RESEARCH ARTICLE

Classification of hearing loss based on residual transfer learning and support vector machine

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Hearing loss (HL) impairs the ability to hear and can be caused by genetics, trauma, infections, aging, and noise exposure. Early and accurate diagnosis is critical for effective management. This research introduced a computer-aided diagnosis (CAD) system which applied machine learning and magnetic resonance imaging (MRI) to diagnose HL. Feature extraction was conducted using a pretrained residual neural network (RNN) with subsequent classification performed through support vector machine (SVM) algorithms. The robustness of the performance of the developed model was evaluated through K-fold cross-validation method. The results demonstrated that the integrated RNN-SVM approach achieved high accuracy and sensitivity in distinguishing between left hearing loss (LHL), right hearing loss (RHL), and health control (HC). This CAD system showed significant potential in aiding otologists with early and precise diagnosis of hearing loss, ultimately enhancing patient care and outcomes.

Keywords: hearing loss; neuroimaging analysis; automated diagnostic systems; deep feature extraction; support vector machine.

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Introduction

Characterized by compromised auditory signal transduction from peripheral to central pathways, hearing loss (HL) constitutes a pervasive sensory disorder with substantial global health implications. HL can have various reasons including genetic predisposition, physical trauma, infections, aging, exposure to excessive noise, and other environmental factors [1]. In terms of severity, HL is typically classified into five distinct categories of mild, moderate, moderate-severe, severe, and profound. This classification system provides a structured tool for understanding the severity of the hearing impairment experienced by an individual, which is crucial for both diagnosis and treatment planning [2]. For example, in case of mild hearing loss, some conversational speech could be heard, while a person suffering from profound hearing loss might not hear sounds at all [3]. By classifying hearing loss in this way, healthcare professionals can better investigate how it affects the daily life and communication abilities of the person. This understanding is essential to develop appropriate intervention measures tailored to the severity of the condition of each individual such as hearing aids, cochlear implants, or auditory rehabilitation programs [4]. In addition, this classification aids in tracking hearing loss progression over time, facilitating timely adjustments in treatment strategies and enhancing overall patient care [5]. In children, hearing loss can strongly affect the development of spoken language, cognitive skills, and social interactions [1]. Early identification and intervention are essential for mitigating these influences and supporting language acquisition and educational development. In adults, however, hearing loss can create difficulties in communication, influencing social interactions and professional life. This can give rise to social isolation, depression, and decline of overall quality of life [6].

Magnetic resonance imaging (MRI) has become an essential tool to detect and understand structural brain changes related to hearing loss [7]. HL patients often present differences in brain structures in comparison to healthy individuals [1]. However, these differences could be subtle and challenging for otologists to identify hearing problems through visual inspection alone [8, 9]. This is where computer-aided diagnosis (CAD) systems become invaluable. The developed diagnostic tool applies deep learning to neuroimaging data to detect microstructural pathologies which are imperceptible through visual inspection [10]. By performing a more detailed and objective analysis, CAD systems enhance diagnostic processes, allowing for more accurate and timely hearing loss detection. This technological advancement not only aids radiologists in their diagnostic efforts but also holds promise for improving patient outcomes via earlier and more precise interventions. Early-stage CAD architectures predominantly integrate rule-based inference engines with classical statistical learning models to establish foundational frameworks for medical image interpretation [11]. These techniques include training algorithms on MRI scans for detecting patterns and abnormalities indicating hearing loss [12, 13]. Although traditional machine learning provides the cornerstone of computer-aided diagnostic systems, remarkable progress is still needed to effectively process the inherent heterogeneity of clinical radiological datasets [10, 14]. Contemporary deep learning architectures, especially convolutional neural networks, have significantly improved computer-assisted diagnostics *via* automated feature extraction from volumetric brain scans with unprecedented precision [15]. These models can identify subtle structural abnormalities which could not be easily identified by naked eye, enhancing diagnostic accuracy and facilitating rapid intervention in hearing-impaired persons [16]. In developing CNN architecture, residual neural network (RNN) is among the most important milestones, enabling the effective training of deeper networks. He *et al*. developed residual networks (ResNets), which effectively countered vanishing gradient obstacles that critically constrained the efficacy of training in deep neural architectures, enabling stable training of deep architectures by preserving gradient flow across layers [17]. However, it generally provides poor performance as the network gets deeper [18]. RNNs facilitate this functionality by integrating residual connections, alternatively referred to as skip connections, enabling the bypassing of one or multiple intermediate layers within network architecture. Innovative skip connection mechanism enables stable gradient flow during deep network optimization, which can effectively prevent training deterioration while substantially improving feature discriminability in visual recognition tasks. This is because it is possible to develop a network with hundreds or thousands of layers at the same time while maintaining high performance and precision. One of the most innovative characteristics of RNNs is the application of residual connections, also called skip connections. Layered architectures can parameterize differential feature mappings relative to input states, rather than direct input-output transformations through identity shortcut pathways. More precisely, RNNs are designed for approximating residual mappings, which are defined as mathematical difference between input activation and target output transformation at a given layer. The optimization process is significantly simplified using this architectural paradigm by enabling direct gradient flow through shortcut connections, effectively solving the common issue of gradient vanishing in deep network architectures. Maximum-margin discriminative models have demonstrated superior performance in pattern recognition applications [19]. This approach develops geometrically optimal decision boundaries by maximizing inter-class separation within transformed feature representations. Critical boundary samples, also called defining instances, determine margin width, quantified as minimal distance among convex hulls of distinct data clusters. Through systematic margin optimization, the developed method enhances predictive robustness, achieving reliable performance for unseen data instances while alleviating overfitting risk [20].

