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Soybean Seed Quality Classification using Magnitude-Enhanced Multiple Channel LBP and SVM

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Abstract
Soybean is a major source of plant-based protein The quality of soybean seed affects resulting food. Therefore, image processing for classifying soybean seed quality is needed. Previous studies mainly used handcrafted or deep learning features and not evaluated local texture representations that using magnitude information for multi-class problems with high visual similarity. Traditional texture descriptors such as LBP or GLCM mainly using sign-based or global statistics and have limitations in representing colour-texture variations. This study aims to classify soybean seed quality using SVM with Multiple Channel Local Binary Pattern (MCLBP) and its enhanced variant with magnitude information (MCLBP+M) for feature extraction by utilizing correlations between colour channels through multi-radius approach. The dataset used is Soybean Seeds includes five classes: intact, spotted, immature, broken, and skin-damaged. This research conduct dataset splitting using 10-fold cross validation, data balancing (SMOTE), feature extraction, SVM model training and testing, and performance evaluation. The results show that MCLBP+M with Lab colour space and RBF kernel achieves accuracy of 86.30%, precision of 86.32%, recall of 85.99%, and F1-score of 86.07%. The results show that magnitude information in MCLBP+M consistently stable and improves classification performance across colour spaces and kernels, making it suitable for soybean seed quality classification.

Keywords: magnitude information; multiple channel local binary pattern; quality classification; soybean seeds; support vector machine.

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INTRODUCTION

Soybean seed are one of the major food commodities with high economic value. Soybean seed are a major source of vegetable protein, containing 40% protein (Guo et al., 2022). Soybean seed also containing 20% vegetable oil (Baisch et al., 2024). The high protein content makes soybean seed the main source of protein and vegetable oil for 60% of the world's production (Duan et al., 2023). Around 20% of the world's soybean seed are used for consumption as edible oil and other food products (Chauhan et al., 2022; Martignone et al., 2024; Singer et al., 2023; Toomer et al., 2023; van den Berg et al., 2022). The food products include tofu, soy sauce, soy milk, soy oil and other processed products. Not only that, the modern food industry also uses soybean seeds to make plant-based meat products (Qin et al., 2022).

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Soybean seed are widely used as raw material in food products, their quality is very important and affects the quality of the resulting food products (Kudełka et al., 2021). One of the main factors influencing the quality of soybean seed is their physical morph characteristics (Wang et al., 2025) and colour characteristics (Balachandan et al., 2025). Those attributes determine the processing process in industry (Çetin, 2022). The colour of soybean seed coats such as black, yellow, brown, and green can affect quality because they are related to the mechanical properties and integrity of the seed coat (Zhang et al., 2023). In addition, the shape of the seed, whether they are good or have defects such as broken or damaged, also determines the quality of the soybean seed and their processed products (Cañizares et al., 2024). These defects are often subtle, presenting high visual similarity between classes due to smooth surface texture, small-scale cracks, or minor discoloration. It makes manual inspection subjective, tricky, and low efficiency (Jin et al., 2022). Therefore, digital image-based classification method can be a good alternative for soybean seed quality classification with high similarity.

Machine learning and deep learning methods have been widely applied in soybean seed classification. There are studies using hand-crafted texture and colour descriptors. Sable et al. (2024) used GLCM and LBP feature extraction with a Support Vector Machine with RBF kernel. The results yielded 95.6% accuracy for good seeds and 96.1% for bad seeds. Although these approaches are computationally efficient and interpretable, conventional descriptors such as GLCM and standard LBP primarily capture global statistics or sign-based local patterns and have limited ability to represent colour-texture variations.

Another study by Zhao et al. (2022) used hyperspectral image and Support Vector Machine (SVM) that was optimized with tree-structured parzen estimator (TPE) with RBF kernel achieved accuracy of 91.6%. Chen et al. (2025) used hyperspectral image and random forests achieved accuracy of 99.6%. Hyperspectral methods provide rich spectral information but require specialized sensors, high computational cost, and complex preprocessing, limiting practical deployment in low-resources agricultural settings. Lastly, there is studies that applied deep learning and transfer learning methods. Pereira et al. (2024) used ViT-Base features achieved an accuracy of 95.89%. Deep learning approaches with modified InceptionV3 achieved accuracy of 98.73% (Gulzar, 2024). Despite their high accuracy, deep learning models require large labelled datasets and high computational resources.

