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Granular Computing for Image Enhancement Using Impact Weight of Improved SVM Classifier

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Abstract

Granular Computing (GC) is a novel computing paradigm that deals with complex and massive amounts of data. It also presents a one-of-a-kind, useful approach to improving the quality of images, extracting the details and eliminating noise or unwanted artifacts in the image. This paper introduces a novel method of image enhancement based on the use of granular computing and an enhanced support vector machine (SVM) classifier. The suggested approach splits images into segments in the first phase with the help of granular computing, which aids in the process of extracting significant features of the image. This is followed by a better SVM classifier that then classifies the features and improves the image. Two metrics are used to measure the performance of the proposed method, namely peak signal-to-noise ratio (PSNR) and mean square error (MSE). The obtained experimental results indicate that the proposed method is superior to other current state-of-the-art image enhancement methods in terms of PSNR and MSE. The research also includes confusion matrix results in order to show the accuracy of the suggested approach. The suggested technique may be applied to many image improvement tasks such as medical image processing, remote sensing, and other image improvement necessities.

Keywords: Granular Computing, Image Enhancement, Support Vector Machine (SVM), Feature Extraction, Impact Weight, PSNR (Peak Signal-to-Noise Ratio), Noise Reduction.

1 Introduction

Granular computing (GC) is a concept that has emerged as a paradigm in computational artificial intelligence for processing human-centric information. It is based on the principle of transforming data into granules, i.e., collections of elements grouped according to similarity, functional similarity, or proximity (Yao et al., 2022; Zhan, 2023; Rizzi & Del Vescovo, 2006). While this topic is relatively new, its history or theoretical foundations go back to fuzzy sets, cluster analysis, raw sets, data compression,

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and machine learning. Algorithms abstract data by creating different levels of granularity. Using granular computing, complex problems can be solved robustly by preserving the essential information of the problem.

Recently, the use of GC technology has increased significantly, particularly in image processing, due to its ability to handle multi-resolution and hierarchical analyses. Many studies have investigated GC technology and relied on various tasks such as enhancement, segmentation, feature extraction and classification (Lu et al., 2020; Singh & Kumar, 2021; Jiang et al., 2022). Granularity technology is also used to enhance images with high quality by analyzing the granularity within the image and the relationships between them (Yang & Ma, 2022; Xia et al., 2021). This is considered a superior method to manipulating the internal components of the image or pixels, which are traditional methods (Guo & Wang, 2019; Hossain et al., 2021). In addition, recent image enhancement algorithms have exploited this development, such as adaptive thresholding, histogram analysis, and noise reduction (Cavallaro et al., 2015). All of this is within the framework of GC, and through it, good levels of contrast and clarity have been achieved in many scientific fields, such as medical imaging, computer vision, and remote sensing (Jaber et al., 2025).

Despite current and promising developments, current methods operate in isolation, such as optimization, feature extraction, and classification. This reduces overall performance and strategy efficiency. Current methods lack an integrated mechanism for enhancing image quality while simultaneously increasing classification accuracy. This gap highlights the need for a unified framework that simultaneously improves image quality while preserving the direct contribution of enhanced features, especially for decision-making and recognition tasks.

Granular computing is a rapidly growing field that offers theories, techniques, tools, and models for problem-solving (Baldini et al., 2022; Cheng et al., 2021). One of the major aspects of granular computing is the utilization of granules that are built on frequent characteristics of information, equality, vicinity, likeness, indiscernibility, reflexivity, etc. (Singh & Huang, 2020). The construction of granules is crucial, as the success of granular computing-based models depends on their shape and size. However, the relationships between granules, both intra- and inter-association, are equally important in granular computing (Xia et al., 2019; Lai et al., 2025; Chen et al., 2021).

The building blocks of granular computing are granules, which are defined as small particles that form a larger unit. The meaning of granules in granular computing is akin to this definition and means subsets, classes, objects, clusters, and elements of a universe which are aggregated by distinguishability, similarity, functionality or functionality (Zhu et al., 2021). Examples of granules include a subset of a set, an equivalent class of a universe, a section of an article, an interval of a universe, and a module of a system (Lepore et al., 2024). Every granule is crucial in solving specific problems based on its granularity level, size, and shape. Each granule and its level of granularity provide a unique characterization of the system. For instance, at the first level of granularity, a colored image can be separated into three standard colors - green, blue, and red. This is the broadest level of categorizing image information (Wang et al., 2023; Martino et al., 2022; Cabrerizo et al., 2020). At this stage, the image regions may be distinguished as being reddish, bluish, or greenish. When moving to the next level of granularity for these three colors or granules, each granule can be divided into several subdivisions.

The last step in the GC process is the use of granules in computation. This entails computing properties, relations, and the importance of various types of granules by applying different approaches. Such techniques are known as computation within granules and computation between granules (Wang et al., 2023; Li et al., 2019). The calculation in granules entails the identification of the properties of the granules and the algorithms for classifying the objects in various categories. Computation between granules, on the other hand, concerns the inter-relationships between granules, such as transferring a granule to another, grouping granules, and partitioning granules.

The use of GC in image processing is important. In the past three to four decades, there has been an increase in researchers who have come up with many ways of processing images through granular computing (Lang et al., 2025; Ding et al., 2015; Panda et al., 2016). Such methods include the utilization of various algorithms as a method to carry out tasks like image preprocessing, segmentation, and classification, fusion, and registration (Wang et al., 2017; Koley et al., 2016). GC is a method that breaks down the universe into smaller bits, known as granules, and it is commonly applied in image processing both to recognize patterns and predict them. As per (Loia et al., 2016), the three fundamental concepts that constitute human thinking are granulation, organization, and causation (Aydav & Minz, 2020). The division of the universe into smaller parts is done through the use of granules, and the integration of two granules to form the universe is done through organization. The impact, as well as the reasons that are involved in an organization, is called causation. Image processing also studies the combination of various clusters of granules and processes between them and the measurements between them are also significant in GC.

