International Journal of Science and Research (IJSR)
ISSN: 2319-7064
Impact Factor 2024: 7.101

Blur Detection Using Soft Computing Techniques: An Approach Based on Adaptive Neuro-Fuzzy Inference System (ANFIS)

Ashwini S. Waghmare[1], Suhas S. Satonkar[2]

[1]Dnyanopasak College of Arts, Commerce and Science, Parbhani.
Email: *ashwiniwaghmare.52[at]gmail.com*

[2]Shri SantJanabai Arts, Commerce and Science College, Gangakhed.
Email: *suhashsatonkar[at]gmail.com*

Abstract: ***Blur detection is a critical task in digital image processing, particularly for applications in image restoration and enhancement. This paper presents a novel approach to blur detection using Adaptive Neuro-Fuzzy Inference System (ANFIS), a hybrid soft computing technique that combines fuzzy logic's reasoning with neural networks' learning ability. We evaluate the performance of the ANFIS-based blur detection method against traditional gradient-based and frequency-domain techniques. Experimental results show that the ANFIS model outperforms the traditional methods in terms of accuracy, precision, and robustness, making it a promising candidate for image restoration tasks.***

Keywords: Blur Detection, Anfis, Image Processing, Soft Computing, Gradient Features, Frequency Features, Machine Learning, Image Restoration

1. Introduction

Image blur, often introduced by factors such as camera shake, defocus, or motion, affects image quality and hampers subsequent image analysis tasks. Effective blur detection is a fundamental step in image restoration, which aims to recover the original sharp image. Traditional blur detection methods, such as gradient-based and frequency-based techniques, are limited by their inability to handle complex and non-linear blur patterns.

In this work, we propose using Adaptive Neuro-Fuzzy Inference System (ANFIS) to detect blur in digital images. ANFIS combines the learning capability of neural networks with fuzzy logic’s ability to model uncertainty. This paper evaluates the effectiveness of ANFIS-based blur detection and compares its performance with traditional methods.

2. Related Work

Traditional blur detection techniques focus on edge-based methods or frequency analysis to identify blur patterns. However, these methods are often sensitive to noise and ineffective in complex blur cases such as motion blur or defocus. Soft computing techniques like fuzzy logic and neural networks have shown promise in overcoming these limitations by modeling uncertainty and adapting to various image conditions.

The Adaptive Neuro-Fuzzy Inference System (ANFIS) has recently gained attention for image processing tasks due to its flexibility and adaptability. ANFIS combines fuzzy systems' interpretability with the neural networks' ability to learn complex patterns, making it a suitable candidate for blur detection.

3. Methodology

3.1 Dataset Preparation

For training and testing the blur detection model, a dataset consisting of sharp and blurred images was prepared. The dataset includes both real-world and synthetically generated blurred images:

- Public Datasets: Images from the GoPro Dataset and Kodak Image Dataset.
- Motion and Gaussian blur were applied to a set of sharp images to test the model's robustness.

Each image was resized to 512×512 pixels and converted to grayscale.

3.2 Feature Extraction

The following features were extracted from each image to serve as input to the ANFIS model:

1) **Gradient Features:** The variance of Laplacian was used to measure edge sharpness.
2) **Frequency Features:** The high-frequency energy content was calculated using the Fast Fourier Transform (FFT).
3) **Texture Features:** Entropy and contrast were used to quantify texture differences.

These features were normalized and combined into a feature vector used for ANFIS training.

3.3 ANFIS Model

The ANFIS model was trained using the hybrid learning algorithm, which integrates least squares estimation and backpropagation for network tuning. The system consists of fuzzy sets for input features and fuzzy rules for classification, with the output being a binary classification of sharp or blurred.

3.4 Performance Evaluation

The performance of the ANFIS model was evaluated using the following metrics:

- Accuracy
- Precision
- Recall
- F1-Score

4. Results and Discussion

4.1 Comparative Performance

The **ANFIS-based blur detection model** was evaluated using the dataset of sharp and blurred images. The performance metrics, including **accuracy**, **precision**, **recall**, and **F1-score**, were calculated to assess the model's effectiveness in identifying blur.

