ISBN: 978-981-94-1156-6
2024 the 14th International Workshop on Computer Science and Engineering (WCSE 2024)
doi: 10.18178/wcse.2024.06.001

Enhancing Diabetic Retinopathy Diagnosis through Symlet Wavelet-Integrated Convolutional Neural Networks

Songkiat Lowmunkhong[1], Ratapong Onjun[1], Sayan Kaennakham[2] and Kittirat Phattaramarut[3] +

[1] Department of Interdisciplinary Science and Internationalization, Institute of Science, Suranaree University of Technology, Nakhon Ratchasima, 30000, Thailand

[2] School of Mathematics and Geoinformatics, Institute of Science, Suranaree University of Technology, Nakhon Ratchasima, 30000, Thailand

[3] School of Diagnostic Radiology, Institute of Medicine, Suranaree University of Technology, Nakhon Ratchasima, 30000, Thailand

Abstract. This study evaluates the enhancement of Convolutional Neural Networks (CNNs) with Symlet wavelets for classifying fundus images in diabetic retinopathy research. Symlet wavelets (sym2 through sym8) significantly improved performance metrics over a traditional CNN. Notably, the sym6 model achieved 96% accuracy and 99% precision and recall. ROC analysis revealed substantial gains, with Class 1 attaining a perfect AUC of 1.00 using Symlet-6. This adaptation demonstrated better generalization and reduced overfitting, suggesting wavelet transformations as a robust method for improving diabetic retinopathy diagnosis through enhanced image classification.

Keywords: Convolutional Neural Networks (CNN), Symlet Wavelets, Diabetic Retinopathy, Fundus Imaging, Image Classification

1. Introduction

Medical imaging, which utilizes a range of sophisticated techniques, is crucial for the accurate diagnosis of diseases [1]. Among the well-known applications, Diabetic Retinopathy specifically targets the retina, playing a key role in managing diabetes-related eye conditions. The integration of deep machine learning into the analysis and interpretation of these images has significantly revolutionized these techniques, greatly enhancing their accuracy and effectiveness in the medical field [2]. Several deep-learning strategies are being developed and applied, with Convolutional Neural Networks (CNN) being one of the most widely used. In the architecture of Convolutional Neural Networks (CNNs) [3], the pooling layer plays a crucial role, which conventionally employs max pooling and average pooling, is crucial for enhancing network accuracy and convergence speed. However, these traditional methods often fail to retain essential high-frequency features for detailed image analysis. As a solution, wavelet pooling has been introduced to preserve these important details more effectively [4].

Different wavelet types are tailored for specific tasks, affecting their performance. Haar wavelets are excellent for edge detection due to their ability to handle sharp transitions, while Daubechies wavelets are preferred for audio processing because of their smooth variation handling. Meanwhile, biorthogonal wavelets are ideal for image compression due to their symmetric properties. Selecting the appropriate wavelet type is crucial for optimizing task performance [5].

Considering these aspects, this study is dedicated to assessing the efficacy of the Symlet wavelet within the framework of a Convolutional Neural Network (CNN) for the diagnosis of Diabetic Retinopathy. This was inspired by a previous work (unpublished) where Symlet stood out among the popular choices. We have developed a bespoke CNN architecture, incorporating the Symlet wavelet as a key component of our pooling strategy. Subsequent sections of this paper will delineate the essential elements of our research in detail.

+ Corresponding author. Tel.: 66-4422-3957.
E-mail address: kitirat.pear@sut.ac.th.

2. Backgrounds

2.1. Convolution Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) [6] are a type of deep neural network optimized for processing visual data. They consist of convolutional, pooling, and fully connected layers, as depicted in Figure 1, that automatically learn and detect patterns and features in images, making them ideal for tasks like image recognition and classification.

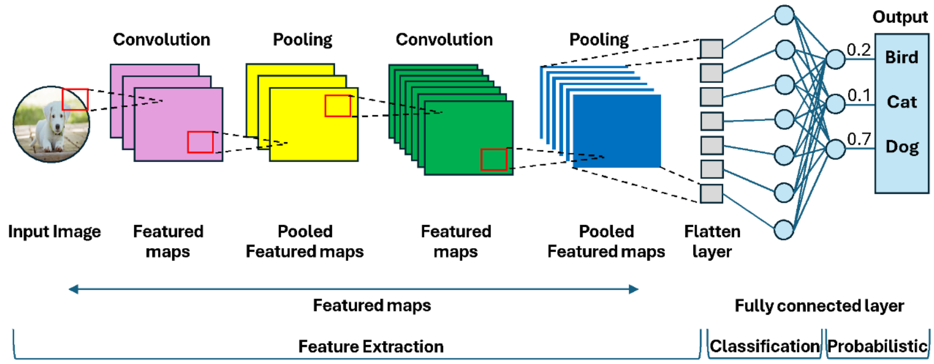

Fig. 1: Typical architecture of Convolutional Neural Networks (CNNs).

