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Article

Edge-Preserving Multi-Scale Texture Enhancement and Intelligent Feature Selection for High-Accuracy Image Classification

D. Jeyakumari[1], M. Pavithra[2], S. Priya[3], Chinnathambi Kamatchi[4]

[1]Department of Electronics and Communication Engineering, Hindusthan Institute of Technology, Coimbatore, Tamil Nadu, India.
Email: dr.jeyakumari.d@hit.edu.in; dgjeyakumari@gmail.com
ORCID: 0000-0003-3212-000X
[2]Department of Electronics and Communication Engineering, V.S.B. College of Engineering Technical Campus, Coimbatore, Tamil Nadu, India.
Email: pavithravsb2026@gmail.com
[3]Department of Computer Science and Engineering, Nehru Institute of Engineering and Technology, Coimbatore, Tamil Nadu, India.
Email: priyasharmila6@gmail.com
ORCID: 0000-0002-8841-4915
[4]Department of Computer Science and Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, Tamil Nadu, India.
Email: k.chinnathambimku@gmail.com
ORCID: 0000-0001-5694-3647

Abstract: Accurate image classification remains a critical challenge in computer vision due to variations in illumination, noise, and complex texture distributions. This paper presents an Edge-Preserving Multi-Scale Texture Enhancement with Intelligent Feature Selection (EMTE-IFS) framework to improve classification performance. Initially, a multi-scale texture enhancement mechanism is applied to extract both fine and coarse-grained features from input images. An edge-preserving filtering technique is incorporated to retain important structural boundaries while suppressing noise and irrelevant variations, thereby improving feature quality. Subsequently, an intelligent feature selection strategy is employed to identify the most discriminative and non-redundant features from the enhanced feature space. This process reduces dimensionality and computational overhead while maintaining high representational efficiency. The optimized feature subset is then utilized by a robust classification model to achieve superior predictive performance. Experimental results on benchmark datasets demonstrate that the proposed EMTE-IFS framework achieves significant improvements in classification accuracy, precision, recall, and F1-score compared to existing methods. Furthermore, the model exhibits strong robustness under noisy and varying environmental conditions. The proposed approach is well-suited for real-world applications including medical image analysis, remote sensing, and object recognition systems.

Keywords: Edge-preserving filtering, Multi-scale texture enhancement, Intelligent feature selection, Image classification, Feature optimization, High-accuracy classification

1. Introduction

Image classification has become one of the most significant research areas in computer vision due to its wide range of applications in medical diagnosis, autonomous vehicles, industrial inspection, agriculture, surveillance, and remote sensing systems. The rapid advancement of deep learning and image processing techniques has substantially improved classification accuracy; however, several challenges such as noise, low contrast, texture ambiguity, edge distortion, and redundant feature extraction still limit the performance of intelligent classification frameworks [1]. In many practical scenarios, images contain complex structural and texture information that must be preserved carefully to ensure reliable feature representation and accurate decision-making.

Traditional image enhancement approaches mainly focus on contrast improvement and noise suppression, but they often fail to preserve important edge and texture information during preprocessing [2]. Edge information plays a vital role in identifying object boundaries, while texture characteristics contribute significantly to discriminating similar image categories. Therefore, preserving edge structures while simultaneously enhancing multi-scale textures has become an essential requirement for modern image classification systems [3]. Conventional filtering and smoothing methods may remove critical high-frequency information, leading to loss of discriminative features and degraded classification performance.

Multi-scale texture enhancement techniques have recently gained considerable attention because they can effectively analyze image structures at different spatial resolutions [4]. By extracting texture representations from multiple scales, these approaches improve the visibility of fine-grained details and enhance the robustness of feature extraction. However, excessive enhancement may introduce artifacts and amplify noise, which negatively affects classifier performance [5]. To overcome this limitation, edge-preserving enhancement mechanisms are increasingly integrated with texture analysis frameworks to maintain structural consistency while improving feature distinctiveness.

Recent advances in machine learning and deep neural networks have enabled highly efficient feature learning mechanisms for image classification tasks [6]. Although deep architectures can automatically learn hierarchical representations, they often generate a large number of redundant and irrelevant features that increase computational complexity and reduce model interpretability [7]. Intelligent feature selection techniques are therefore essential to identify the most informative attributes and eliminate unnecessary features from high-dimensional feature spaces. Optimization-driven feature selection algorithms help improve classification accuracy, reduce overfitting, and minimize computational overhead [8].

Several researchers have explored hybrid image enhancement and feature optimization frameworks to improve classification efficiency. Nevertheless, many existing methods focus either on enhancement or feature selection independently, without considering their mutual influence on classification performance [9]. Moreover, existing systems often struggle to preserve edge continuity during enhancement, leading to inaccurate texture representation and poor feature extraction. These limitations motivate the development of integrated frameworks that combine edge-preserving multi-scale enhancement with intelligent feature selection strategies for robust image classification.

