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Deep Feature Representation and Multi-Kernel SVM Model for Alzheimer's Disease Diagnosis and Dementia Stage Prediction Using Magnetic Resonance Images

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Abstract: The proposed study presents a noble hybrid model for Alzheimer's disease progression diagnosis using DenseNet201 feature extraction and Multi-kernel Support Vector Machine(M-SVM) classification in two stages. Firsty, participants were classified into three groups-Alzheimer's Disease (AD), Cognitive Impairment (CI) and normal group -using DenseNer201 for feature extraction and a M-SVM classifier. The model achieved a validation accuracy of 96.6% with AUC of 0.98 and test accuracy of 97.8% with AUC of 1.0. The second phase reached validation accuracy of 99.5% and an AUC of 1.0 while classifying individuals into non-dementia, mild dementia, moderate dementia, and very mild dementia groups and obtained a test accuracy of 99.8% with an AUC of 1.0. The proposed methodology demonstrates high accuracy and reliability which delivers valuable information for understanding AD progression and serves as an effective diagnostic tool for early detection and differentiation of cognitive impairments and dementia stages. Combining DenseNet201 and M-SVM demonstrates potential benefits for Alzheimer's disease management by improving clinical assessments and treatment approaches for patient care.

Keywords: Alzheimer's disease; dementia; deep feature; SVM; DenseNet201

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0 Introduction

Alzheimer's Disease (AD) represents a progressive brain disease that deteriorates cognitive abilities and leads to the loss of basic functional skills. The disease represents the primary reason for dementia in 60 - 80% of all dementia cases according to research [1]. Beta-amyloid plaques represent a key feature of Alzheimer's disease because they form abnormal protein deposits in the brain. The brain cell communication gets blocked by these deposits and eventually leads to brain cell death. AD symptoms develop slowly before they intensify as the condition progresses. The initial symptoms of AD consisted of slight forgetfulness and difficulty remembering names along with faces or recent events. The progression of the disease leads to increased disorientation and confusion in patients who also struggle with communication and show behavioral and emotional irregularities [2]. A patient with advancing AD will require constant supervision because they will lose their ability to recognize their family members and talk to them or carry out regular tasks.

Mild Cognitive Impairment (MCI) represents a decline in cognitive skills that surpasses normal age-related changes without major disruptions to everyday life activities. This condition serves as an intermediate phase that connects normal age-related cognitive decline with more advanced cognitive impairments observed in Alzheimer's Disease (AD) and other dementia forms [3]. Memory difficulties frequently affect people with MCI by disrupting their capacity to remember information and recent occurrences. People with MCI face elevated risks of progressing to dementia including AD [4]. Several important reasons exist for the immediate diagnosis and detection of MCI. Through early interventions such as dietary

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changes and medication administration people can slow cognitive deterioration while lowering their risk of dementia development. People identified with MCI can check their cognitive health and take necessary support and treatment options [5].

Medical imaging data analysis from PET and MRI demonstrates that image processing methods serve as fundamental tools for Alzheimer's disease diagnosis. Image processing algorithms have the ability to trace brain region dimensions while tracking temporal changes. Alzheimer's disease leads to neuronal loss which causes the hippocampus and cerebral cortex to experience shrinkage. MRI scan analysis through image processing enables researchers and healthcare professionals to detect both the size of brain regions and patterns of atrophy that signify Alzheimer's disease. The combination of image processing techniques with Machine Learning (ML) and Deep Learning (DL) resulted in a powerful tool for diagnosing the diseases according to Refs. [7-9]. These methods enable researchers to extract features and categorize the data when predict the disease. These features include brain abnormalities along with structural brain alterations and patterns of brain degeneration [10-12]. The major contributions of the article are as follows.

1) Novel framework combining DenseNet201 feature extraction and multi-kernel SVM for comprehensive AD diagnosis. Extracting deep DenseNet201 features coupled with cubic SVM model yields accurate AD progression classification. 2) Two-phase study: Initial phase focuses on AD, MCI, and common norms classification, while the second phase categorizes non-dementia, mild dementia, moderate dementia, and very mild dementia groups. 3) Exceptional validation accuracy and Area Under Curve (AUC) values in both phases demonstrate efficacy in diagnosing and differentiating cognitive impairments in AD. 4) Study findings offer valuable insights into AD progression, providing a robust diagnostic tool for early detection and improved patient care strategies.

Organization of this article is as follows. Section 1 includes literature review. This section summarizes and compares existing research on AD diagnosis and progression monitoring. Section 2 includes DenseNet201 along with multi-kernel SVM approaches to accurately stage Alzheimer's disease. Section 3 shows results and discussion. In this section we achieved remarkable validation accuracies of 99.5% and AUC scores of 1.0. We also discuss the clinical implications of our findings at length. Finally, Section 4 is the conclusion. Our proposed framework has the capability to be used as a diagnostic tool. It may allow for detection of early symptoms as well as accurately differentiate patients, creating more effective treatment options for those who suffer from AD.