Although previous studies have demonstrated high accuracy, there is still room for improvement. The magnitude information in colour-based LBP descriptors has not been systematically evaluated for multi-class soybean seed classification with high visual similarity. Most existing studies focus either on conventional handcrafted or deep learning approaches without analysing local texture descriptors with magnitude information. Furthermore, very few studies examine hand-crafted features across different colour spaces and SVM kernels within a consistent experimental. The lack of systematic evaluation of magnitude-enhanced local texture descriptor represents a scientific gap in image-based soybean seed quality classification. Objects such as soybean seeds often have homogeneous colour appearance and subtle surface variations, where sign only texture descriptor may fail to capture information. Therefore, investigating the contribution of magnitude information to local texture representation in necessary.

This study uses the Multiple Channel Local Binary Pattern (MCLBP) and its enhanced variant, MCLBP+M. MCLBP is suitable for colour-texture information by using correlations between multiple colour channels through orthogonal planes, enabling more discriminative local texture representation than conventional LBP or GLCM. The inclusion of magnitude information in MCLBP+M allows the descriptor to capture not only the direction but also strength of intensity changes, which is meaningful in representing surface defects on soybean seeds. Support Vector Machine (SVM) is use as classifier due to its ability in handling high-

dimensional handcrafted features, strong generalization capability, and effectiveness in non-linear classification through kernel functions (Du et al., 2024).

This study aims to analyse the performance of the Multiple Channel Local Binary Pattern (MCLBP) and MCLBP+M methods in classifying soybean seed quality with high visual similarity. Also to evaluate the stability of feature performance across different colour spaces (RGB, HSV, YCbCr, and Lab) and SVM kernels (linear, polynomial, RBF, and sigmoid) in a multi-class classification. The main contribution of this study lies in the systematic evaluation of MCLBP and MCLBP+M, combined with colour spaces and kernel analysis, providing interpretable alternative for image-based agricultural quality classification.

METHOD

In this research, a method design was first carried out. The stages of the research methodology can be seen in Figure 1. In the literature study stage, relevant studies to the research topic was conducted, namely soybean seed quality classification using Multiple Channel Local Binary Pattern, MCLBP+M with SVM, based from accredited journals and scientific sources.

Dataset used was public dataset called "soybean seeds" from Mendeley Data Repository (https://data.mendeley.com/datasets/v6vzvfszj6/6). Soybean seeds were collected from Nanjing Agricultural University. This dataset consists of 5,513 images measuring 227 × 227 pixels and divided into five classes with Chinese Standard Soybean Classification (GB1352-2009) namely intact (1201 images), immature (1002 images), skin-damaged (1127 images), spotted (1125 images), and broken (1058 images). These five classes have high visual similarity in surface texture and colour variation, which makes the dataset challenging and suitable for evaluating colour-texture descriptors. Public dataset also supports experimental reproducibility, although potential domain bias related to acquisition conditions is acknowledged.

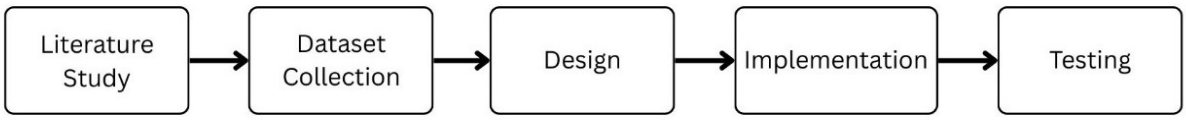

Figure 1. Research methodology stages

Figure 2. Soybean seed images

Model design stage was carried out using supervised learning approach. The dataset will be divided using 10-fold cross validation, which provides a good trade-off between bias and variance that allows stable estimation by using all samples for both training and testing across folds. For each fold, the dataset was split into training and testing. MCLBP and MCLBP+M was used within each fold. SMOTE only applied in training data in each fold. SMOTE was used over under sampling to avoid information loss and over class weighting to explicitly

enriches minority class feature distributions. However, the potential risks synthetic sample overlap or over-smoothing is acknowledged.