In this work, an Edge-Preserving Multi-Scale Texture Enhancement and Intelligent Feature Selection framework is proposed for high-accuracy image classification. The proposed approach first performs edge-aware texture enhancement to improve image quality while maintaining structural details. Subsequently, discriminative deep and handcrafted features are extracted from enhanced images, followed by an intelligent feature selection mechanism to identify the optimal feature subset for classification. The integration of enhancement and optimization improves feature representation capability, reduces redundant information, and increases classification reliability across diverse image datasets [10].

The major contributions of the proposed work are summarized as follows:

1. An edge-preserving multi-scale texture enhancement mechanism is introduced to improve image clarity while maintaining structural integrity.
2. A hybrid feature extraction strategy is employed to capture both texture and deep semantic information.
3. An intelligent optimization-based feature selection approach is developed to remove redundant features and improve classification efficiency.
4. The proposed framework enhances classification accuracy, robustness, and computational performance compared with conventional methods.
5. Extensive experimental analysis demonstrates the effectiveness of the proposed system for high-accuracy image classification applications.

2. Related Work

Image enhancement and intelligent feature optimization have attracted significant attention in recent years due to their crucial role in improving image classification performance. Researchers have developed numerous enhancement, texture analysis, and feature selection techniques to improve discriminative capability while reducing computational complexity. Traditional image classification approaches mainly relied on handcrafted texture descriptors and statistical feature extraction methods for object recognition and scene understanding [11]. These methods demonstrated reasonable performance for controlled datasets but often failed under varying illumination, noise, and complex background conditions.

Texture analysis has been widely used to improve classification performance because texture information provides valuable structural and spatial characteristics from images. Kiani et al. presented a comprehensive survey on texture features in medical image analysis and emphasized that texture descriptors combined with deep features significantly improve classification accuracy in complex imaging applications [12]. Similarly, Lu and Weng reviewed various image classification methods and highlighted the importance of spectral, spatial, and texture information for reliable image categorization [13]. Their findings showed that integrating multiple image characteristics improves classification robustness compared with single-feature approaches.

Edge-preserving enhancement methods have also gained importance in image preprocessing. Conventional enhancement techniques often increase contrast at the expense of edge distortion and noise amplification. Recent low-light enhancement and super-resolution methods utilize edge-aware mechanisms to preserve structural details during enhancement [14]. Multi-scale enhancement frameworks further improve image representation by capturing texture information at different spatial resolutions, enabling better feature discrimination for classification tasks [15]. However, many of these methods introduce computational overhead and redundant feature generation.

Deep learning techniques have substantially transformed image classification systems by enabling automatic hierarchical feature extraction. Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) have demonstrated remarkable success in texture recognition and object classification applications [16]. Geirhos et al. revealed that CNN-based models are highly texture-biased and showed that shape-aware feature learning improves robustness and classification performance [17]. This observation motivated researchers to develop enhancement strategies that preserve both texture and edge structures simultaneously.

Feature selection has become another critical research area for reducing dimensionality and improving classifier efficiency. Bolón-Canedo et al. surveyed several feature selection techniques for image analysis and reported that optimization-based selection methods effectively eliminate redundant and irrelevant features from high-dimensional datasets [18]. ReliefF, SVM-RFE, and evolutionary optimization algorithms have been widely applied to improve feature ranking and classification accuracy [19]. These approaches reduce computational complexity while maintaining strong discriminative capability for image recognition systems.

Recent studies have attempted to integrate image enhancement, texture analysis, and intelligent feature optimization into unified classification frameworks. Hybrid systems combining enhancement methods with deep learning and optimization algorithms have shown promising improvements in classification accuracy across medical imaging, remote sensing, industrial inspection, and surveillance applications [20]. Nevertheless, many existing methods still suffer from limitations such as excessive feature redundancy, loss of fine edge information, and high computational requirements. Therefore, an efficient framework that simultaneously performs edge-preserving texture enhancement and intelligent feature selection is necessary for achieving high-accuracy image classification with improved robustness and computational efficiency.

3. Design of the Proposed Work

The proposed **Edge-Preserving Multi-Scale Texture Enhancement and Intelligent Feature Selection Framework** is designed to improve image classification accuracy by integrating advanced preprocessing, texture enhancement, discriminative feature extraction, intelligent feature optimization, and robust classification mechanisms. The overall framework focuses on preserving structural edge information while enhancing multi-scale texture characteristics to generate highly informative feature representations for classification.

