to provide clinically understandable segmentation rationales and decision boundaries.

ACKNOWLEDGMENT

The authors express sincere thanks to the head of the Department of Zoology, Madras University for the facilities provided carry out this research work.

CONFLICT OF INTERESTS

The authors declare no conflict of interest

ETHICS APPROVAL

Not applicable

FUNDING

This study received no specific funding from public, commercial, or not-for-profit funding agencies.

AI TOOL DECLARATION

The authors declares that no AI and related tools are used to write the scientific content of this manuscript.

DATA AVAILABILITY

Data will be available on request

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