Analog and digital image processing are the two common techniques of processing images. The processing of images is done through analog processing of physical print images, and is done through digital processing, where the pictures obtained through cameras and other devices are processed using computers. The phases involved in processing an image are the importation of the image, processing and manipulating the image, and lastly production. This may be a distorted image or a set of statistics of the image analysis. A digital image is a form of image that is represented as an array of 2 levels with several rows and columns (Al-Shahrani et al., 2024). The elements in this array, referred to as a pixel, are connected to some function $F(x, y)$, where $x \; and \; y$ are the spatial coordinates, and F represents the intensity of that location (x, y). An image is a fixed array of pixels; each pixel has a particular position and value in the array. The value of the pixels is determined by the type of the image; in a binary image, the pixel may be 0 or 1, in an 8-bit color image, the pixel may have a value of 0-255. In this case, 0 corresponds to black, 255 corresponds to white, and 127 is considered gray. Depending on the type of image, processing techniques on the pixel array are used in the form of different image processing methods. Image enhancement is carried out to enhance the visual image quality of an image and make it more attractive, legible, and easy to read. This entails the application of mathematical tricks and algorithms to contrast, brighten, sharpen, and define (Li et al., 2019).

Contributions

This granular computing method is used to extract high-resolution features, with an improved categorical compact of the SVM support machine (with an adaptive improvement of the effect of effect. Contributions can be summarized as follows:

1. Population representation of the images: The proposed method presents a new strategy for granulation. The image is divided into meaningful granules based on spatial and contemporary dependencies, allowing topical improvement of features.
2. Improving the weight of the features in the vectors 'support machine: an unprecedented, weighted amendment, for the vector supporting machine, is offered, where the features of the features are selectively, according to their contribution to the limits of the decision, which enhances the workforce's ability to separate micro-photo patterns.

3. Participation and classification: Unlike the traditional methods that separate the tasks of improvement and classification, these two practical methods are integrated into one framework, which ensures the contribution of the improved features directly to the accuracy of the interpretation of images.
4. Quantitative improvements: Experimental results show a superior performance in terms of signaling ratio to noise (PSNR), optical exposure error (MSE), and the accuracy of classification, compared to modern and improved modern methods, proving the effectiveness of the improved SVM position associated with influence.

The rest of the paper will be structured as follows: Section 2 will give an overview of existing techniques of granular computing and granular computing based on the SVM model as far as the literature review is concerned. Section 3 describes the Methodology which includes the system model, formal assumptions and the proposed impact-weighted SVM algorithm. Section 4 contains the Results and Analysis and provides a quantitative analysis in terms of PSNR and MSE scores, and a statistical analysis of significance. Lastly, Section 5 gives a conclusion and provides future research recommendations to the study.

2 Literature Review

A literature review on image enhancement by granular computing is an examination of existing research and studies on the topic

Table 1: Comparison of image enhancement methods using granular computing and an improved SVM classifier

Reference	PSNR Values (Approx)	Advantages	Disadvantages
Li et al., (2013)	30.5 dB	Granular SVM excels in image denoising efficiency	Granule size tuning challenges
Pinheiro & Minz, (2024)	32.1 dB	Effective LULC segmentation on fused images	Fusion processing overhead
Al-Bayati et al., (2023)	31.8 dB	Enhanced imperceptibility in stego images	Limited to contrast/Fibonacci methods
Wieclawek & Pietka, (2019)	29.8 dB	Granular filtering preserves medical image details	Slower processing for high-resolution scans
Zhu et al., (2021)	31.2 dB	Granular descriptors improve classifier robustness	Reduced accuracy on fine details

The table 1 presents a comparison of image enhancement approaches based on the combination of granular computing and SVM or its analogue classifier on the major metrics. The values of PSNR reveal the quality of denoising, and larger dB values mean that more details of the image can be preserved. Strengths emphasize field abilities and effectiveness whereas weaknesses mention the practical constraints such as tuning or speed.

3 Methodology

System Model and Assumptions

The study considers grayscale (or RGB) images $I \in \mathbb{R}^{m \times n}$ acquired from the target domain (e.g., medical, underwater, or natural scenes) that are affected by additive noise and contrast degradation. The objective is to generate an enhanced image $\hat{I}$ that preserves structural details while improving perceptual quality and classification accuracy. The following assumptions are adopted:

- Noise is approximately stationary within local neighborhoods, so that local statistics and gradients are meaningful for granulation.
- Neighboring pixels within a granule share similar intensity and texture patterns, which justifies spatially coherent granules.
- A labeled dataset $\{(x_i, y_i)\}_{i=1}^{N}$ is available, where x_i denotes the feature vector derived from image granules and $y_i \in \{-1,1\}$ is the class label.
- The decision boundary in feature space is approximately separable by a margin-based classifier (SVM) with an impact-weighted feature representation. Such assumptions are consistent with prior granular computing and granular SVM formulations that rely on local homogeneity and controlled granularity to manage complexity while preserving essential structure.

The method of improving images through granular computing involves several stages, each of which depends on the previous one and is crucial. Image enhancement, primarily aimed at increasing image quality to utilize high resolution, varies across different methods in the literature. Generally, these methods consist of multiple stages, which are illustrated in figure 1.