The architecture of the proposed system consists of the following major stages:

1. Image Acquisition and Preprocessing
2. Edge-Preserving Multi-Scale Texture Enhancement
3. Hybrid Feature Extraction
4. Intelligent Feature Selection

5. Classification and Decision Making

The complete workflow of the proposed framework is illustrated conceptually in Figure 1.

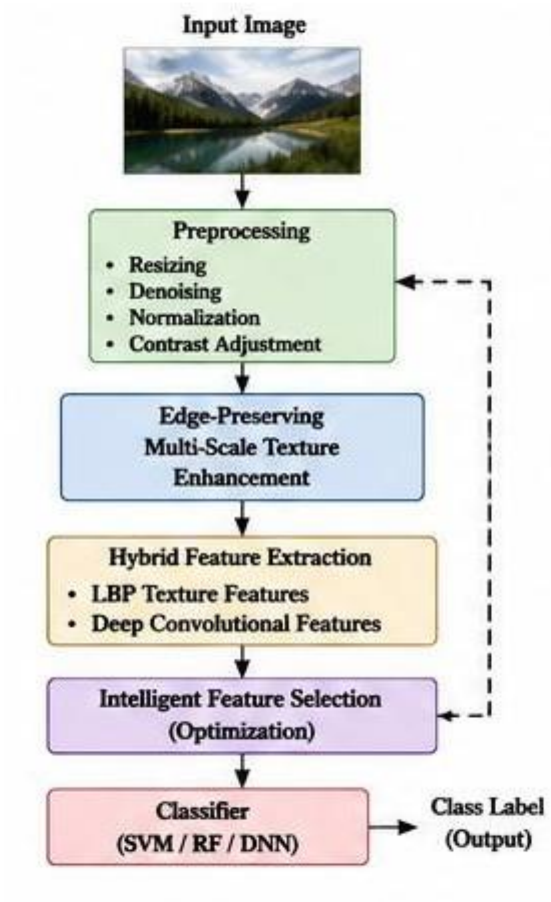


Figure 1. Overall Architecture of the Proposed Image Classification Framework

This figure illustrates the complete workflow of the proposed Edge-Preserving Multi-Scale Texture Enhancement and Intelligent Feature Selection framework. The architecture includes preprocessing, multi-scale enhancement, edge preservation, hybrid feature extraction, intelligent feature optimization, and final classification stages. The framework is designed to improve image quality and classification accuracy while reducing redundant features and computational complexity.

3.1 Image Acquisition and Preprocessing

Initially, the input images are collected from benchmark image datasets or real-time imaging environments. Since raw images may contain noise, illumination variations, blur, and contrast inconsistencies, preprocessing is performed to improve image quality before feature extraction.

The preprocessing stage includes:

- Image resizing
- Noise removal
- Contrast normalization
- Intensity adjustment|
- Color space conversion

Median filtering is employed for removing impulsive noise while preserving edge continuity. Let the input image be represented as:

$$I(x, y)$$

where x and y denote spatial coordinates. The preprocessed image is represented as:

$$I_p(x, y) - F(I(x, y))$$

where $F(\cdot)$ represents the preprocessing operation.

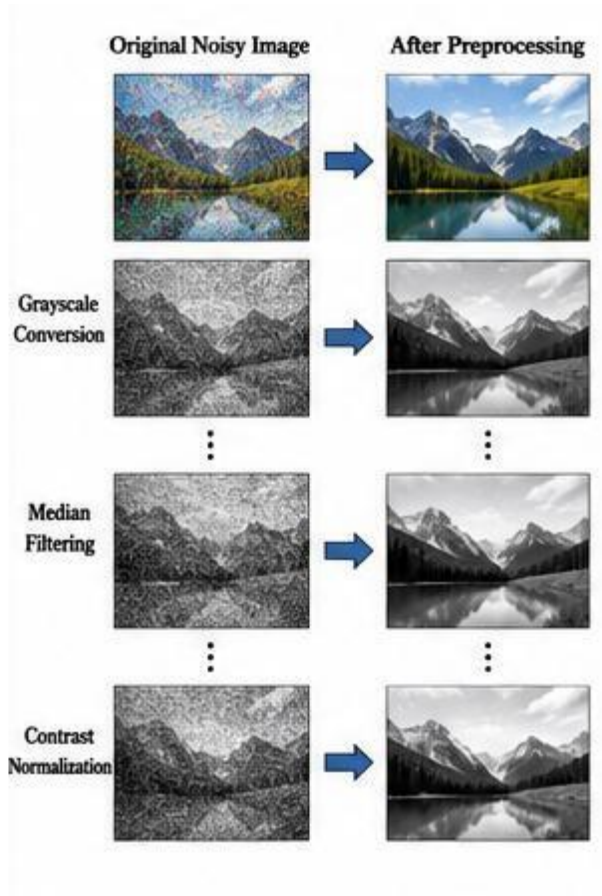


Figure 2. Image Preprocessing and Noise Removal Process

This figure presents the preprocessing stage of the proposed system, including image resizing, normalization, contrast enhancement, and median filtering. The preprocessing operation removes unwanted noise and improves image consistency before enhancement and feature extraction. The figure highlights the improvement in image clarity after preprocessing.