This research aimed to harness the representational learning capabilities of RNNs while simultaneously mitigating overfitting limitations inherent in conventional support vector machine (SVM) approaches, specifically to enhance hearing loss detection accuracy by analyzing brain MRI scans. A new CAD model RNN-SVM for detecting hearing loss based on brain MRIs was proposed. A pre-trained RNN was developed to generate rich and complex representations from brain MRIs, useful for the identification of hearing loss. Support vector machine classifier was employed to differentiate unilateral auditory impairment from normative auditory cohorts through discriminative feature space analysis. Stratified K-fold validation was used to inspect the predictive accuracy of hybrid RNN-SVM architectures in auditory impairment classification compared to baseline diagnostic models. By using advanced representational learning capabilities of RNNs, this research addressed the critical issue of overfitting commonly seen in traditional SVM methodologies, improving the reliability and accuracy of auditory impairment diagnoses. The proposed RNN-SVM model not only enhanced classification of unilateral auditory conditions but also set a precedent for integrating deep learning techniques with conventional machine learning frameworks in medical imaging, which might give rise to better early detection and intervention strategies, ultimately benefiting patients, and advancing research in auditory health and neuroimaging.

Materials and methods

Neuroimaging repository comprised MRI images were obtained from the local hospitals in Yangzhou, Jiangsu, China through Siemens MAGNETOM Skyra 3T MRI scanner (Siemens Healthineers, Erlangen, Bavaria, Germany) with the scanning protocol of T1-weighted imaging to ensure comprehensive neuroanatomical examinations, which contained balanced cohorts stratified by auditory pathology lateralization (left/right unilateral impairment) with an auditory-intact reference group, systematically curated for comparative neuroanatomical analyses [21]. All images were acquired at the resolution of 176 × 256 pixel with adequate spatial details to support robust feature extraction. All procedures of this research were approved by IRB committee of Yangzhou Hospital, Yangzhou, Jiangsu, China.

Residual neural network

Architecturally, residual blocks in RNNs integrated sequential nonlinear transformations, where processed feature tensors underwent additive fusion with initial feature representations *via* identity mapping pathways. Mathematically, assuming x as input, and $F(x)$ as the function representing the convolutional layers, the output of the residual block was as below.

$$y = F(x) + x \tag{1}$$

This method of directly adding inputs helped maintain gradient flow within the network, enabling the training of very deep networks. Deep residual architectures can obtain unprecedented accuracy in visual pattern recognition benchmarks, consistently exceeding human-level classification capabilities across different imaging modalities. The ability of these architectures to maintain accuracy with the increase of depth has made them popular options for complex image analysis tasks, including those in medical imaging [22, 23]. RNN architecture incorporated sequential residual modules, each integrating convolutional operations with batch normalization and ReLU nonlinear activation layers. The output of each block was added to its input to generate the residual connection. Terminal processing stage integrated learnable weight matrices with normalized exponential transformations, operationalizing discriminative categorical assignment *via* probabilistic feature space projections. Softmax function was stated as follows.

$$\sigma(z_i) = \frac{e^{z_i}}{\sum_j e^{z_j}} \quad (2)$$

where z_i was unnormalized log-odds for the i diagnostic category. Using hierarchical feature representations from pretrained RNN, the diagnostic framework achieved discriminative auditory pathology stratification across lateralized impairment subtypes and neurotypical reference cohorts, generating an automated clinical decision support system for otological diagnostics.

