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Optimization of Gray Level Co-occurrence Matrix (GLCM) Texture Feature Parameters in Determining Rice Seed Quality

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Abstract

Rice seed quality assessment is a critical measure in promoting agricultural productivity, as high-quality seeds directly influence crop yield and resilience. One of method for evaluating seed quality is texture analysis, which leverages the Gray Level Co-occurrence Matrix (GLCM) to extract meaningful features from seed images, providing insights into their condition and potential performance. This research aims to determine the optimal performance of GLCM parameters in identifying the texture characteristics of rice seed quality. The experiments were conducted using four angles (0°, 45°, 90°, and 135°) and three-pixel distances (1, 2, and 3), evaluating features such as homogeneity, contrast, dissimilarity, and energy. The results indicate that certain parameter configurations significantly affect the discriminative power of the extracted features, with the Support Vector Machine (SVM) classifier achieving the highest performance at a pixel distance of 1, with an accuracy of 0.73, precision of 0.79, recall of 0.73, and F1-score of 0.72. These findings demonstrate that optimizing GLCM parameter settings directly contributes to improved classification performance, highlighting the method's potential for enhancing rice seed quality assessment.

Keywords: GLCM, rice seed quality, texture parameters, feature optimization, texture analysis.

1. INTRODUCTION

The quality of the rice seeds significantly influences the effectiveness of rice production. High-quality seeds are capable of producing rice with the highest possible weight and resistance to pests and diseases, in addition to increasing the productivity of the harvest [1]. In modern agriculture, using superior seeds has become one of the primary strategies to support global food security. Good seeds can be identified by various indicators and characteristics, such as their ability to withstand extreme environmental conditions and their high germination capacity, which have been demonstrated to increase the efficiency of rice production. The rapid development of technology and methods that can detect and ensure the quality of rice seeds is a critical factor in efforts to enhance the sustainability of the agricultural sector.

Research to enhance seed quality and rice production is conducted in multiple countries, particularly those where rice is a primary export commodity. For instance, Thailand is engaged in research focused on selecting seeds based on morphological and genetic traits to develop superior aromatic rice [2]. India prioritizes the evaluation of seeds using biotechnological methods, particularly molecular techniques such as PCR, ELISA, and SNP markers, to guarantee seeds' genetic integrity and health. This approach enhances the quality of seeds in both domestic and international [3, 4]. Vietnam implements agrotechnology, particularly in soil and water management, which markedly enhances the potential of local rice field seeds by optimizing resource utilization, improving soil health, and augmenting crop yields while reducing environmental impacts [5]. In Malaysia, research is focused on the application of digital technology to monitor seed quality through data processing and sensor-based systems [6]. The global urgency to ensure the availability of high-quality seeds to meet the increasing demand for sustenance is reflected in these studies.

Image processing has become a critical technique for evaluating the quality of seeds, providing a non-destructive and efficient alternative to conventional methods. Researchers have created sophisticated systems that analyze seed characteristics, including size, color, and shape, by applying various algorithms and machine learning models. Consequently, agricultural productivity has been enhanced [7]. The Grey Level Co-occurrence Matrix (GLCM) method is a widely used image processing technique used to evaluate the texture characteristics of seeds in a non-destructive and efficient manner. This method is based on the spatial relationship between pixels and utilizes parameters such as homogeneity, contrast, energy, and dissimilarity [8]. GLCM is capable of detecting texture patterns that are pertinent to seed quality, including the presence of surface roughness, fractures, or other defects.

Support Vector Machine (SVM) is a machine learning algorithm for regression and classification tasks. SVM operates by identifying an optimal hyperplane that distinguishes data from various classes in a high-dimensional space. SVM can effectively manage data that is not linearly separated by employing kernel functions, including the linear, polynomial, or Radial Basis Function (RBF). In image processing, SVM is frequently employed for pattern recognition, including texture analysis, object classification, and face detection. The primary benefit of SVM is its capacity to operate effectively on high-dimensional datasets and generate the highest possible margins between classes.

A comparison between SVM and the Decision Tree (DT) method is implemented. In this investigation, DT constructs a prediction model in the form of a tree, which is predicated on decision criteria. Decision trees divide a dataset into subgroups based on specific attributes, with each branch representing a potential outcome based on the input data. In this study, the quality of rice seeds will be classified by comparing the SVM and Decision Tree methods. The texture feature values will be extracted using the Grey Level Co-occurrence Matrix (GLCM) method, with pre-processing performed beforehand.