1 Literature Review

Numerous studies by researchers have reported AD utilizing several techniques and different kinds of equipment. The techniques implemented range from deep learning to machine learning algorithms to medical imaging. Researchers have analyzed how DL models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) analyze MRI and PET scans to classify and diagnose Alzheimer's disease in its early stages. They have found that deep learning can increase the accuracy and efficiency of Alzheimer's disease detection while providing a platform to better care for patients and understand the disease.

Borkar et al. [13] extracted multimodal brain features from MRI scans. The researchers took the data they obtained and used it to train their model. Results from their study showed that using this model can screen for AD in normal cognition individuals. By merging a CNN and LSTM model with Adam optimization, we can provide a cheaper and non-invasive solution to current models as well as increase accuracy. Our model achieved an accuracy of 99.7%.

The study by Rana et al. [14] introduced different preprocessing methods for MRI images which were then used as model inputs. Researchers suggested detecting Alzheimer's disease through brain MRI scans which utilize multiclass categorization supported by transfer learning techniques. MRI image analysis resulted in four categories: Non-Dementia (ND), Very Mild Dementia (VMD), Moderate Dementia (MOD), and Mild Dementia (MD). The researchers completed model development and conducted extensive performance evaluations. The model reached an accuracy level of 97.31 %.

Shukla et al. [15] introduced a multimodal image-fusion method using PET and MRI. The ensemble classifier implements a feature selection method based on Random Forests to extract features from both fused and non-fused biomarkers. The research analyzed three categories of Alzheimer's disease which included AD as well as those with Mild Cognitive Impairment (MCI) and Cognitive Normal (CN) conditions. The study achieved 99% accuracy for both binary classification tasks AD vs. CN and MCI vs. CN in the subsequent analysis.

Sorour et al. [16] proposed an AD-DL technique which applies brain MRI scans combined with DL techniques to detect early AD. This process includes preprocessing work together with DL model training and evaluation steps. The study provided five DL models which researchers classified into two groups: those without augmentation and those with augmentation. Among them, the CNN-LSTM model demonstrated superior performance compared to other models by achieving an incredible accuracy rate of 99.92%. The provided dataset demonstrates strong performance metrics for detection accuracy, recall, precision, F1 score, training time and testing time which serves to confirm the effective nature of the proposed methodology.

Zhao et al. [17] introduced the core concepts and categories of DL algorithms such as feed-forward neural networks, CNNs, RNNs, and autoencoders. This analysis presented current applications and challenges of deep learning in PET/MR imaging for Alzheimer's disease patients. Deep Learning is promising to improve PET/MR imaging quality for Alzheimer's patients while providing novel insights into disease origins and treatment methods.

Shrivastava et al. [18] used Decision Tree (DT), Random Forest (RF), SVM, Gradient boosting and voting classifiers to identify optimal parameters for AD prediction. The Open Access Series of Imaging Studies (OASIS) data enabled researchers to predict Alzheimer's disease. The research assessed machine learning model performance through precision, recall, F1-score and accuracy metrics. Their proposed method achieved better results on AD test data and reached an optimal average validation accuracy of 80%.

Roncero-Parra et al. [19] utilized a decade-long database including 668 volunteers from five different institutions. The mixed composition of the dataset improved both training procedures and validation outcomes. Their deep learning strategy achieved classification accuracies of 97.03% for patients with Advanced Alzheimer's dementia (ADA) and 97.45% for those with Moderate Alzheimer's dementia (ADM), outperforming all other tested methods.

Zhang et al. [20] introduced an innovative patch-based deep learning network (sMRI-PatchNet) for the diagnosis of AD, which features explainable patch selection and localization. The network is composed of two main parts: The system combines a new patch-based deep feature extraction network that retains position information through embeddings while handling both global and local inter- and intra-patch data for AD classification, and a fast explainable method for selecting the most discriminative patches. Actual datasets have been used to classify Alzheimer's disease and predict the progression of Mild Cognitive Impairment (MCI) to transitional states.

Parra et al. [21] developed deep neural networks utilizing radial basis functions initialized through fuzzy means. Their method achieved the best-balanced accuracy, reaching 96.66% for ADA classification and 93.31% for ADM classification.

Tanveer et al. [22] employed ResNet50 as a deep learning network to extract features from SWI images, which were subsequently classified by an RVFL network with kernel ridge regression. The study introduced an RVFL network using weighted kernel ridge regression, capable of handling imbalanced class distributions and adapting to balanced data. Experimental findings implied that the proposed model outperformed the most advanced models available.

The review of existing studies highlights the application of deep learning to Alzheimer's disease diagnosis. Advanced DL models demonstrate exceptional accuracy according to collective findings, showing a significant transformation in early detection and healthcare treatment.

2 Materials and Methodology

This section starts with the dataset description in Subsection 2.1 and then explains the methodology in Subsection 2.2. The evaluation of performance of proposed methodology is done by testing it on two different datasets.

2.1 About Dataset

This study consists of two stages. In the first phase, AD, CI, and CN were classified. For this purpose, the ADNI (Alzheimer's Disease Neuroimaging Initiative) dataset was used. The distribution of the ADNI dataset and the samples of the data taken for execution are shown in Table 1. Samples of the ADNI dataset are shown in Fig.1. Mild cognitive impairment can lead to dementia. Therefore, in the second phase, the OASIS dataset was used to identify dementia levels. The distribution of the OASIS dataset is shown in Table 2. The OASIS samples are shown in Fig. 2. The image of both the dataset is of 256×256 resolution.

