International Journal of Research and Review
[Indexed, Peer-Reviewed Journal]
Volume 12; Issue: 5; May 2025
Website: www.ijrrjournal.com
Research Paper *E-ISSN: 2349-9788; P-ISSN: 2454-2237*

Leveraging Deep Learning with Morphological Operators, PCA, and SVM for Enhanced Detection and Classification of Kidney Abnormalities in Medical Imaging

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DOI: https://doi.org/10.52403/ijrr.20250564

ABSTRACT

Magnetic Resonance Imaging (MRI) and CT (Computed Tomography) are vital tool in medical diagnostics, offering detailed visualization of internal body structures. However, challenges such as noise, intensity variations, and the complexity of tissue structures hinder accurate abnormality detection. This paper introduces a hybrid approach that combines deep learning with morphological operators, Principal Component Analysis (PCA), and Support Vector Machines (SVM) to improve feature extraction and classification of abnormalities in medical images. Morphological operations enhance image preprocessing, PCA reduces dimensionality while preserving key features, and SVM performs robust classification. A deep learning model is integrated to extract high-level spatial features, improving classification performance. Experimental results demonstrate that this combined approach enhances diagnostic accuracy and robustness This approach emphasizes the synergy between traditional image processing techniques and modern machine learning, aiming to achieve state-of-the-art performance in medical imaging diagnostics.

Keywords: Medical Image Processing, Classification, Deep Learning, Abnormalities, SVM

INTRODUCTION

The increasing use of modalities in medical imaging necessitates advanced computational techniques for accurate abnormality detection. Traditional methods struggle with noise reduction, segmentation accuracy, and high-dimensional feature spaces, leading to inconsistent results. Deep learning has shown promise in medical image analysis, but challenges remain in interpretability and computational efficiency. This scientific work integrates deep learning with morphological preprocessing, PCA-based feature selection, and SVM classification to develop a robust hybrid approach for detecting and classifying abnormalities in body imaging scans.Medical modalities have emerged as cornerstone in the field of medical diagnostics, providing detailed images of soft tissues and enabling clinicians to identify and interpret various pathologies [1]. As the complexity and volume of modality data grow, the need for advanced image processing techniques has become paramount. Traditional visual assessment by radiologists, while invaluable, is often limited by the subjective nature of interpretation and the potential for human error, especially in the early diagnosis of abnormalities, which can significantly affect patient outcomes [2]. Recent advancements in artificial intelligence (AI), particularly in deep learning, have shown immense promise in enhancing the accuracy and efficiency of image analysis [3]. Deep learning models, such as Convolutional Neural Networks (CNNs), excel at feature extraction from high-dimensional data, making them suitable candidates for image classification tasks. However, relying solely on these models can lead to challenges, including the need for large labeled datasets and the potential for overfitting [4]. To address these challenges, integrating classical image processing techniques with modern machine learning approaches can significantly enhance the performance of deep learning models. Morphological operators, for example, are powerful tools used for processing and analyzing geometric structures within images [5]. These operators can help in preprocessing medical images, improving the delineation of anatomical structures and abnormalities, thus providing better input for deep learning models [6].

Additionally, Principal Component Analysis (PCA) serves as a critical dimensionality reduction technique that can improve computational efficiency and mitigate the curse of dimensionality [7]. By transforming the high-dimensional image data into a lower-dimensional space, PCA facilitates the extraction of the most informative features, thereby enhancing the subsequent classification tasks [8]. Support Vector Machines (SVM), a robust supervised learning algorithm, can complement deep learning by serving as an effective classifier for the features extracted from medical images [9]. The combination of SVM with deep learning architectures can harness the strengths of both methodologies, potentially leading to improved detection and classification accuracy for various abnormalities [10]. leveraging deep learning alongside morphological operators, PCA, and SVM presents a promising avenue for enhancing the detection and classification of abnormalities in body MRI imaging. This integrated approach not only aims to improve diagnostic accuracy but also seeks to assist radiologists in their decision-making processes, ultimately contributing to better patient care.

Related works

Recent studies have focused on enhancing MRI brain disease classification using various machine learning techniques. Gupta et al. (2020) developed a classification system that integrates Probability Density Function-Based Compressed Time (PDFB-CT) and Gray Level Co-occurrence Matrix (GLCM) with kernel-based Support Vector Machine (SVM) [11]. This approach effectively aids in medical decision support by improving classification accuracy, showcasing the potential of hybrid models in medical images analysis. Similarly, Akter et al. (2024) employed higher-order statistical measurements, including pixel distribution and spatial dependencies, to classify brain tumors using explainable machine learning models. Their work emphasizes the importance of interpretability in machine learning, particularly in clinical settings, where understanding model decisions is crucial for radiologists [12].