MCLBP feature extraction uses radius parameters of 1, 2, 3, to captures texture information at different spatial scales. The features from the three radius were concatenated into single feature vector. Four colour spaces and three different sequences are used (RGB, HSV, YCbCr, Lab) to analyse feature representation across colour configurations. RGB represents native image acquisition space, HSV provides perceptual separation, YCbCr decouples luminance and chrominance, and Lab offers perceptual uniformity. MCLBP only uses sign information, while MCLBP+M use magnitude information, defined as absolute intensity difference between neighbouring and central pixel, binarized using average threshold. The resulting histogram length will be 5,193 (MCLBP) and 10,386 (MCLBP+M). This study did not use dimensionality reduction or feature selection to preserve complete information.

SVM effectively handles high-dimensional features through margin maximisation and regularisation. Four kernels linear, RBF, polynomial, and sigmoid—were employed. The linear kernel served as a baseline, RBF captured non-linear decision boundaries, while polynomial and sigmoid kernels assessed higher-order decision complexity. Kernel parameters were kept consistent across experiments.Model performance was evaluated using confusion-matrix–based metrics, including accuracy, precision, recall, and F1-score, averaged across all folds. Precision and recall were reported to reflect false acceptance and false rejection rates, and statistical comparisons between MCLBP and MCLBP+M were conducted to assess performance consistency.

RESULT AND DISCUSSION

Result

This section presents all the results obtained from testing the classification model. Testing was conducted using two feature extraction methods, MCLBP and MCLBP+M, each applied to four different colour spaces which is RGB, HSV, YCbCr, and Lab. Each combination of colour space and feature extraction method was then tested using four SVM kernels which is linear, RBF, polynomial, and sigmoid. To ensure stable and unbiased results, all experiments were run using 10-fold cross validation, so the performance presented is the average value of ten consistent tests. The performance will be evaluated through confusion matrix and achieve accuracy, precision, recall, and F1-score.

Table 1 shows the performance of the MCLBP feature extraction method on four colour spaces which is RGB, HSV, YCbCr, and Lab, using four types of SVM kernels. In general, all colour spaces exhibit a consistent performance pattern. RBF kernel consistently outperforms the linear, polynomial, and sigmoid kernels in terms of accuracy, precision, recall, and F1-score. This trend suggests that the feature distributions are not linearly separable. Among the evaluated colour spaces, Lab achieves the most stable performance, especially when using RBF kernel, with an accuracy of 0.8511. Meanwhile, the linear and polynomial kernels resulting stable performance across all colour spaces, although slightly below the RBF kernel, indicating moderate separability of the features. The sigmoid kernel shows the lowest performance across all tests in each colour space. Overall, these results indicate that the choice of colour space and kernel type significantly influences the quality of MCLBP feature extraction classification.

Table 2 shows the performance of the MCLBP+M method on four colour spaces using four SVM kernels. Compared to MCLBP, MCLBP+M produces higher performance across all configurations, indicating that the inclusion of magnitude information provides a richer and more discriminative texture representation. That give a conclusion that non-linear classifiers are better suited for both sign and magnitude information. The Lab colour space achieved the highest performance with the RBF kernel with an accuracy of 0.8630, followed by the RGB

colour space, which achieved 0.8634 with the RBF kernel. The linear and polynomial kernels showed quite same performance, although slightly lower than RBF.