Two types of augmentation were applied: color augmentation and position augmentation. In color augmentation, random affine, brightness, and contrast were executed. Conversely, horizontal and vertical flipping were executed during position augmentation. We used single hold cross-validation. None of the images used in testing were used during either training or validation. By doing this, the images used for testing remain completely independent of each other.

Test Time Augmentation (TTA) was used on the test set to promote more stable predictions. The augmentation included horizontal and vertical flips, as well as slight increases and decreases in brightness and contrast. TTA was used to ensure stability of our model when presented with augmentations common to MRIs such as horizontal and vertical flips and slightly different focuses [24,25]. The horizontal and vertical flips help the model recognize images independent of orientation. MRI scans can be taken facing any direction, adjusting the brightness and contrast settings to accommodate the different lighting used when scanning each patient.

Table 1 Distribution of 2D axial images of ADNI dataset

Classes	No. of Samples	Random selection of samples for execution
AD	1124	1124
CI	2590	1440
CN	1440	1440

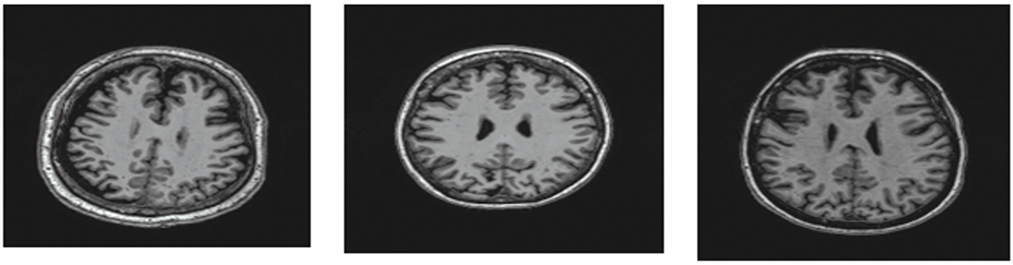

(a) AD (b) CI (c) CN

Fig. 1 Samples of 2D axial images of ADNI dataset of 3 Classes

Table 2 Distribution of OASIS dataset

Level of dementia	Original samples	Colour augmentation (change pixel value) (X)	Position augmentation (change pixel position)	Random selection of samples for execution
Mild dementia	5002	Not applied	Not applied	5002
Moderate dementia	488	1952 (including original)	5856 (including X)	5002
Non-dementia	67,222	Not applied	Not applied	5002
Very mild dementia	13,725	Not applied	Not applied	5002

* X refers to numbers of color augmented images.

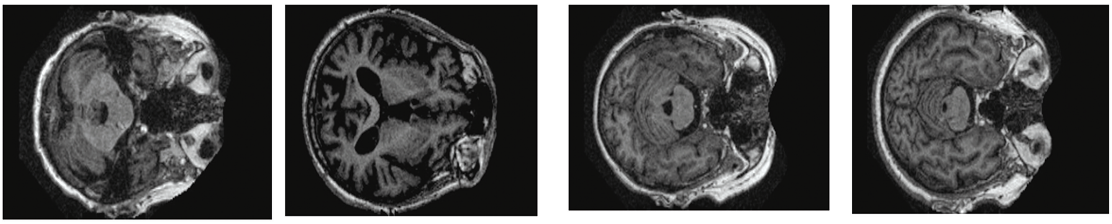

(a) mild dementia (b) moderate dementia (c) non-dementia (d) very mild dementia

Fig.2 Samples of OASIS dataset

In the process of color augmentation, we used a range of techniques such as adjusting brightness and contrast. Random adjustments were made within a range of ±0.2. We then introduced random affine transformations with a probability of 0.5. For position augmentation, we performed horizontal and vertical flipping with a probability of 0.5, as well as random rotation within the range of −15 to +15 degrees and scaling with a range of 0.8 to 1.2 times the original size. The choice of parameters was made to increase the diversity of the dataset while maintaining the clinical characteristics represented in the images.

In terms of discarding about half of the samples from the MCI (Mild Cognitive Impaired) class, this was done for a more balanced representation among classes to improve the robustness of our classification model, as the CI class initially had a larger sample size compared to the AD and CN classes, which could lead to bias.

2.2 Proposed Methodology

DenseNet201 is a CNN which uses a densely connected pattern. To extract features using DenseNet201, an image is passed through convolutional layers. These convolutional layers extract features from the image and become increasingly higher level and more abstract in nature as the data move through the network. In traditional CNNs, each layer is connected to the next layer. In a DenseNet, however, each layer is connected to every other layer that follows it for a certain number of layers. These blocks are called dense blocks. Dense connectivity allows us to reuse features which allows the network to learn more varied information from our input.

2.2.1 *Feature extraction using DenseNet201*

DenseNet201 is a CNN model which utilizes dense connections allowing for feature reusability and stronger gradient flow during backpropagation. As the image passes through the convolutional layers of DenseNet201 to obtain a feature vector, it obtains higher-level and more abstract features. DenseNet constructs a dense block which consists of layers that each receive input from all previous layers, rather than typical CNNs where a layer only receives input from the previous layer. This design not only enables the feature reuse but also allows it to learn more diverse information from the input.