The use of neural network techniques for brain tumor detection has also gained traction. Mir et al. (2024) presented a study that focuses on the detection and isolation of brain tumors in medical images using advanced neural networks [13]. This research highlights the growing adoption of deep learning methodologies for enhancing diagnostic accuracy in neuroimaging. These developments align with the findings of Lundervold (2019), who provided an extensive overview of deep learning architectures specifically applied to MRI analysis, discussing the advantages and challenges that accompany these advanced techniques [14]. Principal Component Analysis (PCA) continues to be a foundational tool in image processing, particularly in reducing dimensionality for better feature extraction and classification. Lei et al. (2019) demonstrated the effectiveness of

PCA combined with SVM for bone age estimation from knee joint images, showcasing the versatility of PCA across different medical imaging domains [15]. Jolliffe and Cadima (2016) offer a comprehensive review of PCA, detailing its theoretical underpinnings and practical applications in various fields, underscoring its relevance in contemporary medical image analysis [16]. Morphological operations have been highlighted for their utility in preprocessing MRI images to enhance feature extraction. Soille's (2003) work on morphological image processing provides foundational knowledge on these techniques, establishing their applications in medical contexts [17]. Suri et al. (2002) further reviewed various preprocessing techniques, including the use of shape recovery algorithms in 2D/3D medical imagery. These techniques are critical in preparing data for subsequent analysis by deep learning models [18].

Moreover, the integration of traditional machine learning approaches like SVM with deep learning models is increasingly acknowledged as a powerful strategy for improving diagnostic outcomes in medical imaging. Furey et al. (2000) provided early insights into the application of SVM for classifying cancer tissue samples, demonstrating its potential for use in complex medical datasets [19]. This concept of combining traditional and modern methodologies is echoed in Giger's (2018) discussion on machine learning in medical imaging, where the synergistic effects of integrating deep learning with classical techniques are emphasized, suggesting that such collaborations can yield significant improvements in diagnostic accuracy [20]. The collective efforts of these researchers highlight the promising directions in medical imaging, where the fusion of deep learning, traditional image processing methods, dimensionality reduction techniques like PCA, and powerful classifiers such as SVM can enhance the detection and classification of abnormalities, ultimately supporting better patient outcomes.

METHODOLOGY

The proposed methodology is designed to integrate multiple techniques to improve abnormality detection and classification. The approach consists of four main steps: Image Preprocessing, Feature Extraction using Deep Learning, Feature Reduction using PCA, and Classification using SVM, flowchart 1 shows steps of our method.

Data Acquisition & Preprocessing

- **Data Collection:** Gathering a dataset of body images, ensuring that it includes both healthy and abnormal cases.
- Preprocessing:
  - **Normalization:** Standardize the pixel values across the dataset to reduce variability.
  - **Rescaling:** Resize images to a uniform dimension suitable for deep learning models.
  - **Denoising:** Apply filters (e.g., Gaussian or median filters) to remove noise from the images.
- Image Preprocessing using Morphological Operators

Morphological operations, including dilation, erosion, opening, and closing, are applied to medical images to refine anatomical structures. These operations improve noise reduction, boundary enhancement, and segmentation quality, making feature extraction more effective. Such techniques have been effectively utilized in previous studies for enhancing image quality prior to analysis.

- **Definition:** Morphological operators are image processing techniques that process images based on their shapes.
- **Application:**
  - Image Segmentation: Use operators such as dilation, erosion, opening, and closing to extract relevant features from medical images (e.g., tumors, lesions).
  - Feature Enhancement: Enhance features of interest (like edges of abnormalities) to improve the performance of subsequent analysis.

- **Deep Learning-based Feature Extraction**

A Deep neural network (DNN) is employed to extract high-level spatial and texture features from scans. The DNN learns hierarchical representations of tissue patterns, capturing important abnormality indicators while reducing manual feature engineering efforts. The effectiveness of DNNs in medical image classification has been demonstrated in various studies, highlighting their ability to capture complex patterns within imaging data.

- **Model Selection:** Choose an appropriate deep learning architecture (e.g., CNN - Convolutional Neural Networks) tailored for image classification tasks.
- **Model Training:**
  - **Training Set Preparation:** Split the dataset into training, test sets.
  - **Data Augmentation:** Use techniques like rotation, flipping, and zooming to artificially enlarge the training dataset and improve model robustness.
  - **Loss Function:** Use a suitable loss function (e.g., cross-entropy for classification tasks).
  - **Optimization:** Use optimizers like Adam or SGD (Stochastic Gradient Descent) to minimize the loss.