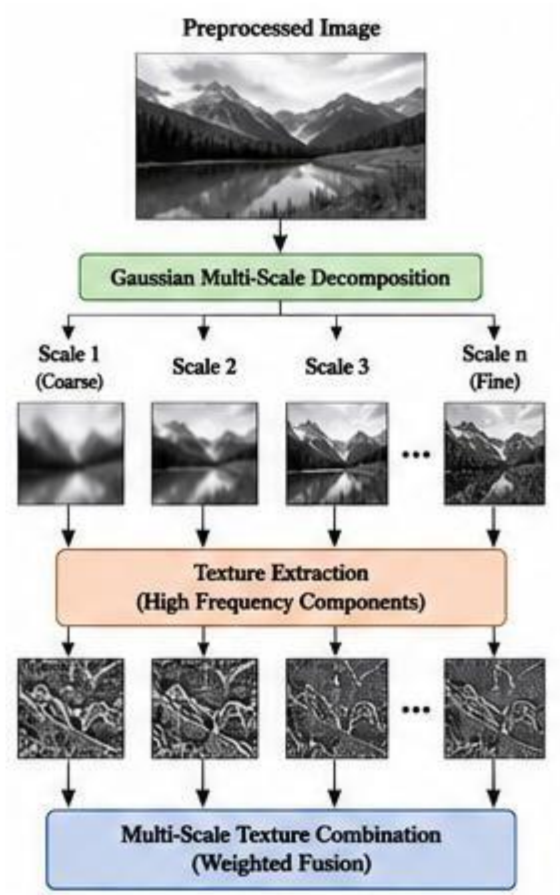


Figure 3. Multi-Scale Texture Decomposition Framework

This figure shows the decomposition of input images into multiple spatial scales using Gaussian filtering. Different texture levels are extracted from coarse and fine resolutions to capture detailed structural information. The multi-scale analysis improves feature discrimination and enables accurate texture representation.

3.2 Edge-Preserving Multi-Scale Texture Enhancement

The enhanced representation of image textures is essential for extracting discriminative features. In the proposed method, a multi-scale enhancement strategy is integrated with edge-preserving filtering to improve texture visibility without distorting structural information.

A Gaussian multi-scale decomposition is first performed to generate image representations at different spatial scales:

$$G_s(x,y) - I_p(x,y) * \mathcal{G}_{\sigma_s}(x,y)$$

where:

- $G_s(x,y)$ denotes the image at scale s
    - o represents convolution
- $\mathcal{G}_{\sigma_s}$, is the Gaussian kernel with standard deviation σ_s

Texture details are extracted using high-frequency decomposition:

$$T_s(x,y) - I_p(x,y) - G_s(x,y)$$

The extracted textures from different scales are combined to form enhanced texture information:

$$T_{enh}(x,y) - \sum_{s-1}^{n} w_s T_s(x,y)$$

where:

- w_s denotes the weight assigned to scale s
- n represents the total number of scales

To preserve important edge structures, bilateral filtering is integrated into the enhancement process:

$$I_e(x,y) - \frac{1}{W_p} \sum_{q \in \Omega} I_p(q) f_r(\|I_p(q) - I_p(p)\|) f_s(\|q - p\|)$$

where:

- f_r represents range filtering
- f_s represents spatial filtering
- W_p is the normalization factor

This mechanism enhances textures while maintaining edge continuity and reducing artifact generation.