DenseNet is unique compared to traditional CNNs in that it is made up of building blocks that allow each layer to connect densely to every other layer. Dense layers allow for efficiency in information propagation and feature reuse which leads to improved flow of gradients. Dense layers consist of convolutional layers which are typically followed by batch normalization and a rectified linear unit activation function. In a dense layer, every layer receives input from all of the previous layers within that dense block. Dense layers allow data to flow from one layer to another regardless of depth. This allows for feature reuse and the extraction of various features at different levels of abstraction. Pooling transition layers are used between dense layers to limit the number of feature maps and reduce computational burden.

Machine learning algorithms, for example SVMs, use these features to perform AD progression classification which requires high-level visual information for correct diagnosis. DenseNet201 feature extraction produces strong image representations which support effective and precise classification across multiple applications. The detail of framework is illustrated in Fig. 3.

2.2.2 *Multi-kernel SVM classification*

SVM algorithm was utilized to classify diseases through features which were first extracted by the CNN model. The effectiveness of SVMs in classification tasks comes from their ability to handle high-dimensional feature spaces well, along with their resistance to data noise. We trained the SVM model on our selected training dataset with various kernel functions including radial basis, polynomial, and linear functions to determine which model performed best for our task. The kernel function can be considered as a hyperparameter to decide the performance of SVM model.

To tune the performance of SVM model, we experimented with several SVM hyper-parameters, including normalization, margin, kernel coefficient (γ), and the penalty term (c) in SVM objective function. We also performed batch normalization to avoid overfitting. Margin is considered as a critical parameter to check how well SVM models generalize. Margin indicates how far the decision boundary is from the closest training example. The training data examples can be categorized into subsets. These subsets can be used as the validation set in cross-validation and the remaining subsets as the training data [23]. Multi-kernel SVM classification achieves better classification accuracy because multiple kernels extract distinct features from the data structure. The kernels are summarized as follows.

The linear kernel determines sample similarity by computing the inner product of their respective feature vectors. This approach demonstrates effectiveness when applied to linearly separable datasets.

$$K(xi,xj) = xi \cdot xj \tag{1}$$

$K(xi,xj)$: kernel function value measuring similarity between samples i and j; xi, xj: feature vectors of samples i and j; $xi \cdot xj$: inner product (dot product) of feature vectors xi and xj.

A quadratic kernel determines sample similarity through a quadratic function which enables detection of nonlinear data patterns.

$$K(xi,xj) = (xi \cdot xj + c)^2 \qquad (2)$$

The cubic kernel measures sample similarity by utilizing a cubic function to capture higher-order nonlinearities analogous to the quadratic kernel.

$$K(xi,xj) = (xi \cdot xj + c)^3 \qquad (3)$$

The fine Gaussian kernel evaluates similarity by using the distribution of Gaussian functions or radial basis functions. This kernel proves effective in identifying detailed features while maintaining sensitivity to subtle data changes.

$$K(xi,xj) = \exp(-(\| xi - xj \|^2 / 2\sigma f^2)) \qquad (4)$$

where, σf refers to standard deviation for the fine Gaussian kernel (fine scale).

The medium Gaussian kernel provides a balance between local details and broader data trends which makes it the best choice for datasets that have features with different scales.

$$K(xi,xj) = \exp(-(\| xi - xj \|^2 / 2\sigma m^2)) \qquad (5)$$

where, σm refers to standard deviation for the medium Gaussian kernel (medium scale).

Coarse Gaussian kernel: The coarse Gaussian kernel identifies broad data patterns through the reduction of local variations. Datasets containing noise or sparse features benefit from this method.

$$K(xi,xj) = \exp(-(\| xi - xj \|^2 / 2\sigma c^2)) \qquad (6)$$

where, σc refers to standard deviation for the coarse Gaussian kernel (coarse/large scale).

In this context xi and xj serve as feature vectors for two samples while c functions as a constant and σ denotes the standard deviation parameter which determines the Gaussian distribution's width. The notation $\| xi - xj \|^2$ represents the squared Euclidean distance between the feature vectors xi and xj. The kernel values remain positive and indicate sample similarity because of the exponential function exp. The standard deviation parameters for fine, medium and coarse Gaussian kernels are represented by σf, σm and σc respectively.