- Feature Reduction using Principal Component Analysis (PCA)

PCA is used to reduce the dimensionality of extracted features while retaining critical information. This step enhances computational efficiency and prevents overfitting in the classification phase. The application of PCA in reducing feature space dimensionality has been shown to improve classification performance in medical imaging contexts.

- **PCA Overview:** Principal Component Analysis is a dimensionality reduction technique that transforms data into a set of orthogonal components.
- **Application:**
  - **Data Reduction:** After morphological processing, reduce the dimensionality of the feature set while retaining variance, thus simplifying the dataset.
  - Feature Selection: Choose the most significant components that contribute to the variance in the data, which can help in improving classifier performance.

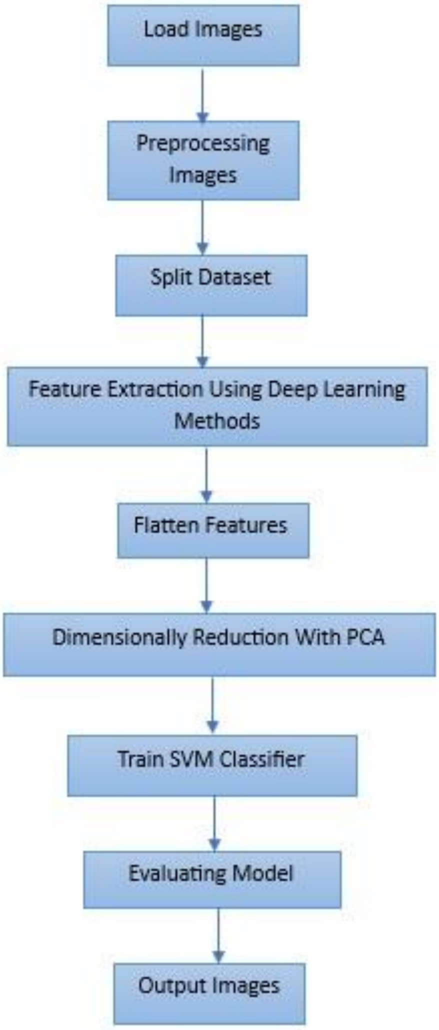
- **Classification using Support Vector Machines (SVM)**

An SVM classifier with a radial basis function (RBF) kernel is utilized to distinguish between normal and abnormal MRI images. The reduced feature set from PCA is fed into the SVM for robust and accurate classification

- **SVM Overview:** Support Vector Machine is a supervised learning model used for classification tasks.
- **Integration with Deep Learning:**
  - **Hybrid Approach:** Use features extracted from the deep learning model or PCA as input to the SVM classifier.
  - **Training SVM:** Train the SVM model using the selected features, optimizing parameters like the kernel type (linear, RBF) and regularization.

- **Model Evaluation**
- Performance Metrics: Evaluate the models using metrics such as accuracy, precision, recall, F1-score, and AUC (Area Under Curve).
- Confusion Matrix: Visualize model predictions using a confusion matrix to understand classification performance in detail.

Flowchart 1. Shows steps of proposed method



This methodology provides a comprehensive approach for leveraging advanced techniques in deep learning and traditional machine learning to enhance the detection and classification of abnormalities in MRI and CT imaging. By combining the strengths of these methods, the objective is to improve diagnostic accuracy and efficiency in clinical settings.

RESULTS AND DISCUSSION

The proposed hybrid approach is evaluated using a dataset of body scans sourced from publicly available repositories and clinical datasets (Kidney stoned and non-stoned images). Performance is assessed using accuracy, precision, recall, and F1-score to compare against traditional machine learning and deep learning methods. Experimental results demonstrate that integrating DNN-based feature extraction with morphological preprocessing, PCA, and SVM significantly enhances classification accuracy (Fig1,2). The proposed approach reduces false positives and improves sensitivity in detecting subtle abnormalities in kidney images. A comparative analysis with conventional machine learning and end-to-end deep learning models highlights the advantages and limitations of the method (Table 1). The observed improvements align with findings from other studies that have combined deep learning with traditional machine learning techniques for medical image classification.