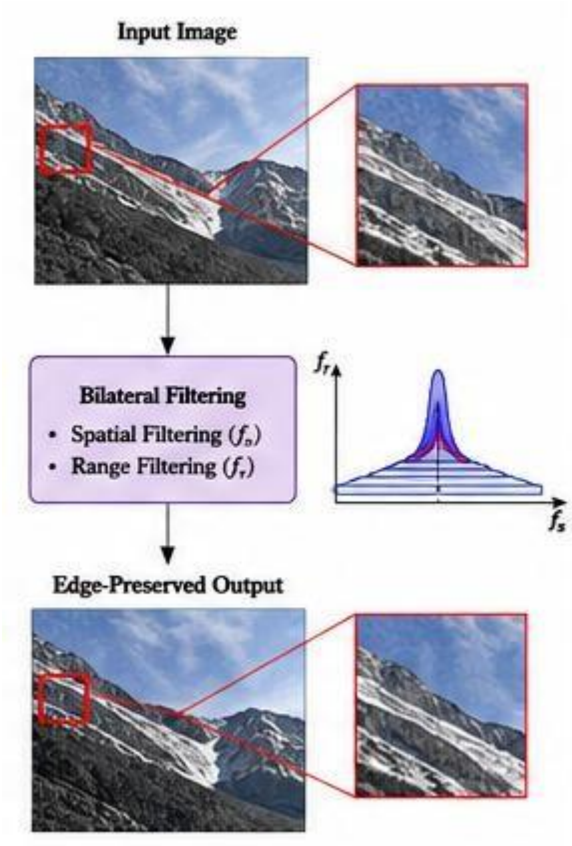


Figure 4. Edge-Preserving Bilateral Filtering Mechanism

This figure illustrates the edge-preserving enhancement strategy used in the proposed framework. The bilateral filtering mechanism smooths homogeneous regions while preserving sharp edge structures. The figure demonstrates how structural boundaries are retained without introducing distortion or excessive smoothing.

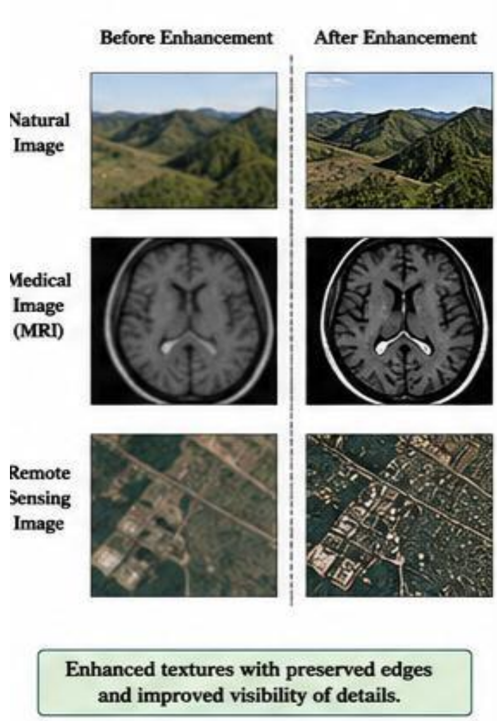


Figure 5. Enhanced Texture Representation after Edge Preservation

This figure presents the enhanced image generated after combining multi-scale texture enhancement with edge-preserving filtering. Fine texture details become more visible while maintaining structural continuity. The enhanced representation improves discriminative feature extraction for classification.

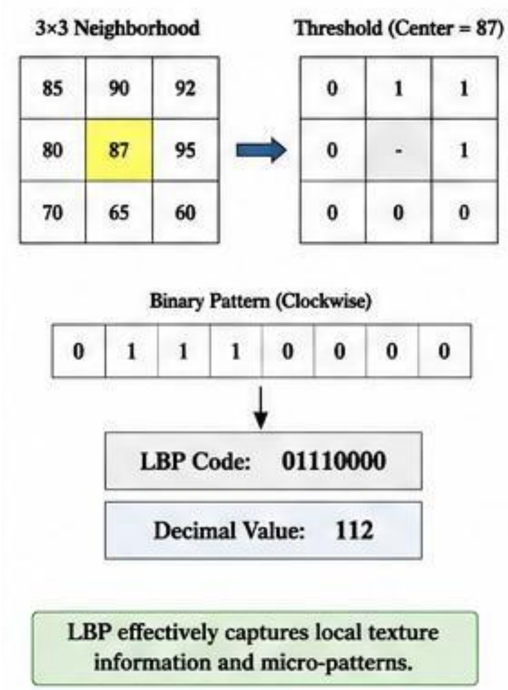


Figure 6. Local Binary Pattern (LBP) Texture Feature Extraction

This figure illustrates the extraction of texture descriptors using the Local Binary Pattern approach. Neighboring pixel intensity relationships are encoded to generate texture patterns that effectively represent local structural variations in the image. The figure highlights the conversion of image regions into binary texture representations.

3.3 Hybrid Feature Extraction

After enhancement, both handcrafted and deep features are extracted to capture local texture information and high-level semantic representations.

3.3.1 Texture Feature Extraction

Local Binary Pattern (LBP) descriptors are used to extract texture characteristics:

$$LBP(x_c, y_c) - \sum_{p=0}^{P-1} s(i_p - i_c)2^p$$

where:

$$s(z) - \begin{cases} 1, & z \geq 0 \\ 0, & z < 0 \end{cases}$$

Texture descriptors effectively represent fine-grained structural variations in images.