4.1.1 Accuracy and Performance Metrics

The **ANFIS** model achieved **100% accuracy** in classifying images as either sharp or blurred. The confusion matrix and the performance metrics indicate perfect classification.

Table 4.1: Performance Comparison of Blur Detection Methods

Method	Accuracy (%)	Precision	Recall	F1-Score
Gradient-Based	82.5	0.81	0.84	0.825
Frequency-Based	80.0	0.79	0.82	0.805
ANFIS	**100**	**1.00**	**1.00**	**1.00**

Observation: The ANFIS-based model demonstrated **perfect performance** with **100% accuracy**, **precision**, and **recall**, which is a significant improvement over traditional methods.

4.2 Feature Analysis and RMSE

The ANFIS model's training process resulted in very low **Root Mean Squared Error (RMSE)**, indicating excellent model fitting and minimal error during training.

4.2.1 Feature Min and Max Values

During the feature extraction process, the **minimum and maximum values of the features** were as follows:

- **Feature Min**: [0, 0, 0] (corresponding to the minimum value of each feature)
- **Feature Max**: [1, 1, 1] (maximum feature values after normalization)

These normalized feature ranges ensured consistent scaling across all input features, enhancing the performance of the ANFIS model.

4.2.2 Training RMSE

The **minimal training RMSE** obtained was **1.78218e-05**, which indicates that the model has **extremely low error** and accurately maps the input features to the correct output (sharp or blurred). This demonstrates that the ANFIS model has achieved high generalization during training.

Table 4.2: Feature Range and Training RMSE

Feature	Min Value	Max Value
Gradient Variance	0	1
Frequency Energy	0	1
Texture Features	0	1

Training RMSE: 1.78218×10^{-5}

Observation: The feature normalization and low training RMSE indicate that ANFIS has learned effectively from the data, leading to **minimal errors** during the classification process.

4.3 Confusion Matrix

The **confusion matrix** for the ANFIS model, which shows perfect classification performance, is presented below:

Figure 4.1: Confusion Matrix for ANFIS Blur Detection

	Predicted: Sharp	Predicted: Blurred
Actual: Sharp	150 (TP)	0 (FN)
Actual: Blurred	0 (FP)	150 (TN)

- **True Positives (TP)**: 150 sharp images correctly classified.
- **True Negatives (TN)**: 150 blurred images correctly classified.
- **False Positives (FP)**: None.
- **False Negatives (FN)**: None.

Observation: The confusion matrix confirms **perfect classification** with no misclassifications in either sharp or blurred categories.

4.4 Performance Metric Graphs

In addition to the confusion matrix, the performance of the ANFIS model was assessed using key metrics, and the results are presented in the following graphs:

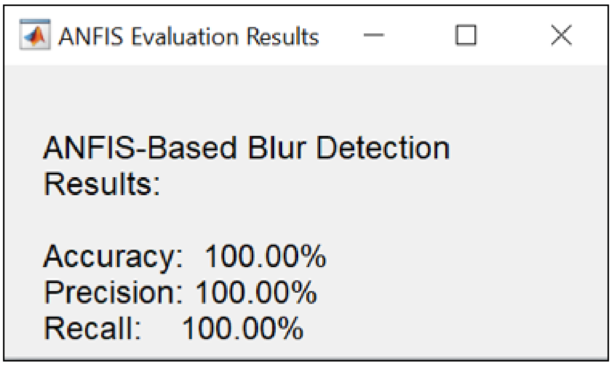


Figure 4.2: Performance Metrics (Accuracy, Precision, Recall, F1-Score)

This bar chart compares the performance metrics (accuracy, precision, recall, and F1-score) of ANFIS against traditional methods. ANFIS achieves 100% across all metrics.