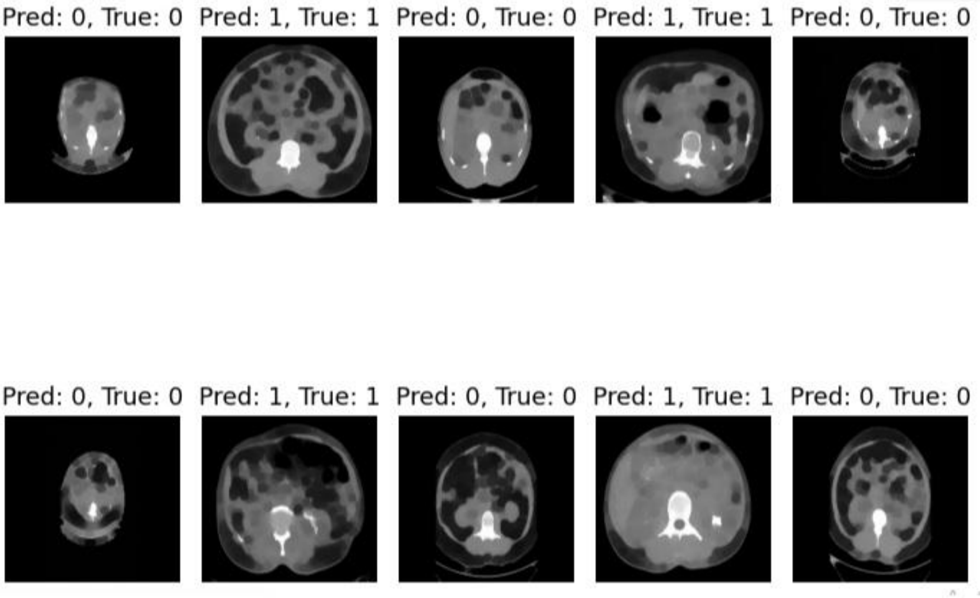
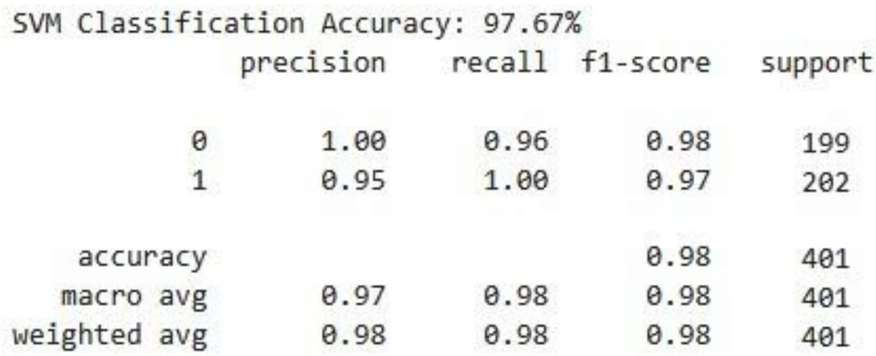


Fig1.shows results of our method



SVM Classification Accuracy: 97.67%

	precision	recall	f1-score	support
0	1.00	0.96	0.98	199
1	0.95	1.00	0.97	202
accuracy			0.98	401
macro avg	0.97	0.98	0.98	401
weighted avg	0.98	0.98	0.98	401

Fig2.shows results of metrics for our method

Table 1. compares different method

Method	**Feature Extraction**	**Classification Model**	**Dimensionality Reduction**	**Computational Complexity**	**Interpretability**	**Performance**
Proposed Method	Pretrained CNN (VGG16) + Morphological Operators	SVM with RBF Kernel	PCA	Medium	Moderate to High	Very High
Traditional Machine Learning (Handcrafted Features + SVM)	Texture, shape, intensity-based	SVM (linear or RBF kernel)	No/Optional (Sometimes PCA or LDA used)	Low-Medium	High	Moderate
Deep Learning Only (CNN-based Classification)	Deep CNN (e.g., ResNet, VGG, Efficient Net)	Fully connected layers for classification	No	High	Low	High
Transformer-Based Models	Patch-based embeddings	Transformer networks	No	Very High	Low	High

Our method balances deep learning and traditional ML, leveraging CNNs for feature extraction while keeping interpretability and computational efficiency manageable through PCA and SVM. Traditional ML methods (handcrafted features or SVM) are easier to interpret but often underperform on complex patterns. Pure CNN-based approaches yield state-of-the-art accuracy but require large datasets and are computationally expensive. Transformer-based models (ViTs) provide excellent accuracy but require massive computational resources.