Support vector machine

Mathematical derivation of maximum-margin decision boundaries involved constrained quadratic programming formulations with geometric constraints to ensure optimal class separability. In each training sample pair, where (x_i, y_i) denoted feature vector and y_i was class label, SVM found the hyperplane defined as follows to maximize the margin.

$$w^T x + b = 0 \quad (3)$$

This was achieved by the following equation.

$$\min_{w,b} \frac{1}{2}\|w\|^2, \text{s.t.}\, y_i(w^{\mathrm{T}} x_i + b) \geq 1, i \in \{1, 2, \ldots, N\} \quad (4)$$

where N was the cardinality of learning instances. The optimal geometric separation interval (M) was mathematically defined through the constrained optimization framework as below.

$$M = \frac{2}{\|w\|} \quad (5)$$

This mathematical equivalence showed that enhancing inter-class separation *via* geometric margin optimization fundamentally corresponded to regularizing model complexity through parameter space constraints $\|w\|$. Maximum-margin classifiers used kernel-induced transformation to respond to nonlinear class separation challenges, where input patterns were implicitly mapped into reproducing kernel Hilbert spaces through similarity operators. This methodology circumvented explicit high-dimensional computations using Mercer-compliant functions—including polynomial, radial basis, and sigmoid mappings to calculate inner products in transformed feature space [24].

$$K(x_i, x_j) = \phi(x_i)^T \phi(x_J) \quad (6)$$

Kernel operator K formalized pairwise pattern similarities through inner product evaluations in Hilbert spaces, eliminating explicit computation of implicit embedding operator ϕ that projected inputs into these enriched feature representations.

RNN-SVM

The developed RNN-SVM for the detection of hearing loss used automated feature learning capability of RNN and trained SVM as the classifier to avoid the overfitting problem since brain MRI dataset was small. MRI images were preprocessed to improve their quality and extract relevant features, which included normalization, noise reduction, and segmentation for the isolation of the region of interest (ROI) in the brain. Normalization was mathematically stated as follows.

$$x' = \frac{x-\mu}{\sigma} \quad (7)$$

where x was the original input intensity. μ was the statistical mean of the dataset. σ was standard statistical deviation. The extracted features were applied to train the developed SVM model. Different kernel functions were