2. RELATED WORKS

Several previous studies have researched the classification of seed quality using an image-processing approach. GLCM has been extensively employed in various agricultural and culinary technology research projects involving image processing. For instance, it is employed to identify diseases in papaya fruit [9], rice variety [10] and analyze the leaf patterns of herbal plants [11]. The benefit of GLCM is its adaptability in capturing diverse textural properties pertinent to specific analytical requirements. The forthcoming research will employ GLCM to assess the quality of rice seeds based on surface texture metrics, which serve as markers of the seeds physical and physiological condition.

A texture-based feature extraction via the GLCM approach to assessing the quality of coffee beans, incorporating texture metrics such as homogeneity, contrast, and energy as inputs for the Support Vector Machine (SVM) and Random Forest algorithms was discussed by [12]. The study demonstrates that GLCM effectively captures texture patterns pertinent to item quality categorization. A combination of SVM and CNN to detect grain quality, yielding very accurate findings from images was described by [13]. The Coarse Tree Classifier (CTC) for the categorization of rice plants using RGB color analysis within the framework of decision tree-based classification was employed by [14].

3. ORIGINALITY

This research is original due to its comparative investigation of the GLCM texture feature extraction approach alongside the SVM and DT classification algorithms to evaluate the quality of rice seeds in Indonesia using digital photographs. This research is compelling as it investigates texture parameters at angles of 0°, 45°, 90°, and 135°, along with distances of 1, 2, and 3 pixels, to determine the optimal configuration for seed quality classification, given that numerous preliminary studies have not addressed parameter variations in GLCM [15][16]. This research also focuses on the normalization and enhancement of image quality utilizing CLAHE to generate consistent images and reduce background noise, a method that is infrequently employed consistently in comparable research [17][18] and Grabcut for separate background with object [19]. This project aims to contribute to the application of image processing technology to enhance the quality of the agricultural sector, particularly in assessing the quality of rice seeds.

4. SYSTEM DESIGN

The research began with image acquisition of rice seeds using a high-resolution digital camera in a controlled lighting environment. The resulting images are grouped into three quality classes, including high, average, and bad seeds. In the initial stage, the number of images successfully acquired in the high class was 164, the average class was 107, and the bad class was 110. Data distribution was done by normalizing the images to be balanced by eliminating inappropriate images, such as those that were blurry or did not match the class's characteristics, so each class's final stage had 100 images each.

The next stage is to improve image quality using the Contrast Limited Adaptive Histogram Equalization (CLAHE) method to clarify image details and increase contrast. The image background is eliminated using the Grabcut Thresholding method to separate the main object from the background so that the image is more aligned and focuses on the rice seeds. Texture feature extraction was carried out using the GLCM method at four angles (0°, 45°, 90°, and 135°) and three distances (1, 2, and 3) on the extracted texture parameters, including homogeneity, contrast, energy, and dissimilarity. The results of this feature extraction are used in the classification process by comparing two classifier methods, namely SVM and DT, to identify the best parameters for detecting the quality of rice seeds. The final stage is to evaluate the performance of the classification model using a confusion matrix, namely accuracy, recall, and F1-score.

This study used SVM and DT algorithms to classify rice seed quality based on texture features extracted using the GLCM method. SVM searches for optimal hyperplanes to separate classes in high-dimensional space using kernel functions such as linear, polynomial, or RBF. Previous studies have shown that SVM is superior in detecting texture-based objects, such as plant leaf damage patterns or microscopic analysis of materials [20]. The SVM stage begins by finding the support vector value using the kernel function, which is the RBF kernel with Equation (1) [21, 22].

$$K(x_i, x_j) = exp\left(-\gamma\|x_i - x_j\|^2\right) \tag{1}$$

where $K(x_i, x_j)$ represents the kernel value between two data points, x_i and x_j. $\|x_i - x_j\|^2$ is the Euclidean distance between two points, and γ is a kernel parameter that controls the influence distance of a data point.