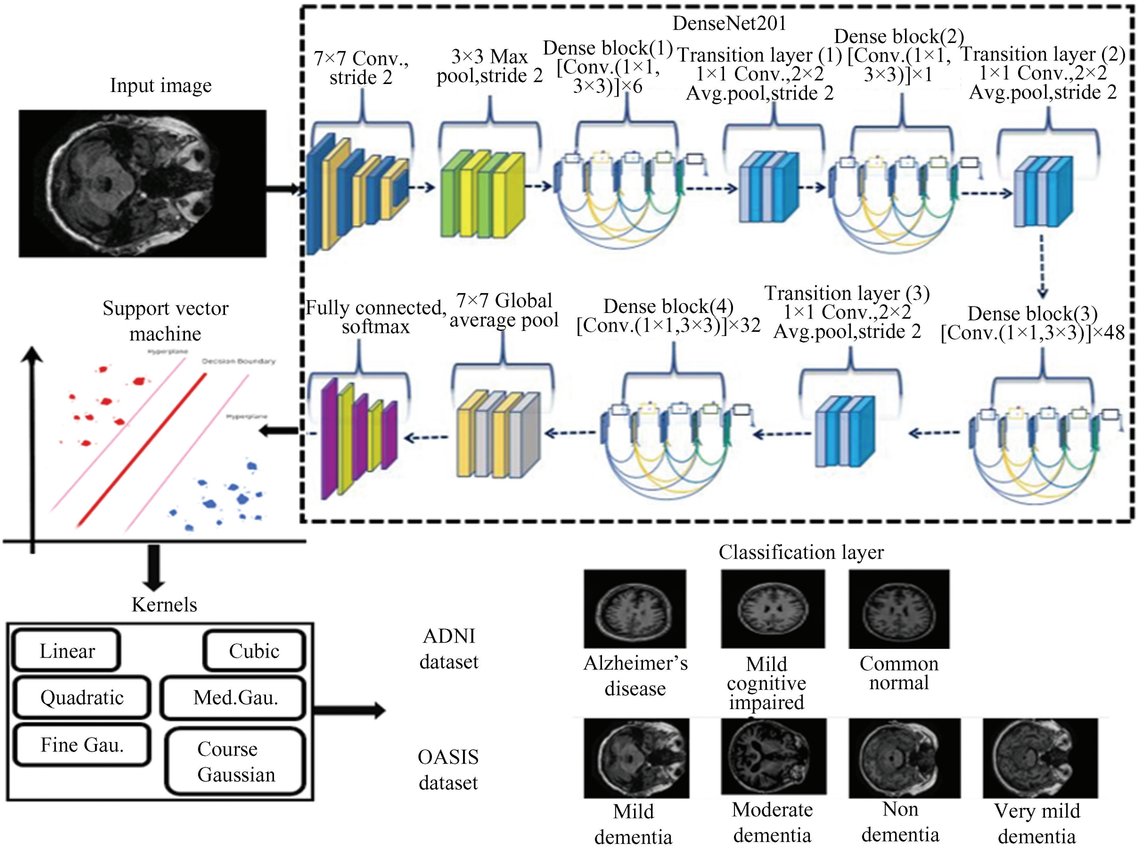


Fig.3 Proposed methodology for Alzheimer's disease progression classification

DenseNet-201 was selected as the classifier because it provides an excellent tradeoff between feature reuse and gradient flow, parameter efficiency, easy training, and state-of-the-art accuracies on medical imaging benchmarks. The densely connected architecture helps to extract richer and more discriminative features, while the cubic SVM can efficiently model the non-linear boundaries between classes. The ensemble of these two helped us achieve better accuracy, sensitivity, specificity and robustness compared to other CNN-classifier models. DenseNet201 was trained using imagenet dataset which helped us initialize our network with well-learned features. We then fine-tuned our DenseNet201 model by unfreezing the last few layers and training on our dataset – specifically, we unfroze the fully connected layers while keeping the convolution layers frozen for first few epochs. This gives us the advantage of learning from features we already have pre-trained and transfer-learned for low level features while learning high level features from our dataset. We extracted the features from the last dense layer of DenseNet201 which gives us a 1024 feature vector on which we trained our SVM model. The suggested input dimensions for our SVM is also 1024.

3 Results and Discussion

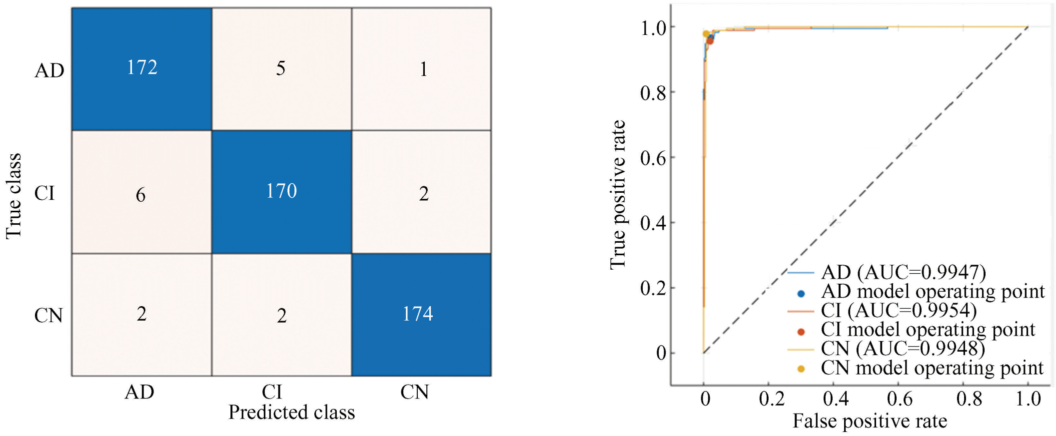
For our work, we used the following system specifications: an NVIDIA GeForce RTX 3080 GPU and 32 GB RAM. All models were trained using this setup.