Table 1. MCLBP feature extraction results

Colour Spaces	Kernel	Accuracy	Precision	Recall	F1-score
RGB	Linear	0.7925	0.7921	0.7887	0.7891
	RBF	0.8297	0.8292	0.8262	0.8266
	Polynomial	0.7671	0.7655	0.7635	0.7634
	Sigmoid	0.6866	0.6863	0.6840	0.6841
HSV	Linear	0.8066	0.8046	0.8023	0.8025
	RBF	0.8232	0.8220	0.8194	0.8195
	Polynomial	0.7811	0.7781	0.7762	0.7760
	Sigmoid	0.6579	0.6663	0.6556	0.6573
YCbCr	Linear	0.7949	0.7936	0.7911	0.7911
	RBF	0.8340	0.8335	0.8310	0.8312
	Polynomial	0.7867	0.7863	0.7830	0.7834
	Sigmoid	0.6478	0.6643	0.6453	0.6477
Lab	Linear	0.8079	0.8232	0.8208	0.8210
	RBF	0.8511	0.8505	0.8479	0.8483
	Polynomial	0.8045	0.8030	0.8015	0.8014
	Sigmoid	0.6460	0.6619	0.6431	0.6469

Table 2. MCLBP+M feature extraction results

Colour Spaces	Kernel	Accuracy	Precision	Recall	F1-score
RGB	Linear	0.8534	0.8521	0.8500	0.8503
	RBF	0.8634	0.8624	0.8601	0.8605
	Polynomial	0.8159	0.8141	0.8126	0.8127
	Sigmoid	0.7650	0.7646	0.7618	0.7615
HSV	Linear	0.8431	0.8422	0.8394	0.8398
	RBF	0.8532	0.8530	0.8498	0.8503
	Polynomial	0.8117	0.8098	0.8083	0.8084
	Sigmoid	0.7117	0.7152	0.7091	0.7101
YCbCr	Linear	0.8288	0.8282	0.8253	0.8256
	RBF	0.8462	0.8459	0.8432	0.8434
	Polynomial	0.8165	0.8163	0.8139	0.8139
	Sigmoid	0.7306	0.7324	0.7271	0.7277
Lab	Linear	0.8527	0.8521	0.8493	0.8497
	RBF	0.8630	0.8632	0.8599	0.8607
	Polynomial	0.8273	0.8266	0.8244	0.8244
	Sigmoid	0.6994	0.7096	0.6975	0.6998

When comparing Table 1 and 2, the average improvement by MCLBP+M ranges from 1-4% in accuracy and F1-score, depending on the colour space and kernel. More importantly, this improvement is consistent across configurations. That means magnitude information plays a significant role in enhancing descriptor. The linear and polynomial kernels continue to show stable but lower performance relative to RBF. Meanwhile, the sigmoid kernel consistently

achieved the lowest performance across all colour spaces. Figure 3 presents macro-average ROC curves for MCLBP and MCLBP+M in the Lab colour space using RBF kernel. Both descriptors exhibit high discriminative capability, with AUC values exceeding 0.96, indicating strong separability among the five soybean classes. MCLBP+M achieves slightly higher macro-average AUC (0.966). That show consistent improvement when magnitude information is used.