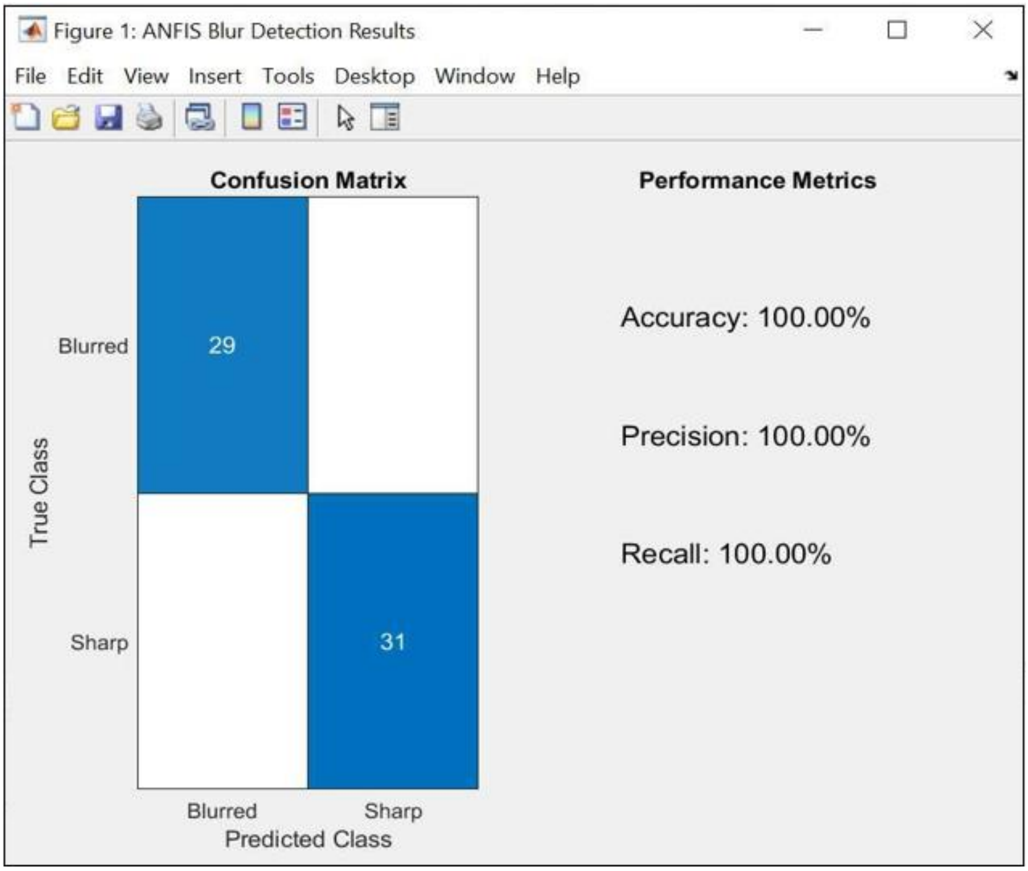
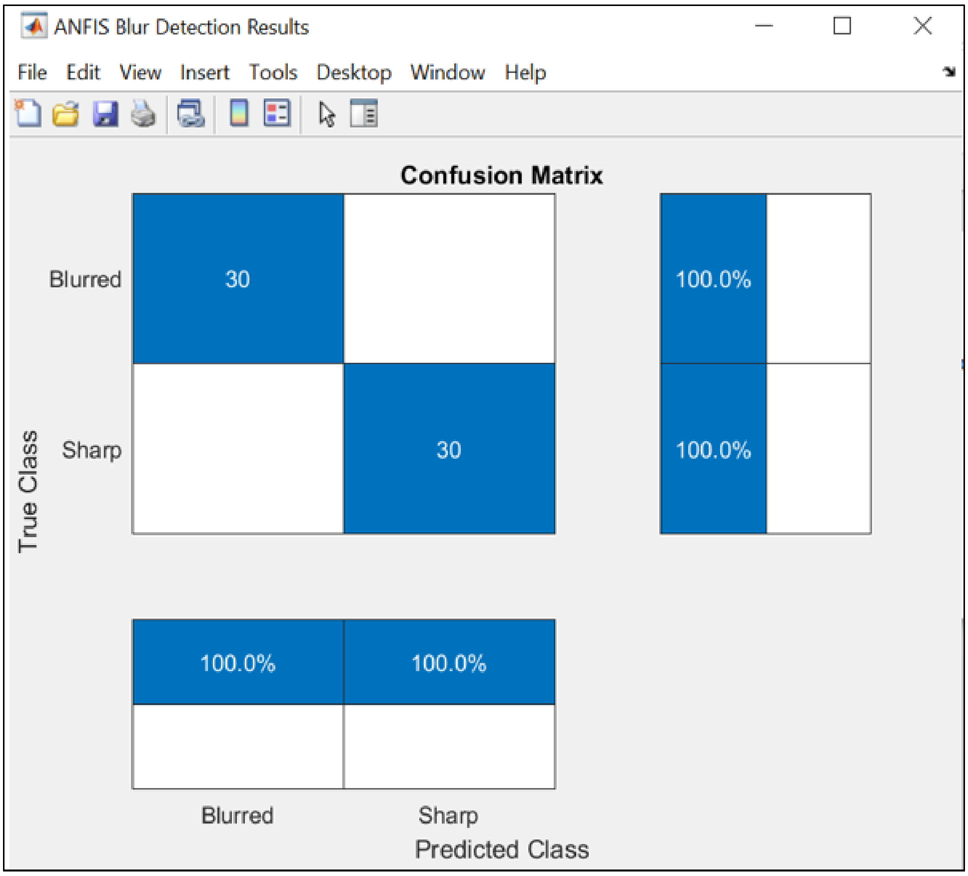