The researchers used DenseNet201 and different SVM kernels to classify Alzheimer's disease progression from the ADNI dataset. The cubic SVM kernel achieved the highest accuracy and AUC in both validation and testing compared to the other kernels. The DenseNet201 architecture combined with cubic kernel SVM reached 96.6% accuracy during validation, which further increased to 97.8% in the testing phase. The model also yielded an AUC of 98% on validation set and a perfect of 100% on the test set. The DenseNet201 architecture demonstrates effective performance for AD progression classification when combined with the cubic kernel SVM. Table 3 contains detailed accuracy and AUC measurements across validation and testing phases for further examination. Fig. 4 presents visual representations of the confusion matrices together with the AUC scores for the validation and test datasets.

Table 3 Performance of proposed model for progression of Alzheimer's diseases on ADNI dataset

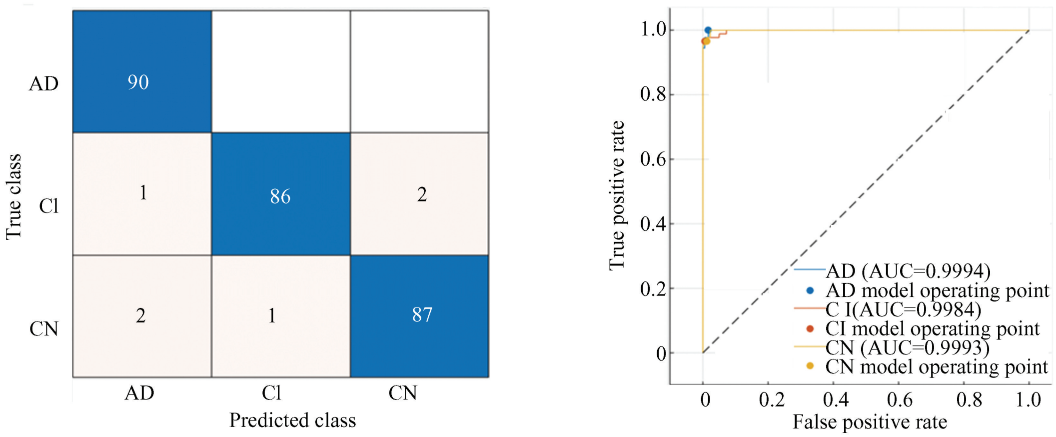
Kernel of SVM	Validation		Test	
	Accuracy	AUC	Accuracy	AUC
Linear	73.6	0.75	77.7	0.78
Quadratic	93.4	0.94	95.9	0.98
Cubic	**96.6**	**0.98**	**97.8**	**1.00**
Fine Gaussian	76.0	0.81	82.2	0.89
Medium Gaussian	92.1	0.93	94.8	0.94
Coarse Gaussian	60.9	0.71	64.3	0.65

Again, various performance metrics, including TPR (True Positive Rate), FNR (False Negative Rate), PPV (Positive Predictive Value), and FDR (False Discovery Rate) were computed using different SVM kernels with features extracted from DenseNet201. Notably, the cubic SVM consistently achieved the highest performance across all types of images within the dataset. Table 4 provides a detailed breakdown of the performance metrics for different SVM kernels in terms of TPR, FNR, PPV, and FDR, specifically on the test data of the ADNI 3-class dataset for Alzheimer's progression classification.



(a) Confusion matrix on validation data

(b) AUC on validation data



(c) Confusion matrix on test data

(d) AUC on test data

Fig. 4 Performance of Densenet201 and cubic SVM on Alzheimer's diseases on ADNI 3-class dataset

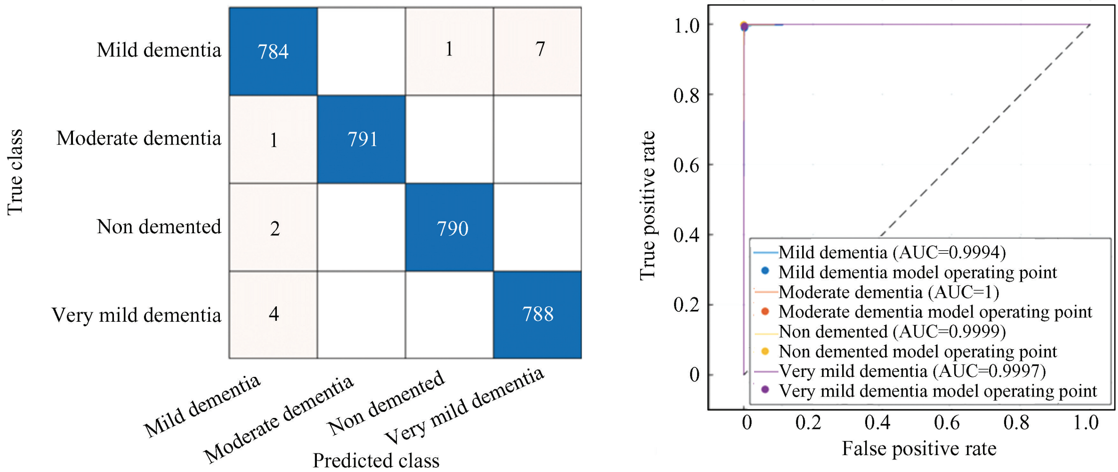
Table 4 Performance of different SVM kernels for Alzheimer's progression in terms of TPR, FNR, PPV, and FDR on test data of the ADNI 3-class dataset