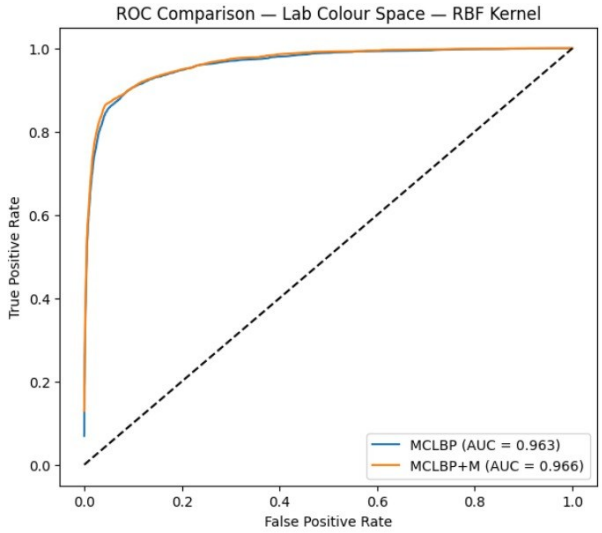

Figure 3. AUC curve of mclbp and mclbp+m for lab-rbf

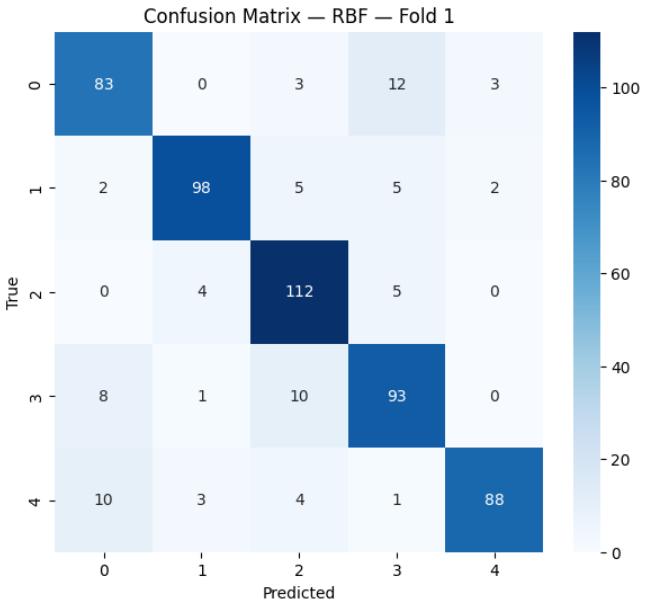

Figure 4. Confusion matrix of mclbp+m-lab-rbf-fold 1

To examine the classification error patterns in more detail, a confusion matrix from the best configuration, the MCLBP+M method in Lab colour space with an RBF kernel is shown in Figure 4. This confusion matrix provides information on the distribution of predictions for each class, including the most frequently misclassified classes. The results show that most classes are well classified, although some errors still occur in classes with very similar texture or minor colour differences, such as intact and immature seeds, or skin-damaged and spotted seeds. Presenting the confusion matrix helps to demonstrate the characteristics of the model's errors of an object with highly similar visual characteristics. Although magnitude information

improves discrimination, certain classes remain challenging due to overlapping texture patterns at local scales.

The results of MCLBP+M shows consistent performance improvements over MCLBP across colour spaces and kernels. The dominance of RBF kernel across all experiments showed the importance of non-linear decision boundaries for colour-texture descriptors. Additionally, the Lab colour space not only achieves high accuracy but also achieves stable performance. These findings shows that robust descriptor design is better than parameter optimisation in multi-class classification with high visual similarity.

Discussion

The results of this study indicate that MCLBP and MCLBP+M methods are able to achieve stable classification performance across various colour spaces and SVM kernels. Although the resulting accuracy varies between configurations, the performance pattern is relatively consistent across each fold, thus reflecting the ability of MCLBP in capturing texture on soybean seeds. This stability supports the suitability MCLBP for analysing agricultural objects with high visual similarity. The higher performance of MCLBP+M compared to MCLBP indicates that the addition of magnitude information contributes significantly to improving feature representation. Unlike MCLBP, which only relies on sign and not using strength, MCLBP+M utilizes magnitude patterns from the absolute intensity difference between the central pixel and its neighbours, making it more sensitive and preserve information related surface texture. The mechanism is particularly relevant for soybean seeds, whose surfaces are generally homogeneous in colour but contain subtle texture such as minor cracks, shallow surface damage, or spots. Sign descriptors lose discriminative information because it only encodes the direction of local intensity changes. By using magnitude patterns, MCLBP+M preserves information related to the strength of local intensity variations. This finding is in line with the argument of Shu et al. (2021) who stated that magnitude patterns can enrich texture descriptions and add depth to spatial information that is not captured by sign. The fact that the performance of MCLBP+M is observed consistently across colour spaces and kernels shows that this improvement is because of enhancement using magnitude in texture representation.