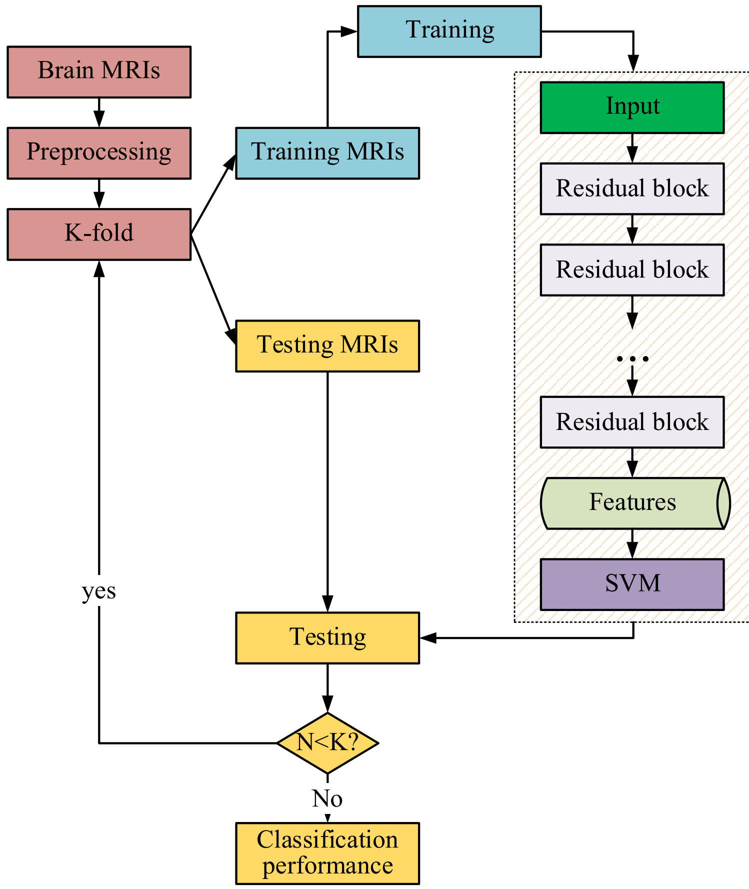

Figure 1. Diagram of the proposed methodology.

evaluated for determining the best-performing model. SVM learned to classify MRI images into the following three categories including left hearing impairment (LHL), right hearing impairment (RHL), and healthy auditory (HC). The decision function of SVM was stated as below.

$$f(x) = w^T \phi(x) + b \tag{8}$$

where w was weight vector. $\phi(x)$ was feature mapping using a kernel. b was bias term. The performance of RNN-SVM was explored with precision and sensitivity. Cross validation was applied to make the model robust and generalizable. This hybrid framework integrated the technical advantages of residual networks and SVMs, specifically optimized for medical image analysis tasks such as auditory dysfunction identification based on brain scans. Residual networks addressed training challenges in deep architectures through cross-layer connection mechanisms, enabling automatic capture of high-level discriminative features from raw data. As a classical classifier, SVM obtained efficient pattern separation by developing maximum-margin decision boundaries in feature space. The proposed method combined deep feature learning with statistical learning theory by using abstract features extracted through residual networks as inputs for SVM and retaining the ability of deep learning to parse complex patterns while inheriting the generalization advantage of SVM in small-sample scenarios. This collaborative strategy significantly enhanced the robustness of medical diagnostic systems, especially suitable for high-precision classification scenarios (Figure 1).

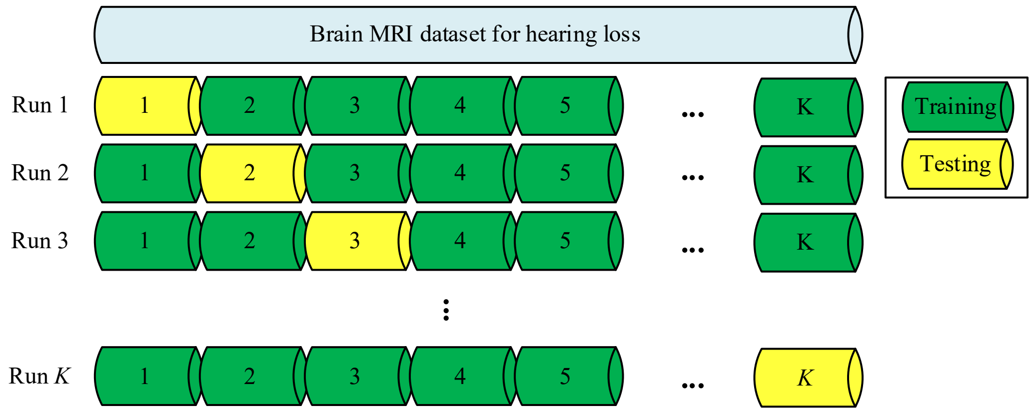

Figure 2. Stratified K-fold validation protocol.

Stratified K-fold validation protocol

To ensure the effectiveness and generalizability of the proposed model, this research employed a stratified K-fold validation protocol for performance evaluation. The proposed method involved a systematic data partitioning and iterative validation process, which included that the original dataset was randomly divided into *K* mutually exclusive and equally sized subsets. Then, one subset was sequentially selected as validation set, while the remaining *K*-1 subsets were applied for model training, completing *K* rounds of independent training-test cycles. The mean values of key metrics such as accuracy and sensitivity from each validation round were calculated, which served as the final performance assessment benchmark for the model (Figure 2). Hierarchical iterative validation strategy effectively mitigated evaluation bias and variance fluctuations due to traditional single partition methods by reusing the entire dataset for model training and assessment. This approach achieved a more stable and representative comprehensive evaluation of the performance of the classifier.