The multi-dimensional Euclidean value is derived from the square root of the sum of the squares of the differences of each feature. This study employs four parameters: homogeneity, contrast, energy, and dissimilarity, which enable SVM to operate with multidimensional GLCM data. Subsequently, identify the best hyperplane by maximizing the margin between the positive and negative classes using Equation (2).

$$optimize = \min_{\omega,b,\xi_i} \frac{1}{2}\|w\|^2 + c\sum_{i=1}^{n} \xi_i \tag{2}$$

where w is the weight vektor, b is the bias hyperplane, ξ_i is the Slack variables to accommodate margin violations in non-linearly separable data, and c is the regularization parameter controls the trade-off between large margins and tolerance to misclassification.

The DT technique employs a rule-based decision framework to construct a tree-structured predictive model. This approach successively partitions the dataset according to the most informative attributes until it attains classification outcomes. Despite being less complex than SVM, decision trees offer a more comprehensible interpretation and are extensively utilized for classification tasks that necessitate transparent result interpretation, such as medical picture segmentation and geospatial data analysis. This research utilizes the findings of GLCM feature extraction at angular parameters of 0°, 45°, 90°, and 135°, and distances of 1, 2, and 3 pixels to compare the performance of two methods utilizing the evaluation metrics of accuracy, precision, recall, and F1-score. Figure 1 illustrates the approach employed in the research.

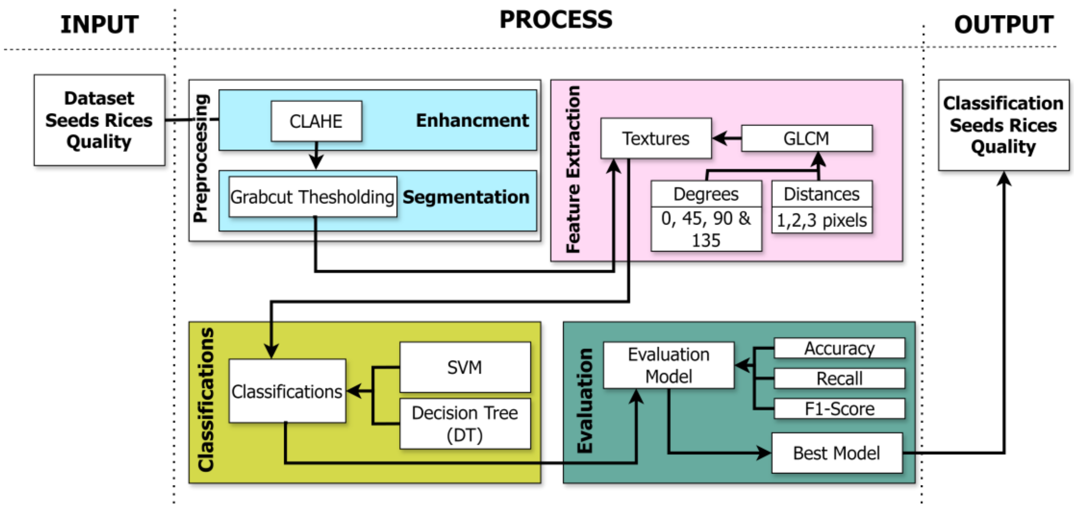


Figure 1. The architecture of the proposed

5. EXPERIMENT AND ANALYSIS

Image quality uniformity can be achieved homogeneously by applying image contrast enhancement techniques or CLAHE. This process is used to increase the intensity of the contrast value so that the basic color is more visible. CLAHE was computed based on Michelson Contrast (MC) with equation (3).

$$MC = \frac{I_{max} - I_{min}}{I_{max} + I_{min}} \tag{3}$$

where I_{max} and I_{min} represent maximum and minimum pixel intensities in seed regions; according to the dataset, the average MC is 0.25 for 300 images, but the average MC for CLAHE is 0.34, indicating a 35% enhancement in contrast. The absence of CLAHE resulted in a classification accuracy of 0.65 for SVM, whereas the inclusion of CLAHE improved it to 0.73, highlighting the essential role of contrast enhancement in distinguishing texture features.

Grabcut is employed to segment seeds from the backdrop, so removing extraneous noise. The decrease of background noise was quantified using the standard deviation (σ) of pixel intensities in non-seed regions as outlined in equation (4).