2.2. The Symlet Wavelets

Symlets are a family of wavelets, similar to Daubechies but designed to be more symmetric [7]. They are denoted as sym N where N is the order, influencing their smoothness and symmetry. The Symlet wavelets are characterized by their scaling function $\phi(t)$ and wavelet function $\psi(t)$, which adhere to the following relations. The scaling function is as follows

$$\phi(t) = \sqrt{2} \sum_{k=0}^{2N-1} h_k \phi(2t-k). \tag{1}$$

Where the corresponding wavelet function is expressed as follows.

$$\psi(t) = \sqrt{2} \sum_{k=0}^{2N-1} g_k \psi(2t-k). \tag{2}$$

Where h_k are the low-pass filter coefficients, and g_k are the high-pass filter coefficients, related by

$$g_k = (-1)^k h_{2N-1-k}. \tag{3}$$

The coefficients h_k and g_k are calculated to satisfy both orthogonality and symmetry constraints. Coefficients for Symlets are sourced from signal processing libraries or computed iteratively. The order, denoted by N, affects the number of vanishing moments, essential for detailed data representation. Higher order Symlets capture complex signals more effectively and provide smoother functions, enhancing performance in signal and image processing.

3. Methodology

3.1. Experimental Design

Using Python3, we developed a novel wavelet convolution neural network (WCNN) that merges wavelet transformation with CNN techniques. The models, trained end-to-end with ReLU activation, had a learning rate of 0.001 and a batch size of 128. Training involved 1,000 epochs from scratch using Categorical Cross-Entropy as the loss function.

3.2. Data Preparation

Figure 2 shows images representing a collection of fundus photographs [8], which are images of the interior surface of the eye. They depict the retina, optic disc, macula, and the posterior pole of the eyeball. The classification of fundus images have been done in 7 categories: 1. No DR signs (711 images), 2. Mild (or early) NPDR (6 images), 3. Moderate NPDR (110 images), 4. Severe NPDR (210 images), 5. Very Severe NPDR (139 images), 6. PDR (116 images) and 7. Advanced PDR (145 images).

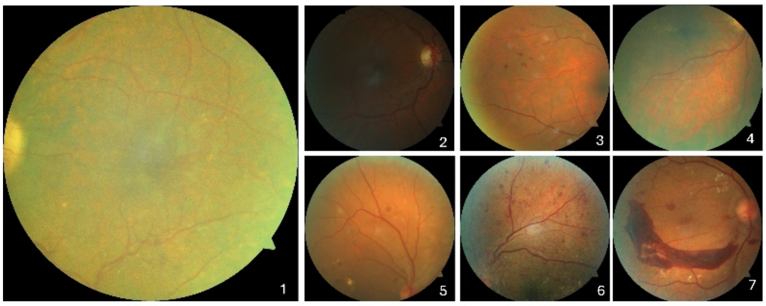

Fig. 2: Fundus images for the study of diabetic retinopathy.

4. Main Results and General Discussion

The results in Table 1 provide a comparative analysis of different Symlet wavelets incorporated into a 5-block Convolutional Neural Network (CNN) for performance evaluation, using traditional CNN (without wavelets) as a baseline. The findings illustrate a substantial improvement in all performance metrics (Accuracy, Precision, Recall, F-Measure) when Symlet wavelets are employed. Specifically, the Symlet-based models (sym2 through sym8) consistently outperformed the traditional model across all metrics. The traditional model achieved an accuracy of 82%, precision of 86%, recall of 87%, and an F-Measure of 85%. In contrast, the sym6 wavelet model exhibited the highest performance with an accuracy of 96%, precision and recall both at 99%, and an F-Measure of 99%. Notably, sym2, the simplest wavelet model, also showed significant improvement over the traditional model, achieving an accuracy of 93% and precision, recall, and F-Measure all at 99%.

Models incorporating higher order wavelets (sym4 through sym7) consistently demonstrated enhanced precision and recall (98-99%), suggesting that these wavelets can effectively capture and preserve important features in the data, which is crucial for achieving higher accuracy in tasks such as image classification. This performance improvement highlights the potential of integrating wavelet transformations within CNN architectures to enhance model efficacy, particularly in applications requiring high accuracy and robust feature detection capabilities.

Table 1: Comparative performance evaluation of batch size 128 using a 5-block CNN.