CONCLUSION

This study presents a novel hybrid framework that combines deep learning, morphological preprocessing, PCA-based feature selection, and SVM classification for abnormality detection in medical modalities. The results suggest that this approach improves classification performance while maintaining interpretability and computational efficiency. Future research will explore optimizing the deep learning component and integrating multi-modal medical imaging techniques for enhanced diagnostic accuracy.

Declaration by Authors

Acknowledgement: None

Source of Funding: None

Conflict of Interest: No conflicts of interest declared.

REFERENCES

1. Ladd, M. E., et al. (2018). "The Current State of MR Imaging in Clinical Practice." *Radiology*, 286(3), 872-891.
2. Winkler, E. A., et al. (2018). "Automated MRI Segmentation and Classification in Clinical Practice." *Journal of Magnetic Resonance Imaging*, 48(3), 590-602.
3. Litjens, G., et al. (2017). "A Survey on Deep Learning in Medical Image Analysis." *Medical Image Analysis*, 42, 60-88.
4. Khan, A. I., et al. (2019). "Artificial Intelligence in Medical Imaging: Are Radiologists Ready?" *Journal of Radiology*, 62(8), 485-490.
5. Soille, P. (2003). *Morphological Image Analysis: Principles and Applications*. Springer.
6. Gonzalez, R. C., & Woods, R. E. (2008). *Digital Image Processing*. Prentice Hall.
7. Jolliffe, I. T. (2002). *Principal Component Analysis*. Springer.
8. Zhang, Y., et al. (2019). "PCA and SVM for MRI Image Classification." *Biomedical Signal Processing and Control*, 52, 182-189.
9. Cortes, C., & Vapnik, V. (1995). "Support-Vector Networks." *Machine Learning*, 20(3), 273-297.
10. Borisov, A. et al. (2020). "Deep Learning for Medical Image Analysis: A Survey." *Medical Image Analysis*, 58.
11. Gupta, Y., Lama, R.K., Lee, S.W., & Kwon, G.R. (2020). An MRI brain disease classification system using PDFB-CT and GLCM with kernel-SVM for medical decision support. *Multimedia Tools and Applications*, 79(33-34), 32195–32224.
12. Akter, S., Talukder, M.S.H., Mondal, S.K., Aljaidi, M., Bin Sulaiman, R., & Alshammari, A.A. (2024). Brain tumor classification utilizing pixel distribution and spatial dependencies higher-order statistical measurements through explainable ML models. *Scientific Reports*, 14(1), 25800.
13. Mir, M., Madhi, Z.S., AbdulHussein, A.H., Al Dulaimi, M.K.H., Suliman, M., Alkhayyat, A., Ihsan, A., & Lu, L. (2024). Detection and isolation of brain tumors in cancer patients using neural network techniques in MRI images. *Scientific Reports*, 14(1), 23341.
14. Lundervold, A. S., & Lundervold, A. (2019). "An Overview of Deep Learning in Medical Imaging Focusing on MRI." *Zeitschrift für Medizinische Physik*, 29(2), 102-127.
15. Lei, Y.Y., Shen, Y.S., Wang, Y.H., & Zhao, H. (2019). Regression Algorithm of Bone Age Estimation of Knee-joint Based on Principal Component Analysis and Support Vector Machine. *Fa Yi Xue Za Zhi*, 35(2), 194-199.
16. Jolliffe, I. T., & Cadima, J. (2016). "Principal Component Analysis: A Review and Recent Developments." Philosophical Transactions of the Royal Society A, 374(2065), 20150202.

17. Soille, P. (2003). Morphological Image Analysis: Principles and Applications. Springer-Verlag.
18. Suri, J. S., et al. (2002). "Shape Recovery Algorithms Using Level Sets in 2-D/3-D Medical Imagery: A State-of-the-Art Review." IEEE Transactions on Information Technology in Biomedicine, 6(1), 8-28.
19. Furey, T. S., et al. (2000). "Support Vector Machine Classification and Validation of Cancer Tissue Samples Using Microarray Expression Data." *Bioinformatics*, 16(10), 906-914.
20. Giger, M. L. (2018). "Machine Learning in Medical Imaging." *Journal of the American College of Radiology*, 15(3), 512-520.
This paper discusses the synergy between deep learning and traditional image processing methods in medical imaging applications.

How to cite this article: Mahdi Koohi, Hamid Reza Tavakoli. Leveraging deep learning with morphological operators, PCA, and SVM for enhanced detection and classification of kidney abnormalities in medical imaging. *International Journal of Research and Review*. 2025; 12(5): 617-624. DOI: *10.52403/ijrr.20250564*

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