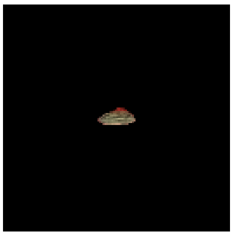
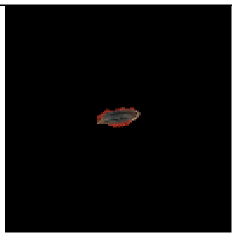
$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \quad (4)$$

where x_i represents pixel intensity, μ is the mean, and N signifies the number of pixels. Before implementing the GrabCut method, the standard deviation of background pixel intensity σ_{raw} = 0.18 demonstrated significant fluctuation attributable to noise and illumination distortions. Following the application of GrabCut, the standard deviation $\sigma_{\text{processed}}$ = 0.13 diminished by 28%, signifying a more uniform background. In one sample image, the mean background intensity was μ=120, with pixel fluctuations between 110 and 130 prior to the application of GrabCut. Subsequent to processing, this variation was diminished to a range of 115 to 125, indicating enhanced segmentation quality.

Table 1 displays samples of seed classes, including high, average, and bad, by carrying out the pre-processing stages of CLAHE and grabcut thresholding.

Table 2 illustrates various patterns and distinctions in texture characteristics according to rice seed quality classifications (high, average, and poor) utilizing GLCM parameters. The High class typically demonstrates lower values for the homogeneity parameter than the Average and Bad classes at same distances. Contrary to the first assertion, the Bad class frequently attains the greatest homogeneity values of 0.992 at distance 1, indicating a more uniform distribution of pixel intensity in lower-quality seeds. The contrast parameter is markedly elevated in the High class, especially at angles of 45° and 90° with a distance of 3 pixels, measuring 455.433 at 45°, indicating enhanced pixel intensity fluctuation and more intricate textural characteristics.

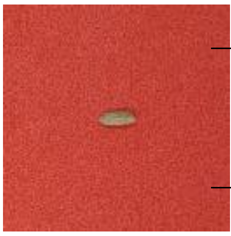
Table 1. Seeds Rice Quality Class

ID	Original	CLAHE	Grabcut	Class
0				High
1				Average
2				Bad

The High class consistently exhibits lower energy parameter values compared to the Average and Bad classes, signifying diminished homogeneity in pixel intensity distribution. Conversely, the dissimilarity parameter is elevated in the High class, particularly at a distance of 3 pixels and an angle of 0°, at 0.908, which highlights more significant disparities in pixel intensity. The trends indicate that integrating contrast, dissimilarity, and homogeneity metrics can proficiently distinguish rice seed quality. Additional assessment using metrics such as accuracy and F1-score is necessary to confirm the effectiveness of these parameters.

Table 2. GLCM Feature Extractions

Images	Dis	Deg	Hom	Con	Dis	En	Class
	1	0	0.779	243.950	0.939	0.767	High
	1	45	0.775	350.799	0.913	0.766	High
	1	90	0.778	276.332	0.931	0.767	High
	1	135	0.776	332.561	0.917	0.767	High
	2	0	0.992	31.475	0.929	0.991	High
	2	45	0.991	71.229	0.840	0.991	High
	2	90	0.991	106.387	0.761	0.990	High
	2	135	0.991	57.216	0.871	0.991	High
	3	0	0.774	370.729	0.908	0.765	High
	3	45	0.771	455.433	0.887	0.763	High
	3	90	0.772	449.626	0.888	0.764	High
	3	135	0.774	397.786	0.9015	0.766	High
	4	0	0.995	18.450	0.845	0.994	High
	4	45	0.994	25.320	0.790	0.993	High