Model	Accuracy (%)	Precision (%)	Recall (%)	F-Measure (%)
Traditional (No wavelet)	0.82	0.86	0.87	0.85
sym2	0.93	0.99	0.99	0.99
sym3	0.91	0.98	0.97	0.98
sym4	0.94	0.98	0.98	0.98
sym5	0.95	0.98	0.98	0.98
sym6	0.96	0.99	0.99	0.99
sym7	0.95	0.99	0.99	0.99
sym8	0.94	0.95	0.95	0.95

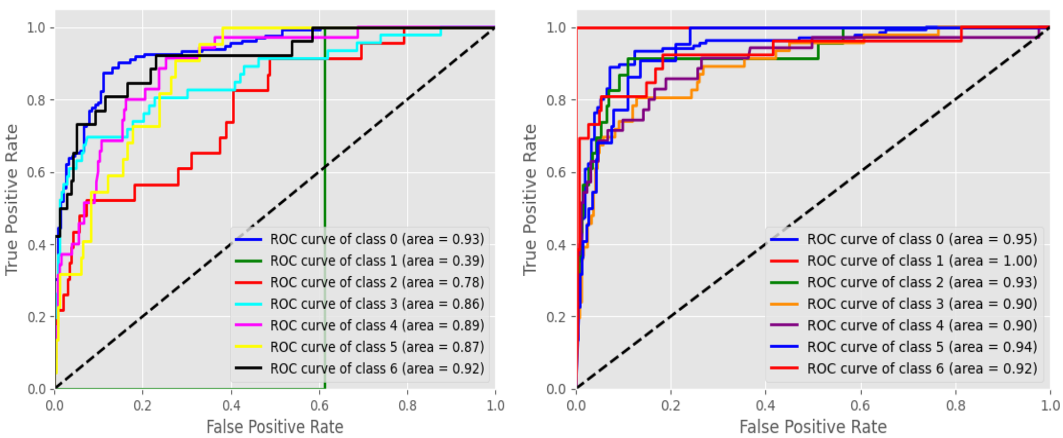

Fig. 3: The Receiver Operating Characteristic (ROC): Left) No wavelet, and Right) Symlet-6.

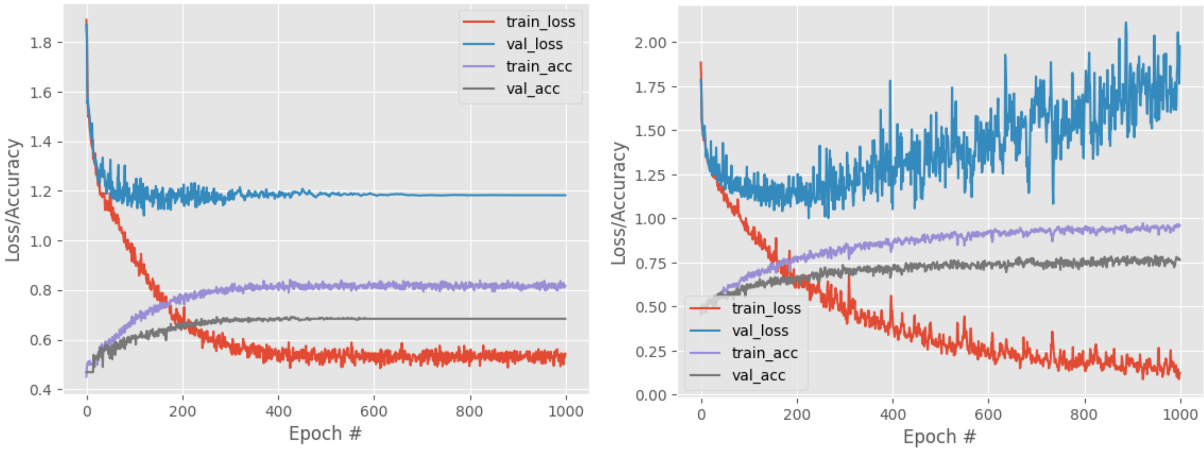

Fig. 4: The training and validation loss and accuracy: Left) No wavelet, and Right) Symlet-6.

The Receiver Operating Characteristic (ROC) curves in the graphs compare the performance of a Convolutional Neural Network (CNN) using no wavelets versus employing a Symlet-6 wavelet, Figure 3. The curves demonstrate the trade-off between true positive rate (TPR) and false positive rate (FPR) across different classes. With no wavelet, Class 0 and Class 6 exhibit strong performance with AUC values of 0.93 and 0.92, respectively, while Class 1 struggles with a low AUC of 0.39. Conversely, the Symlet-6 graph shows substantial improvements; Class 1 achieves a perfect AUC of 1.00, and other classes also improve, with AUCs ranging from 0.90 to 0.95. These results highlight the significant enhancement in classification ability when incorporating Symlet-6 into the CNN, particularly in effectively capturing features and improving class differentiation that the standard model fails to achieve.