Performance assessment

Various performance measures including confusion matrix, precision, and sensitivity were applied to explore the validity of the proposed method. This evaluation system quantified the diagnostic efficacy of brain MRI images using a multidimensional indicator system model. The predicted results were systematically compared to actual results by generating a confusion matrix, which organized the predictions of the model into four distinct categories including true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). To generate this matrix, the model first classified each sample in the dataset based on the features extracted from MRI images. Then, each sample was assigned to one of the four categories by evaluating its predicted and true labels. This structured comparison allowed for a clear assessment of the performance of the model, enabling the calculation of key metrics such as sensitivity and accuracy, which provided insights into the diagnostic capabilities of the developed model. The accuracy of classification was the primary evaluation metric and was calculated as the proportion of correctly classified samples out of the total sample size as follows.

$$accuracy = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}} \quad (9)$$

This method intuitively represented the overall discriminatory power of the model. Supplementary metrics such as precision were further incorporated to construct a multi-dimensional evaluation system to comprehensively validate the clinical applicability of the diagnostic system. Accuracy indicated the proportion of MRI brain images correctly classified into LHL, RHL, and HC. Sensitivity, also termed recall or true positive

Table 1. Results of the proposed RNN-SVM.

Run	HC	Left	Right	Overall accuracy
1	95.00	93.33	96.67	95.00
2	91.67	95.00	93.33	93.33
3	98.33	96.67	98.33	97.78
4	96.67	91.67	95.00	94.44
5	98.33	93.33	93.33	95.00
6	96.67	95.00	98.33	96.67
7	93.33	95.00	98.33	95.56
8	95.00	93.33	96.67	95.00
9	93.33	88.33	93.33	91.67
10	93.33	91.67	93.33	92.78
MSD	95.17 ± 2.28	93.33 ± 2.36	95.67 ± 2.25	94.72 ± 1.80

rate, measured the ability of the diagnostic system for accurate detection of true positive cases, calculated as the ratio of correctly identified positives to all actual positive instances.

$$sensitivity = \frac{\text{TP}}{\text{TP+FN}} \quad (10)$$

This metric proved highly valuable to evaluate the proficiency of the model in detecting true positive cases within clinical datasets.

Comparison Methods

The proposed RNN-SVM model was compared with three commonly used methods for the detection of hearing loss including wavelet entropy (WE) combined with genetic algorithm (GA) (WE+GA), least squares support vector machine (LS-SVM), and improved artificial bee colony (IABC) to evaluate its performance. WE+GA method leveraged wavelet entropy features in conjunction with a GA to optimize classification process [11]. LS-SVM was a variant of traditional SVM that minimized least squares error function [18]. IABC aimed to more accurately and efficiently detect hearing loss using a nature-inspired algorithm, which employed discrete wavelet transform (DWT) to extract texture features from brain images followed by principal component analysis (PCA) to decrease dimensionality. A multi-layer perceptron (MLP) classifier trained using IABC was applied, which enhanced exploration and exploitation capabilities compared to traditional artificial bee colony (ABC) algorithms [12].

Results

The results of 10-fold cross-validation

The results of hearing loss classification using the proposed RNN-SVM model for MRI data showed that the proposed model demonstrated the consistent ability to differentiate healthy individuals and those with hearing impairments. Overall accuracy varied across the runs with the highest and lowest accuracies of 97.78% and 91.67% observed in Runs 3 and 9, respectively (Table 1). The results indicated that, while the model performed well on average, there were some fluctuations in effectiveness, which could be attributed to variations in training and validation subsets. The mean sensitivity of each category was calculated as 95.17 ± 2.28% for HC, 93.33 ± 2.36% for LHL, and 95.67 ± 2.25% for RHL, respectively. The results indicated that the model maintained a high accuracy level across all categories, suggesting that it was equally effective in identifying both hearing loss types and distinguishing healthy individuals. The mean overall accuracy of 94.72 ± 1.80% reflected the strong performance of the proposed model across all runs. This high accuracy was crucial for clinical applicability as it indicated that the model could reliably assist in diagnosing hearing loss

Table 2. Comparative analysis of the performance of mainstream technical solutions.