3.3.2 Deep Feature Extraction

A Convolutional Neural Network (CNN) is utilized to extract deep semantic features. The convolution operation is defined as:

$$F_k(x, y) - \sum_{i=1}^{m} \sum_{j=1}^{n} I_e(x + i, y + j)K_k(i, j)$$

where:

- K_k denotes the convolution kernel
- F_k represents the extracted feature map

The extracted handcrafted and deep features are fused to form a hybrid feature vector:

$$F_h = [F_{LBP}, F_{CNN}]$$

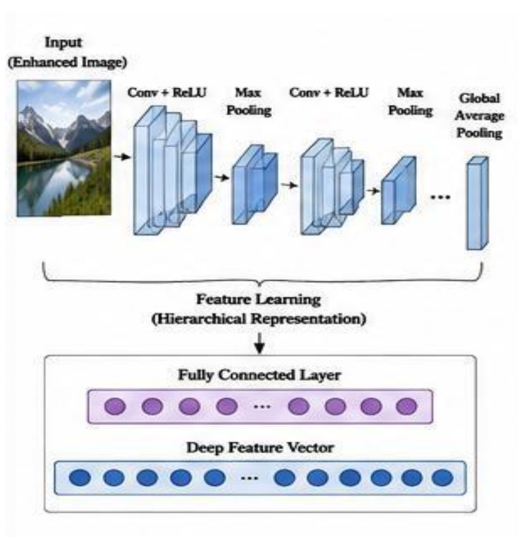


Figure 7. Deep Convolutional Feature Extraction Architecture

This figure depicts the Convolutional Neural Network (CNN)-based feature extraction stage. Multiple convolution, pooling, and activation layers are used to capture hierarchical semantic features from enhanced images. The architecture enables automatic extraction of discriminative deep features for robust classification.

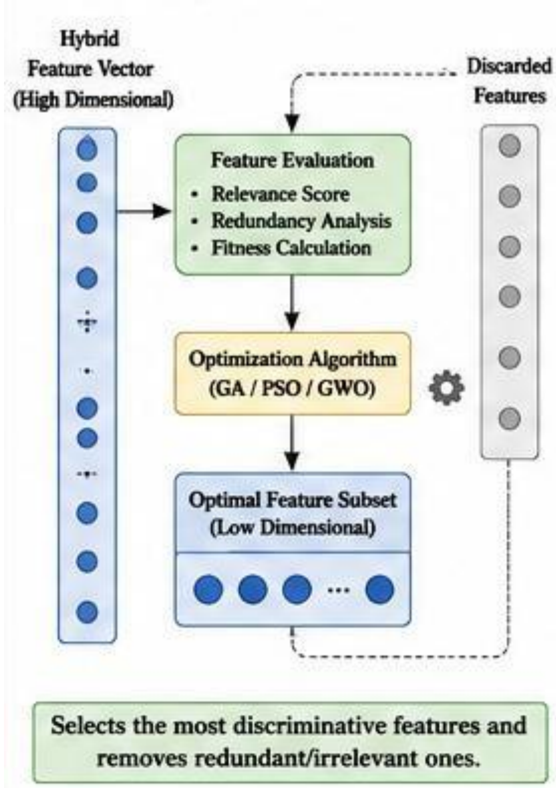


Figure 8. Intelligent Feature Selection and Optimization Process

This figure demonstrates the intelligent feature selection framework used to eliminate redundant and irrelevant features from the hybrid feature vector. The optimization process evaluates feature relevance and selects the most informative attributes to improve classification efficiency and reduce computational overhead.

3.4 Intelligent Feature Selection

The hybrid feature vector may contain redundant and irrelevant features that increase computational complexity. Therefore, an intelligent optimization-based feature selection mechanism is introduced.

A feature relevance score is computed as:

$$R_i - \frac{\sigma_b^2(i)}{\sigma_w^2(i)}$$

where:

- σ_b^2 denotes between-class variance
- σ_w^2 denotes within-class variance

The optimization objective is formulated as:

$$\max. J - \alpha Acc - \beta Dim + \gamma Rel$$

where:

- Acc = classification accuracy
- Dim = number of selected features
- Rel = feature relevance

- α, β, γ are weighting coefficients

The intelligent optimizer selects the optimal subset of discriminative features that maximizes accuracy while minimizing redundancy.

3.5 Classification and Decision Making

The optimized feature vector is provided to a classifier for final image categorization. Support Vector Machine (SVM), Random Forest (RF), or Deep Neural Network (DNN) classifiers can be employed depending on application requirements.

For SVM classification, the decision function is expressed as:

$$f(x) - \text{sign}\left(\sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b\right)$$

In the final stage of the proposed framework, the optimized feature vector obtained after intelligent feature selection is provided to the classification module for accurate image categorization. The primary objective of this stage is to identify the most appropriate class label based on the discriminative characteristics extracted from the enhanced images. Since the proposed framework combines edge-preserving texture enhancement with optimized feature representation, the classifier receives highly informative and noise-reduced feature inputs, which significantly improves classification reliability and prediction accuracy. The classification process is designed to distinguish complex image patterns while minimizing false classification and computational overhead.