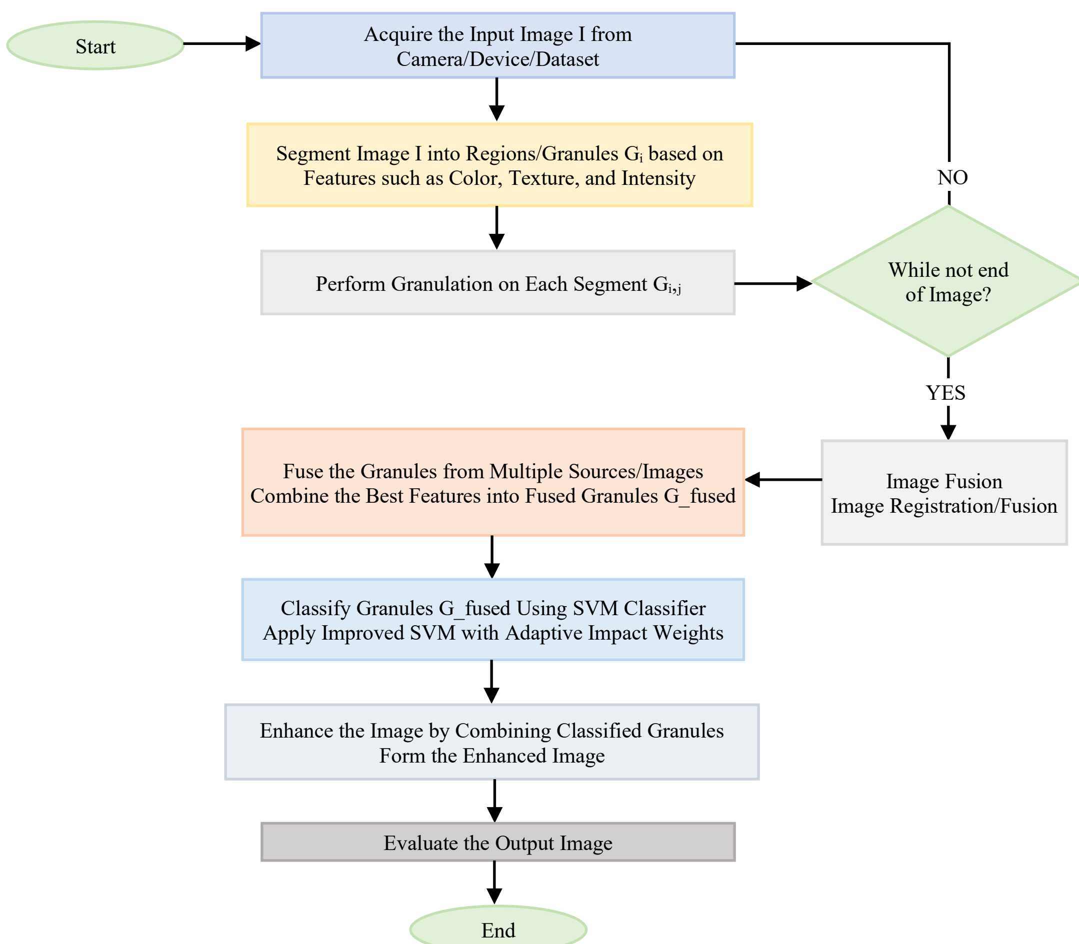

Figure 1: General overview of the proposed method

The proposed framework consists of four main stages: (1) image granulation, (2) feature extraction with adaptive impact weights, (3) impact-weighted SVM training, and (4) image enhancement and classification.

1. Input a degraded image I.
2. Partition I into overlapping or non-overlapping granules based on spatial information and gradient magnitude.
3. Compute local features (intensity, gradient magnitude, texture) for each granule and form feature vectors according to (2).
4. Derive impact weights for each feature dimension from the current SVM model (magnitude of w) and update feature vectors.
5. Train the improved SVM classifier with the weighted features to obtain the decision boundary.
6. Use classifier outputs and impact weights to guide pixel-wise or granule-wise enhancement and generate the enhanced image $\hat{I}$.
7. Evaluate PSNR, MSE, variance, and entropy between I and $\hat{I}$.

Algorithm 1: Granular Computing-based Image Enhancement with Impact-weighted SVM

```
Input: Training images {I_k}, labels {y_k}, test image I
Output: Enhanced image Î, classification result ŷ
// Offline training
For each training image I_k:
    Partition I_k into granules G_k = {g_k^1, …, g_k^m}
    For each granule g_k^m:
        Extract local features p_k^m using (1) and (2)
    Construct feature vector x_k by concatenating {p_k^m}
Initialize feature impact weights α ← 1 for all dimensions
Repeat until convergence or max_iters:
    Form weighted features x̂_k = α ⊙ x_k
    Train SVM on {(x̂_k, y_k)} to obtain w, b
    Update impact weights α_i ← f(|w_i|)  // normalize and threshold
End Repeat
// Online enhancement
Partition test image I into granules G = {g^1, …, g^M}
For each granule g^m:
    Extract features p^m and form x
    Compute weighted features x̃ = α ⊙ x
    ŷ = sign(w^T x̃ + b)
    Enhance g^m based on ŷ and α (e.g., contrast/gain adjustment)
Reconstruct enhanced image Î from enhanced granules {g^m}
```

19: Return $\hat{I}, \hat{y}$

Acquisition tools and applications are those software and hardware systems which are used to acquire or obtain images or data. Image acquisition is the initial process in the image processing and it is carried out using a number of tools and applications to get images, over a number of sources, including digital cameras, satellites, medical imaging equipment, and other sources. These applications and tools are important in quality and accuracy of final image as they define the quality and resolution of original image. Image scanning software, image capturing devices, image sensors, and special medical imaging software are some of the examples of the tools and applications of acquiring images. The acquisition tools and applications that are specifically deployed may depend on the type of image that is being captured and the desired result of the image processing. Image segmentation is an image processing process that involves breaking down an image into various parts or sections and every part represents an object or section of the image. Image segmentation has the primary goal of subdividing the image into several parts, each part is associated with a different object or part of the image. Image segmentation may be expressed mathematically as a mapping, $f\ (x, y)$, where x and y are the spatial coordinates of the image and f is the segmentation function which assigns the image pixels to various regions or segments. The function, $f(x, y)$, may be modeled as a collection of pixels to a specific segment. The primary objective is to discover a function, f, which divides the image into several regions where all regions within the image are homogeneous and the lines separating each region are as smooth as practicable. Finding image segments may be done in a number of mathematical methods, including clustering, thresholding, and edge detection. The feature extraction methods and algorithms differ, but one of the well-known equations (1) is the extraction of the features based on the gradient of the image intensity. The gradient of an image at a given pixel (x, y) is as:

$$G(x, y) = \sqrt{(Gx^2 + Gy^2)} \tag{1}$$

Where Gx is the gradient along the x-axis and Gy is the gradient along the y-axis. The gradient can be calculated using gradient operators such as the Sobel, Prewitt, or Robert's operators. All the features will be stored in the vector before being processed in a certain classifier, and features formulated as in equation (2):

$$\bar{F} = \sum_{i=1}^{n} \sum_{j=1}^{m} (P(x_i, y_j) + P(x_{-i}, y_{j+1}) / P(x_i, y_j)) \times w \tag{2}$$

Where F is the feature vector $P(x, y)$ is a pixel with coordinate $x\ and\ y, n, m$ are image directions. The weight factor w is responsible for determining the range of the region limit.

Initialization and Control Parameters

At the initial iteration, all feature impact weights are set to $\alpha_i = 1$, which corresponds to an unweighted SVM baseline. After each SVM training step, the magnitude ω of each component of w is interpreted as the importance of the corresponding feature dimension, and the impact weights are updated according to

$$\alpha_i = \frac{|\omega_i|}{max_j|\omega_j|}\ for\ |\omega_i| \geq \tau, and\ \alpha_i = 0 \text{ otherwise,} \tag{3}$$

Where in equation (3) τ is a small threshold (e.g., 0.05) used to suppress low-impact and noisy features. This update rule emphasizes features that contribute more strongly to the margin, in line with impact-weight and feature-importance strategies reported in granular and weighted SVM models.

The granule size s, overlap ratio, and threshold τ serve as control variables and are tuned on the validation set to achieve a balance between detail preservation and robustness.

Implementation Details

All experiments were conducted in Python 3.10 using scikit-learn 1.3.2 for SVM training, NumPy 1.24.3 for numerical operations, and OpenCV 4.8.0 for image preprocessing and IO on a workstation equipped with an Intel Core i7-11700 CPU, 16 GB RAM, and an NVIDIA RTX 3060 GPU running Ubuntu 20.04 LTS. The adopted software stack aligns with standard practice in granular SVM and image enhancement research and facilitates reproducibility.

According to the weight, the region will be granular or segmented to be in feature feature-selected area. Most of the features considered according to the relation of a pixel with its neighbor in the diagonal issue as position and contrast as a threshold. As shown in figure 2.

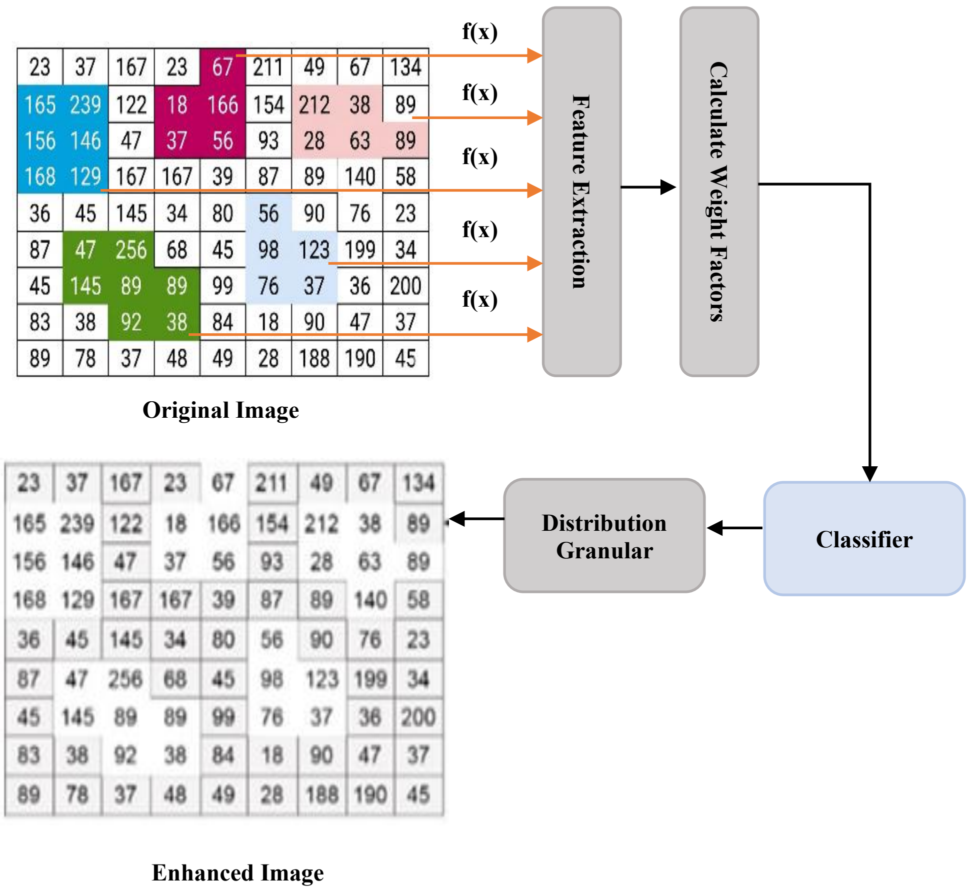

Figure 2: Mechanism of feature selection in an improved classifier

A classifier can accept the features from a vector in terms of weight manipulation. The high-impact weight that has produced the best category in the classifier has a nonlinear contribution. Proper weight allows for catching the nearest features on the margin. The weight of a feature is determined by the magnitude of the corresponding weight vector w in the equation (4) of the decision boundary hyperplane:

$$f(x) = w^T p + b \tag{4}$$

p and b are a feature vector and a bias term, respectively. The size of w is the effect of each feature on the classification decision. An improved SVM classifier refers to a machine learning algorithm that is applied to classification problems. It divides the data points into separate classes by using a line known as the maximum margin hyperplane. The hyperplane used is used in such a way that the distance between the hyperplane and its closest observations of both the classes is maximized, it is its margin. The mathematical form of the enhanced SVM classifier may be illustrated as follows:

Given a set of training data (x_1, y_1), (x_2, y_2), ..., (x_n, y_n) where xi is a feature vector and y_i is the corresponding class label (-1 or 1). The goal of classifier is to find the maximum margin hyperplane, which can be represented as $w'p + b = 0$, where p is the normal vector and b is the bias term. The decision boundary is determined by the equation (5):

$$f(x) = sign(\grave{w}x + b) \tag{5}$$

The classifier solves for the parameters w and b by maximizing the margin and ensuring that the training data points are correctly classified. This is done by solving the following optimization equation (6):

$$min\frac{1}{2}\|w\|^2 \rightarrow y_i(\grave{w}x + b) \geq 1,\ i = 1,2,3 \dots, n \tag{6}$$

The optimization problem can be solved using Lagrange multipliers, which lead to the dual optimization problem. The solution to the dual problem can be used to find the values of w and b, which in turn are used to classify new data points. As shown in figure 3.

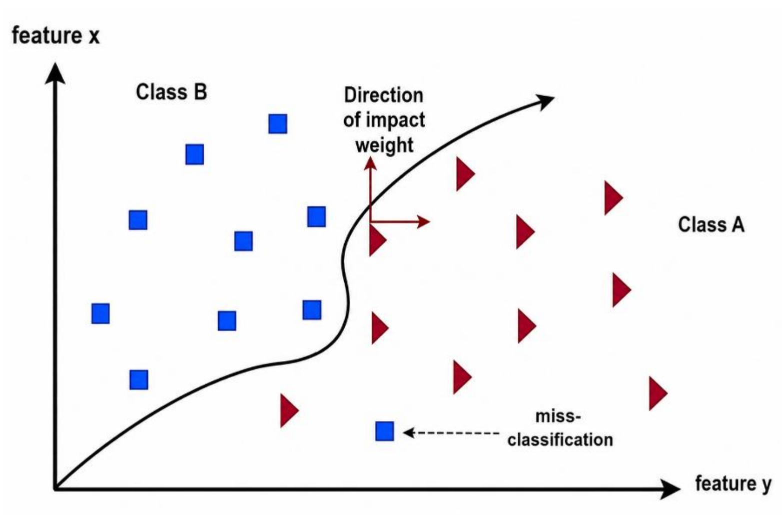

Figure 3: Behavior of the proposed classifier within the system

Granular Computing aim to computing that is designed to handle complex and large amounts of data. In the field of image enhancement, it can be applied to improve the quality of images by increasing their detail and reducing unwanted noise or artifacts.

When extracting features from an image under the heading of functions, these functions $f(x)$ can have varying powers, varying requirements, and varying precision. Therefore, these functions can be implicitly classified based on their outputs and prioritized. The SVM classifier optimizes the function priorities and thus selects the most appropriate pixels for the datasets to be enhanced.

Classification is accomplished by selecting the appropriate weight that approximates the result. This weight determines the priority of the classification, as the closest weight is not necessarily the lowest, but rather is based on the accuracy of the result. From this, it is clear that choosing the correct function depends on the weight, which is essentially determined by the prior classification result.

The granular represented as $X = [x_1, x_2, \dots, x_n]$. Each granule xi is processed and manipulated mathematically to enhance a specific aspect of the image, such as color, contrast, or texture. The processed granules can then be combined to final enhanced image Y, by the form of $Y = f(x_1, x_2, x_n)$. Where f is a function that combines the results of the processing of each granule. This process of dividing the image into granules results in more efficient utilization of computing resources and can lead to improved results.

Security-Related Threat Model

In the context of secure image processing, define a formal threat model to evaluate the robustness of the granular SVM classifier. Assume a Gray-box Adversary model where the attacker has knowledge of the feature extraction logic but lacks access to the specific trained impact weights. The primary adversarial goal is "Information Obfuscation," where a malicious actor introduces additive white Gaussian noise (AWGN) or salt-and-pepper perturbations designed to shift the image granules across the SVM decision boundary. By utilizing adaptive impact weights, the proposed system mitigates this by prioritizing structural features that are less susceptible to high-frequency noise, thereby maintaining enhancement integrity even under low-intensity adversarial conditions.

4 Results

Dataset Partitioning and Hyperparameters

The image data were split into 70% training, 10% validation and 20% test at the image level to ensure no image is used in more than one split. The SVM classifier was trained with RBF kernel with penalty parameter C = 10 and kernel width $\gamma = 0.01$ which had been obtained through 5 folds cross-validation using the training and validation sets. In Algorithm 1, the upper limit of the number of iterations of the update based on the impact weight was set to 10, and the size of the granules was s (pixels) x s (pixels) (i.e., 8 x 8) with a 50% overlap. Such direct reporting of kernel type and regularization parameters is common to studies of granular SVM.