performance metric	Kernel of SVM	AD	CI	CN
TPR	Linear	75.6	75.3	82.2
	Quadratic	98.9	93.3	95.6
	Cubic	**100.0**	**96.6**	**96.7**
	Fine Gaussian	65.6	100.0	81.1
	Medium Gaussian	98.9	92.1	93.3
	Coarse Gaussian	63.3	57.3	72.2
FNR	Linear	24.4	24.7	17.8
	Quadratic	1.1	6.7	4.4
	Cubic	**0.0**	**3.4**	**3.3**
	Fine Gaussian	3.4	0.0	18.9
	Medium Gaussian	1.1	7.9	6.7
	Coarse Gaussian	36.7	42.7	27.8
PPV	Linear	71.6	78.8	83.1
	Quadratic	94.7	97.6	95.6
	Cubic	**96.8**	**98.9**	**97.8**
	Fine Gaussian	100.0	65.0	100.0
	Medium Gaussian	91.8	97.6	95.5
	Coarse Gaussian	62.8	65.6	65.7
FDR	Linear	28.4	21.2	16.9
	Quadratic	5.3	2.4	4.4
	Cubic	**3.2**	**1.1**	**2.2**
	Fine Gaussian	0	35.0	0
	Medium Gaussian	8.2	2.4	4.5
	Coarse Gaussian	38.0	34.6	34.3

The OASIS dataset was used to test DenseNet201 alongside multiple SVM kernels. The cubic SVM kernel achieved both the highest validation accuracy and AUC compared to other kernels during the validation period. The cubic kernel demonstrated consistently superior performance during the testing phase by achieving the highest accuracy and AUC values. The DenseNet201 architecture combined with cubic kernel SVM produced a validation accuracy of 99.5% that increased to 99.8% during testing. The model achieved perfect AUC scores of 100% throughout both validation and testing phases. The combination of DenseNet201 and cubic kernel SVM proves highly effective for classifying AD progression. Table 5 provides a detailed summary of both accuracy and AUC metrics across validation and testing phases. Fig. 5 simultaneously displays the confusion matrices alongside their corresponding AUC values for the validation and test datasets.

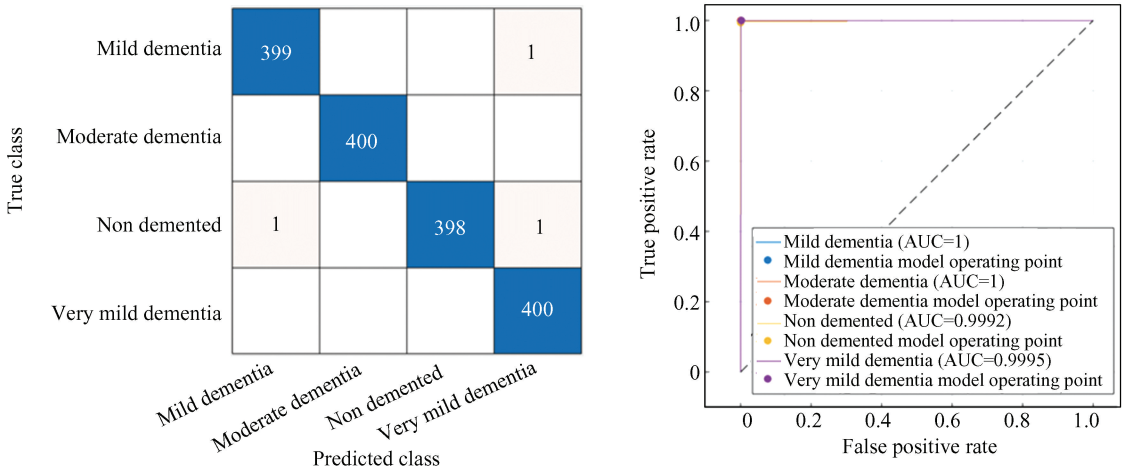
Table 5 Performance of proposed model for progression of Alzheimer's diseases in OASIS dataset

Kernel of SVM	Validation		Test	
	Accuracy	AUC	Accuracy	AUC
Linear	86.2	0.86	88.4	0.89
Quadratic	98.9	0.98	99.3	1.00
Cubic	**99.5**	**1.00**	**99.8**	**1.00**
Fine Gaussian	69.3	0.71	69.6	0.78
Medium Gaussian	99.1	1.00	99.8	1.00
Coarse Gaussian	77.8	0.82	80.8	0.81



(a) Confusion matrix on validation data

(b) AUC on validation data



(c) Confusion matrix on test data

(d) AUC on test data

Fig.5 Performance of Densenet201 and cubic SVM on Alzheimer's diseases on OASIS dataset

Various performance metrics, including TPR, FNR, PPV, and FDR, were computed using different SVM kernels with features extracted from DenseNet201. Notably, the cubic SVM consistently achieved the highest performance across all types of images within the dataset. Table 6 provides a detailed breakdown of the performance metrics for different SVM kernels in terms of TPR, FNR, PPV, and FDR, specifically in the test data of the OASIS class dataset for Alzheimer's progression classification. Further, the comparative analysis was carried out, which is illustrated in Table 7.