Images	Dis	Deg	Hom	Con	Dis	En	Class
	4	90	0.995	20.110	0.830	0.994	High
	4	135	0.994	22.750	0.810	0.993	High
	5	0	0.996	15.890	0.860	0.995	High
	5	45	0.995	18.240	0.840	0.994	High
	5	90	0.996	12.670	0.890	0.995	High
	5	135	0.995	16.980	0.855	0.994	High
	1	0	0.991	29.726	0.897	0.991	Average
	1	45	0.991	59.194	0.797	0.990	Average
	1	90	0.991	35.818	0.876	0.991	Average
	1	135	0.992	20.487	0.929	0.991	Average
	2	0	0.991	58.729	0.800	0.990	Average
	2	45	0.991	59.719	0.796	0.990	Average
	2	90	0.990	67.308	0.770	0.990	Average
	2	135	0.992	19.995	0.931	0.991	Average
	3	0	0.990	81.721	0.722	0.990	Average
	3	45	0.989	110.475	0.626	0.989	Average
	3	90	0.990	98.052	0.667	0.990	Average
	3	135	0.991	37.071	0.874	0.991	Average
	4	0	0.993	10.220	0.920	0.992	Average
	4	45	0.992	15.340	0.875	0.991	Average
	4	90	0.993	8.950	0.940	0.992	Average
	4	135	0.992	12.560	0.900	0.991	Average
	5	0	0.994	7.890	0.950	0.993	Average
	5	45	0.993	9.120	0.930	0.992	Average
	5	90	0.994	6.450	0.965	0.993	Average
	5	135	0.993	8.760	0.945	0.992	Average
	1	0	0.992	25.839	0.825	0.992	Bad
	1	45	0.992	33.233	0.776	0.991	Bad
	1	90	0.992	13.753	0.907	0.992	Bad
	1	135	0.992	19.271	0.870	0.992	Bad
	2	0	0.991	44.200	0.703	0.991	Bad
	2	45	0.992	33.233	0.776	0.991	Bad
	2	90	0.992	25.833	0.826	0.992	Bad
	2	135	0.992	19.271	0.870	0.992	Bad
	3	0	0.990	61.161	0.591	0.990	Bad
	3	45	0.990	58.383	0.611	0.990	Bad
	3	90	0.992	33.273	0.777	0.991	Bad
	3	135	0.991	34.806	0.768	0.991	Bad
	4	0	0.994	5.670	0.960	0.993	Bad
	4	45	0.993	8.340	0.925	0.992	Bad
	4	90	0.994	4.220	0.980	0.993	Bad
	4	135	0.993	6.890	0.940	0.992	Bad
	5	0	0.995	3.450	0.985	0.994	Bad
	5	45	0.994	5.120	0.955	0.993	Bad
	5	90	0.995	2.980	0.990	0.994	Bad
	5	135	0.994	4.560	0.965	0.993	Bad

Note: dis (distance), deg (degree), hom (homogeneity), con (contrast), dis (dissimilarity), en (energy).

The comparative examination of distances 4 and 5, as provided in Table 2, indicates that the assertion that increased distance generally promotes class difference is not universally applicable. At a distance of 3 pixels, the High-quality class has markedly greater contrast, measuring 455.433 at 45° and a dissimilarity of 0.887 at 45°, in comparison to distances of 4 and 5, especially at angles of 45° and 90°. The energy value at distance 3, ranging from 0.763 to 0.766, is much lower than at distances 4 and 5, which range from 0.991 to 0.995, suggesting diminished uniformity in pixel intensity distribution for the High class. This indicates that whereas greater distances may boost individual parameters for particular classes, they may not consistently augment discriminative power across all parameters or classes.

The significance of distance 3 in this work resides in its capacity to harmonize textural sensitivity with computational feasibility. The heightened contrast and variance at this distance are particularly adept at revealing small textural differences in high-quality seeds, essential for precise quality separation. Despite the energy parameter lacking a regular trend, the stability of contrast and dissimilarity patterns at distance 3 offers a solid basis for classification. Moreover, distance 3 enhances the balance between recording distinctive spatial correlations and reducing computational complexity, rendering it a practical option for real-world applications in agricultural quality evaluation.

Figure 2 illustrates a sample of the outcomes from preprocessing a high-quality rice seed texture image captured at a distance of 1 and a scale of 25 degrees. This photograph clearly illustrates the distinct variations in the texture of the seed's surface.