The effects of colour space also provide important insights. Although the Lab colour space achieves the highest and stable performance, this should not be interpreted as Lab being universally optimal. Instead, its superiority can be explained by its separation of luminance and chromaticity components and its perceptual uniformity, which allow local texture descriptors to work consistently. The relatively similar performance on RGB, HSV, and YCbCr suggests that descriptor design plays a more dominant role than colour space. This finding aligns with computer vision literature, which emphasises that robust local descriptors should maintain discriminative power across different colour representations rather than relying on specific colour encoding (Alimoussa et al., 2022). The dominance of RBF kernel across all experiments can be understood because feature histogram generated by MCLBP and MCLBP+M form high-dimensional feature that are inherently non-linearly separable. The RBF kernel is well suited to modelling such distributions by mapping features into higher-dimensional where complex class boundaries can be separated. The linear and polynomial kernels achieve more stable but lower performance, reflecting their capacity to model complex non-linear in high-dimensional features. While, sigmoid kernel performs poorly due to its sensitivity to feature scaling and its incompatibility with histogram-based feature distributions. A deeper examination of confusion matrix reveals that misclassifications occur between soybeans classes that have visual similarities, such as intact and immature seeds, or skin-damaged and spotted seeds rather than algorithmic failure. Such overlap is expected as certain quality defects differ only subtly in surface texture or colour.

Several previous studies have reported higher classification accuracy. Pereira et al. (2024) reported 95.89% accuracy using ViT-Base deep features, benefiting from hierarchical feature learning at the expense of high computational cost and limited interpretability. Sable et al. (2024) obtained accuracy above 95% using GLCM and LBP with RBF SVM, although the classification task was limited to binary quality classes. In contrast, the present study addresses a more challenging multi-class problem involving five soybean seed categories with high similar visuality. The use of hand-crafted descriptors is intentionally aimed at stability and interpretability across colour spaces and kernel configurations.

Although the results are lower than some previous studies, this study still has an important contribution that shows the magnitude information is able to distinguishing factor for texture discrimination in objects with homogeneous colour and subtle surface variations. This study also show the stability of performance across colour spaces and the systematic evaluation offers methodological guidance for future agricultural vision studies. In terms of implications, these results indicate that MCLBP+M has the potential to be an efficient alternative when computing resources are limited. Furthermore, the performance patterns across colour spaces provide insight that selecting the right colour space can improve texture sensitivity to soybean surface variations.

However, the high visual similarity between classes make colour-texture features alone insufficient for optimal separation. Furthermore, while SMOTE successfully balances classes, it can potentially produce synthetic samples that are too similar, thus not fully expanding the natural class distribution. Future research can be done with hybrid MCLBP+M combine with deep learning models to integrate local texture with global feature learning. This study also did not explore more comprehensive feature selection, dimensionality reduction, or hyperparameter tuning techniques such as Bayesian optimization or genetic algorithms. Furthermore, SVM kernel optimization method would help to improve model generalization and trade-off between performance and complexity.

CONCLUSION

Based on the research results and discussion, it can be concluded that Multiple Channel Local Binary Pattern and MCLBP+M methods are able to provide stable classification performance. The experimental results show that the best performance was achieved using the MCLBP+M method in the Lab colour space with RBF kernel, which obtained an accuracy of 86.30%, precision of 86.32%, recall of 85.99%, and F1-score of 86.07%. The results provide that magnitude information in MCLBP+M consistently improves texture discrimination compared to MCLBP. This improvement shows that magnitude information play a significant role in capturing subtle surface variations on soybean seeds compared to only sign information. Although its performance has not surpassed several previous studies, this study shows that MCLBP+M remains an efficient and competitive method. The consistent performance across different colour spaces and kernels also shows that the discriminative capability of the method is by texture structure rather than global colour representation alone. Nevertheless, the high visual similarity among soybean seed classes limits the separability and the use of SMOTE may introduce synthetic samples that do not fully reflect natural data. This study also did not explore dimensionality reduction or hyperparameter optimisation. These results can be the basis for the development of hybrid methods with deep feature techniques and applying feature reduction techniques to manage feature dimension to achieve higher accuracy in future research.

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