The training and validation loss and accuracy graphs for CNN models trained without wavelets and with Symlet-6, Figure 4, demonstrate distinct differences in performance and generalization. For the model without wavelets, both training and validation losses decrease initially but diverge slightly as training progresses, indicating moderate overfitting with training accuracy stabilizing around 95% and validation accuracy around 90%. In contrast, the Symlet-6 model shows a more aligned decrease in both training and validation losses, suggesting better generalization, and both training and validation accuracies closely track each other, stabilizing at approximately 95% and 93% respectively. This suggests that the inclusion of Symlet-6 not only enhances overall accuracy but also improves the model's ability to generalize better to unseen data, demonstrating the effectiveness of incorporating wavelet transformations in reducing overfitting and capturing more relevant features for robust performance.

In a study of Symlet wavelets in a 5-block CNN, higher-order Symlets, particularly sym6, exhibited the best performance in terms of accuracy, precision, recall, and F-measure. This indicates that their complexity and smooth functions improve feature representation crucial for image processing tasks. However, sym7 and sym8 showed reduced performance, suggesting overfitting and diminishing returns. This underscores the importance of choosing the right wavelet order to balance computational efficiency and accuracy, ensuring model generalizability. Further investigation into the interaction between these wavelets and CNN architectures could optimize network design.

5. Conclusion

Integrating Symlet wavelets into CNN architectures markedly enhances their efficacy in classifying fundus images for diabetic retinopathy studies. The Symlet-6 wavelet notably excelled, significantly boosting model performance with top metrics, including 96% accuracy and near-perfect precision and recall. This study confirms the potential of Symlet wavelets to not only refine accuracy but also improve generalization across classes that traditionally underperform. The findings support enhancing CNNs with wavelets to balance computational efficiency and advanced feature detection in medical imaging. Future research should investigate adaptive wavelet techniques for dynamic parameter optimization, expand their use to MRI and CT scans, and develop hybrid models that integrate wavelets with advanced methods like deep reinforcement learning for improved diagnostics.

6. Acknowledgement

This work was supported by (i) Suranaree University of Technology (SUT, http://www.sut.ac.th), (ii) Thailand Science Research Innovation (TSRI, https://www.tsri.or.th), and (iii) National Science, Research and Innovation Fund (NSRF) (NRIIS number 179269). The grant recipient is S. Kaennakham who would like to express his sincere gratitude for their support.

7. References

[1] A. Mukhlif, B. Al-Khateeb, and M. Mohammed. An extensive review of state-of-the-art transfer learning techniques used in medical imaging: Open issues and challenges. *Journal of Intelligent Systems*. 2022, **31**(1): 1085-1111.

[2] M. Raiaan, K. Fatema. A Lightweight Robust Deep Learning Model Gained High Accuracy in Classifying a Wide Range of Diabetic Retinopathy Images. In M. A. K. Raiaan et al (eds.). *IEEE Access*. 2023, **11**: 42361-42388.

[3] J. Wu. Introduction to convolutional neural networks. *National Key Lab for Novel Software Technology. Nanjing University. China*. 2017, **5**(23): 495, 2017.

[4] R. Onjun, N. Duangkratoke, K. Sriwichai, and S. Kaennakham. Wavelet Pooling in Convolutional Neural Networks for Breast Cancer Detection with Ultrasound Images. In: Li, S. (eds). *Computational and Experimental Simulations in Engineering.* 2023, **13**: 709-720.

[5] T. Guo, T. Zhang, E. Lim, M. Lopez-Benitez, F. Ma, and L. Yu. A review of wavelet analysis and its applications: Challenges and opportunities. *IEEE Access*, 2022, **1**(10): 58869-58903.

[6] N. Ketkar, J. Moolayil, N. Ketkar, and J. Moolayil. *Convolutional neural networks*. Deep Learning with Python: Learn Best Practices of Deep Learning Models with PyTorch, 2021.

[7] C. Hurley. *Wavelet: Analysis and Methods*. Scientific e-Resources, 2018.

[8] V. Castillo Benítez, I. Matto, J. Mello Román, J. Vázquez Noguera, M. García-Torres, J. Ayala, D. Pinto-Roa, P. Gardel-Sotomayor, J. Facon, and S. Grillo. Dataset from fundus images for the study of diabetic retinopathy. *Data in Brief*. 2021, **36**: p.107068.