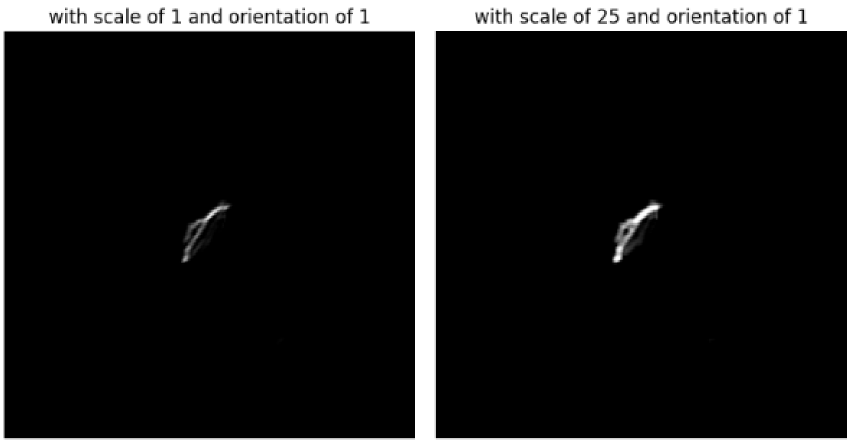


Figure 2. Comparative Texture with GLCM

The assessment of rice seed quality classification performance indicates notable trends for SVM and Decision Tree (DT) algorithms at different distances. The SVM method attains optimal performance at a distance of 1, yielding an accuracy of 0.73, precision of 0.79, recall of 0.73, and an F1-score of 0.72, highlighting its proficiency in identifying essential texture patterns at reduced distances. Nonetheless, SVM demonstrates a significant decrease in performance at distance 2, with accuracy falling to 0.47 and F1-score to 0.38, indicating that texture features become less discriminative as the spatial associations between pixels expand. At a distance of 3, the SVM demonstrates a considerable recovery, achieving an accuracy of 0.57 and an F1-score of 0.53; nevertheless, its precision and recall scores of 0.57 are suboptimal in comparison to distance 1.

Conversely, the DT method exhibits increasingly enhanced performance with greater distances, albeit it maintains lower overall metrics compared to SVM. At a distance of 1, the decision tree achieves an accuracy of 0.40 and an F1-score of 0.37, indicating restricted discriminative capability. Performance exhibits a marginal enhancement at distance 2, with an accuracy of 0.43 and precision of 0.5, and reaches its zenith at distance 3, attaining a maximum accuracy of 0.57, precision of 0.64, and F1-score of 0.54. At a distance of 3, Decision Trees (DT) marginally surpass Support Vector Machines (SVM) in precision, achieving 0.64 compared to DT's precision of 0.57, and aligns with its accuracy of 0.57, demonstrating DT's flexibility to broader spatial patterns.

The Support Vector Machine (SVM) employs optimization parameters at various distances for the Gray Level Co-occurrence Matrix (GLCM). For a distance of 1, the optimal configuration is C = 1000 and gamma = 0.1 using the Radial Basis Function (RBF) kernel. At a distance of 2, the best parameters are C = 100 and gamma = 1 with the RBF kernel. Finally, for a distance of 3, the highest C value is 500 and gamma = 1, also utilizing the RBF kernel. Figure 3 presents a heatmap of the confusion matrix utilized for evaluating accuracy, recall, precision, and F1-Score.

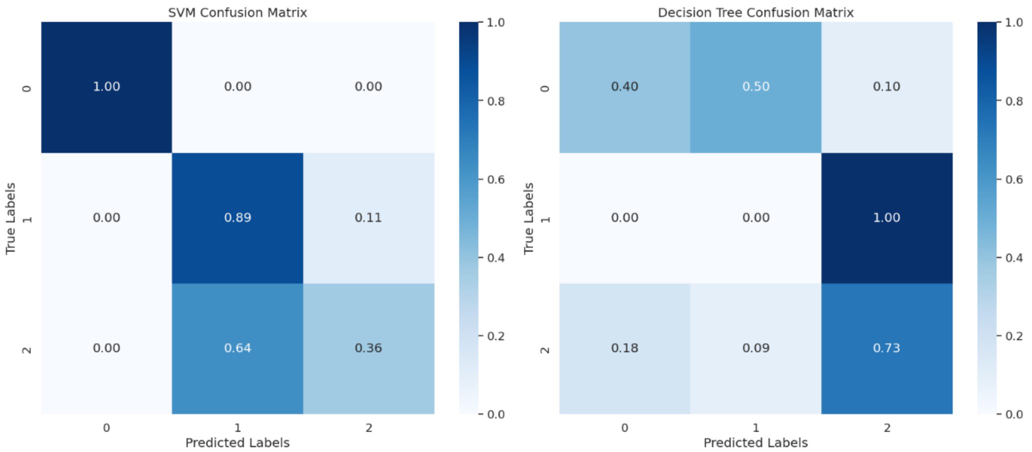


Figure 3. Heatmap SVM & DT Classifier

SVM classification uses optimization parameters at several appropriate distances for GLCM distance 1, the best configuration with parameters C = 1000, gamma = 0.1 with the RBF kernel, while in GLCM with a distance of 2, the best parameter optimization is with a value of C = 100, gamma = 1 with the RBF kernel and finally in GLCM with a distance of 3, the highest C value is 500, gamma = 1 with the RBF kernel.