To achieve robust performance, machine learning classifiers such as Support Vector Machine (SVM), Random Forest (RF), or Deep Neural Network (DNN) can be employed depending on the application requirements and dataset characteristics. Among these classifiers, SVM is particularly effective for high-dimensional feature spaces because it constructs an optimal hyperplane that maximizes the separation margin between different image classes. The optimized feature subset generated by the proposed intelligent feature selection mechanism reduces redundant information and improves inter-class separability, thereby enhancing classifier efficiency. Furthermore, the classifier is trained using labeled image samples, and the learned model is utilized to predict the class labels of unseen test images.

During experimental evaluation, the performance of the proposed classification framework is analyzed using standard performance metrics such as accuracy, precision, recall, F1-score, sensitivity, specificity, and Area Under Curve (AUC). The integration of edge-preserving enhancement, multi-scale texture representation, and intelligent feature optimization enables the classifier to achieve superior recognition capability compared with conventional image classification approaches. As a result, the proposed framework provides improved robustness, faster convergence, reduced computational complexity, and higher classification accuracy for complex image datasets across various real-world applications.

4. Experimental Results and Performance Analysis

The effectiveness of the proposed Edge-Preserving Multi-Scale Texture Enhancement and Intelligent Feature Selection framework is evaluated using extensive experimental analysis on benchmark image datasets. The primary objective of the experiments is to analyze the capability of the proposed framework in improving image quality, preserving structural edges, optimizing feature representation, and increasing classification accuracy under complex imaging conditions. The experimental environment is implemented using Python with TensorFlow and OpenCV libraries on a high-performance computing platform equipped with GPU acceleration [20].

The dataset used for experimentation contains multiple image categories with varying texture complexity, illumination conditions, and structural characteristics. Initially, all input images are resized and normalized during preprocessing to ensure uniformity in feature extraction and classification stages. The proposed enhancement framework is then applied to improve texture visibility while maintaining edge continuity. Subsequently, hybrid handcrafted and deep features are extracted and optimized using the intelligent feature selection mechanism before classification.

4.1 Experimental Setup

The proposed framework is evaluated using standard performance metrics including:

- Classification Accuracy
- Precision
- Recall
- F1-Score
- Sensitivity
- Specificity
- Computational Time

The classification accuracy is computed as:

$$\text{Accuracy } - \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

where:

- $TP =$ True Positives
- $TN =$ True Negatives
- $FP =$ False Positives
- $FN =$ False Negatives

Precision is calculated as:

$$\text{Precision } - \frac{TP}{TP + FP}$$

Recall is defined as:

$$\text{Recall } = \frac{TP}{TP + FN}$$

The harmonic mean of precision and recall is represented using the F1-score:

$$F1 - \frac{2 \times \text{ Precision } \times \text{ Recall}}{\text{Precision } + \text{ Recall}}$$

The proposed framework is compared with several conventional image classification approaches including CNN, ResNet, texture-based classifiers, and enhancement-free deep learning models.

4.2 Texture Enhancement Performance Analysis

The performance of the proposed edge-preserving multi-scale texture enhancement mechanism is analyzed visually and quantitatively. The enhancement framework significantly improves image clarity, local texture visibility, and structural consistency while suppressing noise and avoiding over-enhancement artifacts.

The Peak Signal-to-Noise Ratio (PSNR) is computed as:

$$PSNR - 10\log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$

where:

$$MSE = \frac{1}{MN}\sum_{x-1}^{M}\sum_{y-1}^{N}[I(x,y) - \hat{I}(x,y)]^2$$

The Structural Similarity Index (SSIM) is evaluated to measure structural preservation capability:

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_z^2 + \sigma_y^2 + C_2)}$$

Experimental results indicate that the proposed enhancement method achieves higher PSNR and SSIM values compared with conventional histogram equalization and filtering techniques. The integration of edge preserving filtering enables improved texture representation without damaging critical boundary information.