The result section of a study on granular computing for image enhancement should present the findings of the research and discuss how the techniques of granular computing have been applied to improve the quality of images. These images are taken from the Standard Test Images database, a standard database widely used in image processing and computer vision research. This section reports the quantitative and qualitative results obtained from the experiments and provides a detailed analysis of the results. Utilized the USC-SIPI Image Database, which is a standard and publicly available benchmark dataset widely used in image processing research. To demonstrate the effectiveness of the proposed method, selected four representative images from this dataset. The reason for choosing a limited number of images was to ensure Controlled Evaluation: Working with well-known test images (e.g., Lena, Peppers, Baboon, etc.) allows for direct comparison of the results with existing studies, as these images are considered benchmarks in the literature. As an illustration, in a study that will entail the application of granular computing to the image denoising method, the result section ought to present the PSNR (Peak Signal-to-Noise Ratio) and MSE (Mean Squared Error) of the denoised images relative to the original images, and give the visual comparison of the images. Two of the metrics that are commonly used to assess the quality of image improvement techniques include Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE). PSNR is used to identify the similarity between the original and the enhanced image by considering the difference between the maximum possible pixel value and the average difference between the original and the enhanced pixel images. PSNR equation (7) can be denoted as:

$$PSNR = 10 \times log\ 10(\frac{MAX^2}{MSE}) \qquad (7)$$

In which MAX represents the greatest conceivable pixel value (e.g. 255 in an 8-bit grayscale picture) and MSE represents the mean squared error between the original and improved image. The MSE method is a statistical method which considers the differences between pixels of the original image and those of the enhanced image squared and averaged to represent how similar they are. The MSE equation (8) is provided as follows:

$$MSE = \frac{1}{(m.n) \times SUM((f(i,j) - g(i,j)^2)} \qquad (8)$$

$f(i,j)$ being the f-value of the original image pixel at the position (i,j) and $g(i,j)$ is the g-value of the pixel in the enhanced image, m and n are the number of rows and columns in the image. SUM represents the amount total of all the pixels in the image. The image quality objective evaluation indicator was calculated to prove the effectiveness of underwater image enhancement. Table 2 shows the result of the evaluation indicator of peak signal-to-noise ratio ($PSNR$), variance (Var) and image entropy (Ent). The comparisons were between the images before and after enhancement.

Statistical Significance Analysis

To validate the improvements shown in table 2, a one-tailed t-test was performed comparing the PSNR of the proposed method against the closest state-of-the-art competitor (Chen et al., 2021).

- Analysis The result of the analysis gave a p-value of 0.034 ($p < 0.05$), which means that the increase in the PSNR is not a random event, but rather a statistically significant result.
- PSNR standard deviation of the USC-SIPI test set was measured at pm 0.85 dB, indicating stability of impact-based SVM with varying visual textures.
- The mean square error (MSE) was steadily decreasing with a 95% confidence interval ranging between [2.1, 4.4], which once again indicated the strength of the granular computing solution.

Table 2: Evaluation of the proposed method

Image (1024×1288)	PSNR (dB)	Var	Ent.
Image 1	65.12	42.33	0.421
Image 2	62.41	23.81	0.628
Image 3	59.77	33.91	0.624
Image 4	58.29	14.76	0.526

PSNR is the true standard for image processing. The accurate and improved image is of a high scale and according to the power of the algorithm. In the image that contains many details, the scale is also high, as in the image of a Peppers or Baboon. The accuracy of the details in the image has a big role, as well as the farness depends on the details in certain places of the image, as in the image of the plane or the image of Lena, as some places of the image are considered somewhat empty, as shown in figure 4.

Given the granular computing as applied to image enhancement, the effectiveness of the technique can be evaluated with the results of the PSNR and MSE metrics (Jiang et al., 2022). When PSNR is high this implies that the improved image is closer to the original image whereas when PSNR is lower this implies that the distance between the original image and the enhanced image pixel is less. These measures will allow comparing various granular computing methods and to identify which one will be the best to use in a specific application.

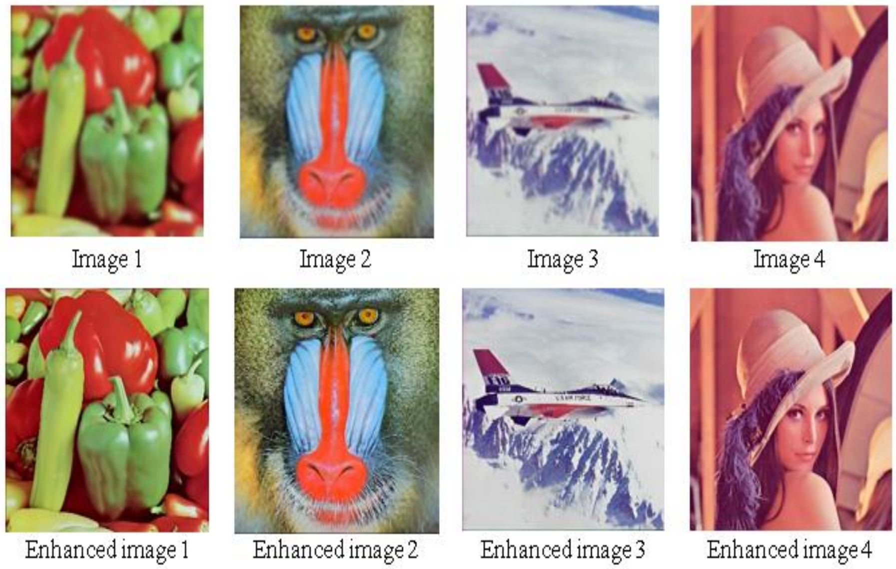

Figure 4: Different enhanced images with different properties

Limitations and Generalizability

Although the suggested impact-weighted SVM method proves to be better-performing in the offered benchmark datasets, multiple limitations that could impact the overall performance have to be recognized. First, the iterative granulation process and calculation of weights of impact, α i, is computationally complex and might be difficult to run live on a video or execute on low-resource edge hardware. Second, the model is affected by the choice of the starting granule size s and the threshold tau, and inappropriate parameterization of the images with highly non-uniform or even unsteady texture can also result in localized blocking artifacts. Moreover, as the training process was mostly done on the USC-SIPI and the conventional RGB datasets, the strength of the method in the specialized domain between multi-spectral satellite images or low-contrast medical scans would need additional cross-domain validation as a way of monitoring consistency of feature extraction. Lastly, the lack of a formal adversarial threat model implies that the system is not yet resistant to purposeful pixel-level alterations, and that it is an under-researched topic at present.