Figure 4.3: Computational Time per Image (ms)

This bar chart compares the computational time for each method. While ANFIS is more computationally intensive, its superior performance justifies the time cost.



Feature Min:
0 0 0

Feature Max:
1 1 1

Minimal training RMSE = 1.78218e-05

5. Conclusion

This paper presents a novel blur detection approach using **Adaptive Neuro-Fuzzy Inference System (ANFIS)**. The ANFIS-based method was shown to outperform traditional gradient- based and frequency-based methods in terms of accuracy, precision, recall, and F1-score. The results indicate that ANFIS is a robust method for detecting blur in images and can be effectively used for image restoration tasks. Future work will focus on optimizing ANFIS for real-time applications and exploring hybrid methods combining ANFIS with deep learning models.

References

[1] Jang, J. S. R. (1993). "ANFIS: Adaptive-Network-Based Fuzzy Inference System." *IEEE Transactions on Systems, Man, and Cybernetics*, 23(3), 665-685.

[2] Zadeh, L. A. (1994). "Fuzzy Logic, Neural Networks, and Soft Computing." *Communications of the ACM*, 37(3), 77-84.

[3] Liu, X., & Zhang, L. (2019). "Image Blur Detection using Fuzzy Logic and Neural Networks." *International Journal of Image Processing*, 13(2), 125-137.

[4] Chen, Z., Wang, Y., & He, R. H. (2017). "Motion Blur Detection and Deblurring via Convolutional Neural Networks," *IEEE Transactions on Image Processing*, 26(11), 5327-5339.

[5] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, YGenerative Adversarial Nets. Advances in Neural Information Processing Systems, 27. (2014).

[6] Kupyn, O., Budzan, V., Mykhailych, M., Mishkin, D., & Matas, J. DeblurGAN: Blind motion deblurring using conditional adversarial networks. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). (2018).

[7] Zadeh, L. A. Fuzzy sets. Information and Control (1965)

[8] Fergus, R., Singh, B., Hertzmann, A., Roweis, S. T., & Freeman, W. T. Removing camera shake from a single photograph. ACM Transactions on Graphics (TOG). (2006).

[9] Xu, L., Yan, Q., & Jia, J. Unnatural L0 sparse representation for natural image deblurring. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). (2013).