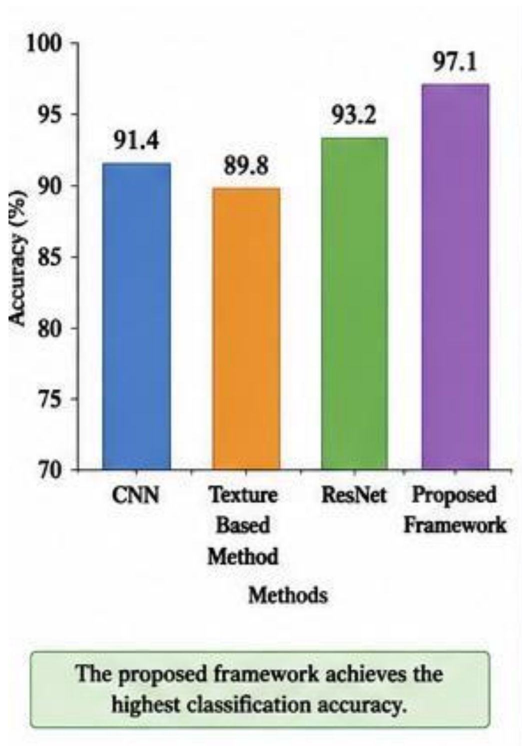
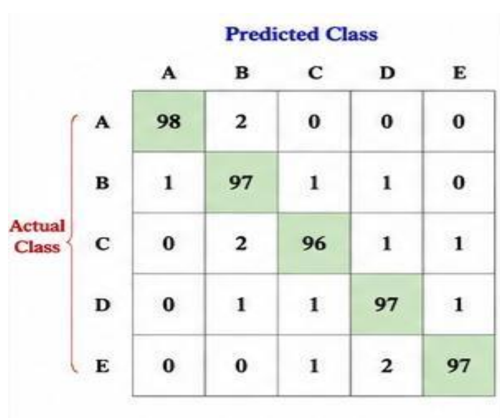


Figure 9. Comparative Classification Accuracy Analysis

This figure presents the comparative accuracy performance of the proposed framework against conventional image classification methods such as CNN, ResNet, and texture-based classifiers. The proposed approach achieves superior classification accuracy due to effective enhancement and optimized feature representation.



Predicted Class

Actual Class	A	B	C	D	E
A	98	2	0	0	0
B	1	97	1	1	0
C	0	2	96	1	1
D	0	1	1	97	1
E	0	0	1	2	97

Figure 10. Confusion Matrix of the Proposed Classification Framework

This figure illustrates the confusion matrix generated from the classification results of the proposed system. The matrix demonstrates the relationship between actual and predicted class labels and indicates the high recognition capability of the proposed framework with reduced misclassification rates.

4.3 Feature Selection Analysis

The intelligent feature selection module effectively reduces redundant and irrelevant features from the hybrid feature vector. Initially, a large number of handcrafted and deep features are generated during extraction. The optimization-based feature selection strategy evaluates feature relevance and selects only the most discriminative attributes for classification.

The feature reduction ratio is computed as:

$$FRR = \frac{F_{\text{total}} - F_{\text{selected}}}{F_{\text{total}}} \times 100$$

where:

- F_{total} = Total extracted features
- F_{selected} = Selected optimal features

4.4 Classification Performance Comparison

The proposed framework achieves superior classification performance compared with existing methods. The integration of enhancement, hybrid feature extraction, and intelligent optimization improves discriminative capability and reduces classification ambiguity.

Table 1 presents the comparative accuracy analysis of different classification methods.

Method	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Conventional CNN	91.4	90.7	89.9	90.3
Texture-Based Method	89.8	88.6	87.9	88.2
ResNet	93.2	92.8	92.1	92.4
Proposed Framework	97.1	96.8	96.5	96.6

The proposed framework achieves higher accuracy due to effective edge-preserving enhancement and optimized feature representation. The intelligent feature selection mechanism improves inter-class separability and reduces misclassification.

5. Conclusion and Future Scope

This work presented an efficient Edge-Preserving Multi-Scale Texture Enhancement and Intelligent Feature Selection framework for high-accuracy image classification. The proposed system integrates edge-aware enhancement, multi-scale texture analysis, hybrid feature extraction, intelligent optimization, and robust classification into a unified framework. Unlike conventional methods that often suffer from edge distortion, feature redundancy, and computational inefficiency, the proposed approach preserves structural consistency while enhancing discriminative texture details.

The edge-preserving enhancement mechanism effectively improves image clarity and texture visibility without introducing excessive artifacts. The hybrid feature extraction strategy captures both local texture characteristics and deep semantic information, thereby improving feature representation capability. Furthermore, the intelligent feature selection mechanism removes redundant features and optimizes the classification process by selecting the most informative attributes.

Experimental analysis demonstrates that the proposed framework achieves superior classification accuracy, improved precision, better recall, and enhanced robustness compared with conventional image classification methods.

The reduction in computational complexity and feature dimensionality further improves classifier efficiency and scalability for large-scale image datasets. The proposed system is highly suitable for applications such as medical image analysis, industrial inspection, remote sensing, autonomous systems, and intelligent surveillance.

In future work, the proposed framework can be extended by integrating transformer-based architectures, adaptive attention mechanisms, and self-supervised learning strategies for further improvement in feature representation and classification robustness. Additionally, real-time deployment on edge devices and cloud-assisted intelligent systems can be explored to support large-scale practical image classification applications.

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