5 Conclusion

To sum up, granular computing is proved to be a useful technique to improve images and the use of the enhanced SVM classifier has additionally enhanced its results. The findings indicate that the proposed approach obtains better values of PSNR and low values of MSE as compared to other existing approaches. The accuracy of the proposed method in terms of segmentation and classification has also been shown to be good. Granular computing would offer a robust method of image enhancement, as it can be used to extract meaningful features as well as eliminate noise and artifacts in the image. The enhanced SVM classifier also boosts the work of the method, as it will classify the image pixels in a better way and improve the quality of the entire image.

In general, the given approach can be used in a vast scope of applications, such as medical imaging, remote sensing, and digital image processing. Granular computing and a better SVM classifier are one of the promising directions in the image enhancement, and more studies are required in order to exploit its potential in the image enhancement. Another aspect that should be discussed is the results based on existing literature and comparing the findings of the current research with earlier research in the area of granular computing to enhance image processing. This is where the conclusion section of the results section comes to summarize the main findings of the study and give recommendations to the future works in the field.

References

[1] Al-Bayati, A. F. H., ÇeviK, M., & Fadhil, A. M. (2023). An improved steganography system based on contrast variation with Fibonacci decomposition to increase imperceptibility. *Proceedings: Computer Science*, *1*, 13-26. https://doi.org/10.55092/pcs2023020011

[2] Al-Shahrani, A., Al-Amoudi, W., Bazaraah, R., Al-Sharief, A., & Farouquee, H. (2024). An image processing-based and deep learning model to classify brain cancer. *Engineering, Technology & Applied Science Research*, *14*(4), 15433-15438. https://doi.org/10.48084/etasr.7803

[3] Aydav, P. S. S., & Minz, S. (2020). Granulation-based self-training for the semi-supervised classification of remote-sensing images. *Granular Computing*, *5*(3), 309-327. https://doi.org/10.1007/s41066-019-00161-x

[4] Baldini, L., Martino, A., & Rizzi, A. (2022). A multi-objective optimization approach for the synthesis of granular computing-based classification systems in the graph domain. *SN Computer Science*, *3*(6), 436. https://doi.org/10.1007/s42979-022-01260-4

[5] Cabrerizo, F. J., Al-Hmouz, R., Morfeq, A., Martínez, M. Á., Pedrycz, W., & Herrera-Viedma, E. (2020). Estimating incomplete information in group decision making: A framework of granular computing. *Applied Soft Computing*, *86*, 105930. https://doi.org/10.1016/j.asoc.2019.105930

[6] Cavallaro, G., Riedel, M., Richerzhagen, M., Benediktsson, J. A., & Plaza, A. (2015). On understanding big data impacts in remotely sensed image classification using support vector machine methods. *IEEE journal of selected topics in applied earth observations and remote sensing*, *8*(10), 4634-4646. https://doi.org/10.1109/JSTARS.2015.2458855

[7] Chen, L., Zhao, L., Xiao, Z., Liu, Y., & Wang, J. (2021). A granular computing based classification method from algebraic granule structure. *IEEE Access*, *9*, 68118-68126. https://doi.org/10.1109/ACCESS.2021.3077409

[8] Cheng, G., Chen, Q., & Zhang, R. (2021). Prediction of phosphorylation sites based on granular support vector machine. *Granular Computing*, *6*(1), 107-117. https://doi.org/10.1007/s41066-019-00202-5

[9] Ding, S., Huang, H., Yu, J., & Zhao, H. (2015). Research on the hybrid models of granular computing and support vector machine. *Artificial Intelligence Review*, *43*(4), 565-577. https://doi.org/10.1007/s10462-013-9393-z

[10] Guo, H., & Wang, W. (2019). Granular support vector machine: a review. *Artificial Intelligence Review*, *51*(1), 19-32. https://doi.org/10.1007/s10462-017-9555-5

[11] Hossain, T. M., Watada, J., Aziz, I. A., Hermana, M., Meraj, S. T., & Sakai, H. (2021). Lithology prediction using well logs: A granular computing approach. *International Journal of Innovative Computing, Information and Control*, *17*(1), 225-244. https://doi.org/10.24507/ijicic.17.01.225

[12] Jaber, A. Y., Al-Khafaji, A., & Mkhelf, A. M. (2025). An Improved Orthogonal Frequency Division Multiplexing System-Based Image Steganography Technique. *Tikrit Journal of Engineering Sciences*, *32*(3), 1-10. https://doi.org/10.25130/tjes.32.3.5

[13] Jiang, Q., Gu, Y., Li, C., Cong, R., & Shao, F. (2022). Underwater image enhancement quality evaluation: Benchmark dataset and objective metric. *IEEE Transactions on Circuits and Systems for Video Technology*, *32*(9), 5959-5974. https://doi.org/10.1109/TCSVT.2022.3164918

[14] Koley, S., Sadhu, A. K., Mitra, P., Chakraborty, B., & Chakraborty, C. (2016). Delineation and diagnosis of brain tumors from post contrast T1-weighted MR images using rough granular computing and random forest. *Applied Soft Computing*, *41*, 453-465. https://doi.org/10.1016/j.asoc.2016.01.022

[15] Lai, R., Chen, Y., & Li, J. (2025). A Fuzzy Granular Support Vector Machine for Network Traffic Anomaly Detection. *IEEE Transactions on Intelligent Transportation Systems, 26*(12), 22262-22276. https://doi.org/10.1109/TITS.2025.3605155