In our research, we did not perform standard preprocessing techniques such as skull stripping and bias correction on the MRI images. The original images from the ADNI and OASIS datasets were utilized without undergoing these preprocessing steps. This absence of standard preprocessing may limit the generalizability of our findings due to potential variability in image quality and signal sensitivity. Skull stripping is crucial for eliminating non-brain tissues that can introduce noise, while bias correction is essential for addressing intensity inhomogeneities that may affect feature extraction. Future studies should consider incorporating these preprocessing steps to enhance image quality and improve the robustness of the model's performance.

Table 6 Performance of different kernels of SVM for Alzheimer's progression in terms of TPR, FNR, PPV, and FDR in test data of OASIS dataset

Performance metric	Kernel of SVM	Mild dementia	Moderate dementia	Non-demented	Very mild demented
TPR	Linear	85.2	96.8	87.5	84.0
	Quadratic	99.2	99.8	99.5	98.8
	Cubic	**99.8**	**100.0**	**99.5**	**100.0**
	Fine Gaussian	54.0	100.0	62.0	62.3
	Medium Gaussian	100.0	99.8	99.5	99.8
	Coarse Gaussian	77.2	90.2	80.2	75.2
FNR	Linear	14.7	3.2	12.5	16.0
	Quadratic	0.7	0.2	0.5	1.2
	Cubic	**0.2**	**0.0**	**0.5**	**0.0**
	Fine Gaussian	46.6	0.0	38.0	37.7
	Medium Gaussian	0.0	0.2	0.5	0.2
	Coarse Gaussian	22.8	9.8	19.8	24.8
PPV	Linear	80.4	98.0	94.1	82.2
	Quadratic	99.0	100.0	99.5	98.8
	Cubic	**99.8**	**100.0**	**100.0**	**99.5**
	Fine Gaussian	100.0	45.1	100.0	100.0
	Medium Gaussian	99.3	100.0	100.0	99.8
	Coarse Gaussian	66.5	96.0	92.5	73.1
FDR	Linear	19.6	2.0	5.9	17.8
	Quadratic	1.0	0.0	0.5	1.2
	Cubic	**0.2**	**0.0**	**0.0**	**0.5**
	Fine Gaussian	0.0	54.9	0.0	0.0
	Medium Gaussian	0.7	0.0	0.0	0.2
	Coarse Gaussian	33.5	4.0	7.5	26.9

Table 7 Comparative analysis with state-of-art

Study / Method	CNN / Feature extractor	Classifier	Dataset used	Accuracy (%)	Key findings
Nawaz et al. [11]	Deep feature extractor	ML Classifier	ADNI	94.50	Good stage detection but limited by shallow feature representation.
Choi et al. [12]	Custom CNN	Softmax	ADNI MRI	89.90	Performance affected by class imbalance and shallow architecture.
Borkar et al. [13]	Deep learning model	Softmax	ADNI MRI	92.00	Effective for early detection; sensitive to noise and requires heavy preprocessing.
Rana et al. [14]	DL model	Softmax	ADNI	95.70	Robust model but computationally expensive.
Shukla et al. [15]	PET + MRI fusion DL model	Ensemble classifier	ADNI	96.20	Fusion improves accuracy; ensemble adds complexity.
Sorour et al. [16]	Deep CNN	Softmax	ADNI MRI	93.80	Performs well but lacks interpretability.
Zhao et al. [17]	PET/MR DL network	Softmax	PET/MR Dataset	94.10	Multimodal approach effective but computationally heavy.
Shrivastava et al. [18]	Manual feature extraction	SVM / RF / XGBoost	OASIS	91.00	Traditional ML works but limited due to manual features.
Roncero-Parra et al. [19]	CNN	Softmax	Multi-hospital MRI	90.50	Good cross - site performance; accuracy affected by variability.
Zhang et al. [20]	sMRI-PatchNet	Softmax	ADNI	96.80	Patch-based model captures fine local features, improving accuracy.

4 Conclusions

DenseNet201 feature extraction and multi-kernel SVM classifier combined method was successfully implemented for diagnosis of AD progression. Our exhaustive experiments and analysis show that our method has promise in accurately diagnosing and classifying stages of Alzheimer's disease. In our research，our model achieved state-of-the-art performance with a testing accuracy of 99.8% and an AUC of 100%. Our model outperformed across all metrics achieving the highest True Positive Rate（TPR）and Positive Predictive Value（PPV）and the lowest False Negative Rate（FNR）and False Discovery Rate（FDR）for all stages of Alzheimer's progression. Training the DenseNet201 model took around 12 h using an NVIDIA GeForce RTX 3080 GPU. Inference time for a single image was approximately 1.5 s. As proved by our research，we were able to accurately diagnose and classify AD progression in a method that shows promise for clinical application. More testing in the form of large-scale clinical studies and real world experience is required for our approach to be implemented clinically.

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