Table 3. *Confusion Matrix* GLCM

Classifier	***Distance***	***Acc***	***Pre***	***Rec***	**F1**
SVM	1	0.73	0.79	0.73	0.72
	2	0.47	0.32	0.47	0.38
	3	0.57	0.57	0.57	0.53
	4	0.52	0.50	0.52	0.49
	5	0.48	0.45	0.48	0.44
Decision Tree	1	0.40	0.39	0.40	0.37
	2	0.43	0.51	0.42	0.40
	3	0.57	0.64	0.57	0.54
	4	0.55	0.60	0.55	0.53
	5	0.53	0.58	0.53	0.51

Table 3 explains that the efficacy of SVM diminishes progressively from distance 1 to 5, with accuracy values declining from 0.73 to 0.48, as the GLCM feature forfeits essential local features necessary for hyperplane delineation. SVM attains superior performance at a distance of 1, achieving an accuracy of 0.73, whereas DT exhibits optimal performance at a distance of 3 with an accuracy of 0.57. The decision-making process of SVM is based on determining an ideal hyperplane for effective class separation [23]. This method is most effective when features exhibit high discriminative power, particularly at reduced GLCM distances, such as distance 1, resulting in an accuracy of 0.73 and an F1-score of 0.72. As the distance grows, the extracted texture features diminish in local discriminative details and become more coarse, resulting in a notable fall in SVM performance. At a distance of 2, the accuracy of SVM declines to 0.47, while the F1-score decreases to 0.38. Although SVM demonstrates a marginal improvement at distance 3 with an accuracy of 0.57, its precision and recall, both at 0.57, are subpar relative to shorter distances, indicating diminished feature significance for hyperplane optimization.

Conversely, Decision Tree (DT) utilizes a rule-based hierarchical methodology, which is more adept at exploiting extensive spatial linkages and coarser texture patterns. This adaptability enables DT to enhance its performance incrementally at greater distances, reaching a maximum at distance 3 with an accuracy of 0.57, precision of 0.64, and F1-score of 0.54. At a distance of 3, DT attains superior precision compared to SVM, recording 0.64 against 0.57, so illustrating its efficacy in leveraging global texture information. Despite DT's overall accuracy being worse to SVM's maximum performance at distance 1, its consistency over distances underscores its resilience in managing less granular features. Consequently, SVM's dependence on localized discriminative characteristics renders it more effective at short distances, while DT's hierarchical structure facilitates competitive performance at greater sizes by leveraging broader spatial patterns.

6. CONCLUSION

The study effectively implemented the texture feature extraction technique utilizing GLCM with angular parameters of 0°, 45°, 90°, and 135°, as well as distances of 1, 2, and 3 pixels, for the classification of rice seed quality. The procedure commences with image acquisition and data normalization to ensure balanced distribution and enhance image quality with CLAHE and GrabCut. Feature extraction yields characteristics including homogeneity, contrast, energy, and dissimilarity, which are employed for classification using SVM and DT. Assessment relies on accuracy, precision, recall, and F1-score measures to determine the optimal parameters for seed quality detection.

The enhancement in classification accuracy, achieving 0.73 with SVM at a distance of 1, directly indicates the efficacy of GLCM parameter optimization since the chosen configurations produced texture characteristics that optimized class separability. The performance of the SVM at distances 2 and 3 exhibited a notable decline, with accuracies of 0.47 and 0.57, the results correspond with the findings of Singh et al. (2022) [23]. Decision Trees exhibit more consistent performance while overall inferior to Support Vector Machines at distance 3, achieving a maximum accuracy of 0.57, precision of 0.64, recall of 0.57, and an F1-score of 0.54. According to these results, SVM demonstrates optimal performance at distance 1, establishing it as the preeminent model for assessing rice seed quality based on textural data. Concurrently, DT exhibits more consistent performance, reaching its apex at distance 3.

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