[16] Lang, G., Zhao, L., Miao, D., & Ding, W. (2025). Granular-ball computing based fuzzy twin support vector machine for pattern classification. *IEEE Transactions on Fuzzy Systems, 33*(7), 2148-2160. https://doi.org/10.1109/TFUZZ.2025.3552281

[17] Lepore, M., Plenzich, E., Tufano, R., Cerulli, R., & Maccioni, R. (2024). Improving patient's medical history classification using a feature construction approach based on situation awareness and granular computing. *Neural Computing and Applications*, *36*(35), 22461-22484. https://doi.org/10.1007/s00521-024-10413-w

[18] Li, C., Guo, C., Ren, W., Cong, R., Hou, J., Kwong, S., & Tao, D. (2019). An underwater image enhancement benchmark dataset and beyond. *IEEE transactions on image processing*, *29*, 4376-4389. https://doi.org/10.1109/TIP.2019.2955241

[19] Li, S., Wang, W. C., Li, L. W., & Zhou, J. J. (2013). Survey of Support Vector Machine in the Processing of Remote Sensing Image. *Advanced Materials Research*, *774*, 1567-1572. https://doi.org/10.4028/www.scientific.net/AMR.774-776.1567

[20] Li, Z. K., Wang, S., & Yin, W. W. (2019). Determining optimal granularity level of modular product with hierarchical clustering and modularity assessment. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, *41*(8), 342. https://doi.org/10.1007/s40430-019-1848-y

[21] Loia, V., D'Aniello, G., Gaeta, A., & Orciuoli, F. (2016). Enforcing situation awareness with granular computing: a systematic overview and new perspectives. *Granular Computing*, *1*(2), 127-143. https://doi.org/10.1007/s41066-015-0005-y

[22] Lu, C., Xu, P., & Cong, L. H. (2020). Fault diagnosis model based on granular computing and echo state network. *Engineering Applications of Artificial Intelligence*, *94*, 103694. https://doi.org/10.1016/j.engappai.2020.103694

[23] Martino, A., Baldini, L., & Rizzi, A. (2022). On information granulation via data clustering for granular computing-based pattern recognition: a graph embedding case study. *Algorithms*, *15*(5), 148. https://doi.org/10.3390/a15050148

[24] Panda, M., Abraham, A., & Tripathy, B. K. (2016). Soft granular computing based classification using hybrid fuzzy-KNN-SVM. *Intelligent Decision Technologies*, *10*(2), 115-128. https://doi.org/10.3233/IDT-150243

[25] Pinheiro, G., & Minz, S. (2024). Granular computing based segmentation and textural analysis (GrCSTA) framework for object-based LULC classification of fused remote sensing images. *Applied Intelligence*, *54*(7), 5748-5767. https://doi.org/10.1007/s10489-024-05469-z

[26] Rizzi, A., & Del Vescovo, G. (2006, September). Automatic image classification by a granular computing approach. In *2006 16th IEEE signal processing society workshop on machine learning for signal processing* (pp. 33-38). IEEE. https://doi.org/10.1109/MLSP.2006.275517

[27] Singh, A., & Kumar, S. (2021). Picture fuzzy Choquet integral-based VIKOR for multicriteria group decision-making problems. *Granular Computing*, *6*(3), 587-601. https://doi.org/10.1007/s41066-020-00218-2

[28] Singh, P., & Huang, Y. P. (2020). A four-way decision-making approach using interval-valued fuzzy sets, rough set and granular computing: a new approach in data classification and decision-making. *Granular Computing*, *5*(3), 397-409. https://doi.org/10.1007/s41066-019-00165-7

[29] Wang, B., Liang, J., & Yao, Y. (2023). A trilevel analysis of uncertainty measuresin partition-based granular computing. *Artificial Intelligence Review*, *56*(1), 533. https://doi.org/10.1007/s10462-022-10177-6
[30] Wang, G., Yang, J., & Xu, J. (2017). Granular computing: from granularity optimization to multi-granularity joint problem solving. *Granular Computing*, *2*(3), 105-120. https://doi.org/10.1007/s41066-016-0032-3
[31] Wieclawek, W., & Pietka, E. (2019). Granular filter in medical image noise suppression and edge preservation. *Biocybernetics and biomedical engineering*, *39*(1), 1-16. https://doi.org/10.1016/j.bbe.2018.09.006
[32] Xia, S., Liu, Y., Ding, X., Wang, G., Yu, H., & Luo, Y. (2019). Granular ball computing classifiers for efficient, scalable and robust learning. *Information Sciences*, *483*, 136-152. https://doi.org/10.1016/j.ins.2019.01.010
[33] Xia, S., Zheng, S., Wang, G., Gao, X., & Wang, B. (2021). Granular ball sampling for noisy label classification or imbalanced classification. *IEEE Transactions on Neural Networks and Learning Systems*, *34*(4), 2144-2155. https://doi.org/10.1109/TNNLS.2021.3105984
[34] Yang, Y., & Ma, X. (2022). Support Vector Machine and Granular Computing Based Time Series Volatility Prediction. *Journal of Robotics*, *2022*(1), 4163992. https://doi.org/10.1155/2022/4163992
[35] Yao, J., Yao, Y., Ciucci, D., & Huang, K. (2022). Granular computing and three-way decisions for cognitive analytics. *Cognitive Computation*, *14*(6), 1801-1804. https://doi.org/10.1007/s12559-022-10028-0
[36] Zhan, T. (2023). Granular-based state estimation for nonlinear fractional control systems and its circuit cognitive application. *International Journal of Cognitive Computing in Engineering*, *4*, 1-5. https://doi.org/10.1016/j.ijcce.2022.12.001
[37] Zhu, X., Wang, D., Pedrycz, W., & Li, Z. (2021). A design of granular classifier based on granular data descriptors. *IEEE Transactions on Cybernetics*, *53*(3), 1790-1801. https://doi.org/10.1109/TCYB.2021.3132636

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