Method	HC	LHL	RHL	Overall accuracy
WE+GA	81.25 ± 4.91	80.42 ± 5.57	81.67 ± 6.86	81.11 ± 1.34
LS-SVM	84.83 ± 2.54	85.17 ± 5.52	84.67 ± 3.58	84.50 ± 1.77
IABC	95.07	98.63	98.63	97.33
RNN-SVM	95.17 ± 2.28	93.33 ± 2.36	95.67 ± 2.25	94.72 ± 1.80

based on brain MRI scans. Balanced performance across HC, LHL, and RHL categories suggested that RNN-SVM model could effectively support clinicians in making accurate diagnosis. The low variability observed in the accuracy enhanced the credibility of the model as a diagnostic tool, which was essential in clinical settings where precision was critical.

Comparative analysis of different methods

The proposed RNN-SVM model demonstrated good performance across all categories with high sensitivity for HC, LHL, RHL and robust overall accuracy, while IABC showed slightly higher sensitivity for LHL, RHL, and overall accuracy. The proposed RNN-SVM model performed comparably and significantly better than WE+GA and LS-SVM (Table 2). The hybrid architecture optimized by combining residual networks with SVMs achieved a classification accuracy of 94.72 ± 1.80%, proving its reliability in distinguishing among different categories of hearing loss. High sensitivity values were achieved for HC, LHL, RHL as 95.17 ± 2.28, 93.33 ± 2.36, 95.67 ± 2.25, respectively, comparing to that of WE+GA and LS-SVM. Although IABC method demonstrated superior sensitivity and accuracy, the competitive performance of RNN-SVM was noteworthy given the challenges associated with small datasets. The slight edge seen in IABC could be attributed to its specific algorithmic enhancements or feature selection techniques that might not have been fully used in RNN-SVM approach, which presented an opportunity for future research to explore hybrid models or integrate feature selection techniques to further boost performance. The proposed model showed outstanding efficacy in capturing positive cases, which was crucial for clinical applications.

Discussion

The main advantage of the proposed RNN-SVM hybrid architecture lied in its ability to perform well even for samples with limited sizes. The combination of residual learning in RNN architecture and regularization capabilities of SVM classifier provided a balanced framework that maintained high generalization performance, which was especially crucial in medical imaging as the cost of misdiagnosis could be significant. The capability of RNN-SVM model to deliver precise and dependable diagnoses of hearing loss using MRI data held substantial significance for clinical practice. Accurate early diagnostic approaches could secure crucial time windows for clinical intervention, significantly enhancing long-term patient outcomes and quality of life by optimizing treatment timeliness. The model could be integrated into clinical workflows, assisting radiologists and audiologists in making informed decisions based on quantitative data. This research proposed an innovative diagnostic framework that integrated medical image analysis with deep learning for accurate identification of auditory function disorders by combining magnetic resonance brain scan data with machine learning techniques. The main architecture of the proposed system used a deep residual network for multi-scale feature extraction and combined SVM to construct classification decision boundaries. This approach effectively distinguished unilateral auditory damage (left/right) and healthy control groups, exhibiting superior accuracy and sensitivity metrics in diagnostic processes. A comprehensive K-fold cross-validation protocol was systematically implemented to ensure the efficiency of the proposed method and enhance the generalizability of research findings. The empirical results derived from this rigorous validation framework revealed that the proposed computational model exhibited robust diagnostic capabilities with consistent performance across all validation folds. The developed CAD system represented a significant advancement in radiological diagnostics, offering potentials for augmenting clinical decision-making processes by precise detection of subtle neuroanatomical alterations associated with auditory dysfunctions. This technological innovation facilitated early intervention strategies and optimized therapeutic outcomes through improved diagnostic accuracy and decreased inter-observer variability in radiological assessments.

Future research should focus on systematic optimization of the proposed computational framework to narrow its performance gap with current leading methodologies, especially IABC algorithm. This optimization endeavor incorporated several strategic approaches including implementation of Bayesian optimization for tuning hyperparameters to maximize the efficiency of the model, development of hybrid ensemble architectures combining multiple machine learning paradigms, and evaluation of advanced kernel mapping mechanisms including radial distance-based exponential kernels with polynomial high-dimensional spatial projection kernels to enhance the discriminative abilities of SVM. In addition, expansion of training dataset *via* the inclusion of diverse MRI imaging data from multiple clinical centers and encompassing different demographic profiles and pathological variations would significantly improve the generalizability and diagnostic precision of the model. Such dataset augmentation should be accompanied by rigorous quality control protocols and standardized preprocessing pipelines to ensure data consistency and reliability.

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