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Application of Convolutional Neural Networks for Enhancing Gemstone Classification Performance

Lukkana Poempool*
Department of Automated Manufacturing Engineering
Faculty of Industrial Technology
Rajabhat Rajanagarindra University
Chachoengsao, Thailand
lukkana.po@gmail.com

Phornsin Pumpakar
Department of Computer and Information Sciences, Faculty of Applied Science
King Mongkut's University of Technology North Bangkok (KMUTNB)
Bangkok, Thailand
p.phornsin@gmail.com

Chaibwoot Ratanavilisagul*
Department of Computer and Information Sciences, Faculty of Applied Science
King Mongkut's University of Technology North Bangkok (KMUTNB)
Bangkok, Thailand
chaibwoot.r@sci.kmutnb.ac.th

San Ratanasanya
Department of Computer and Information Sciences, Faculty of Applied Science
King Mongkut's University of Technology North Bangkok (KMUTNB)
Bangkok, Thailand
san.r@sci.kmutnb.ac.th

Gemstones have different values and characteristics, such as color, shape, and texture. These differences make manual classification and counting difficult and time-consuming, especially when gemstones have similar appearances. In practice, gemstone classification is still mainly performed by humans, which can lead to errors caused by fatigue or repeated counting. This study applies image processing and deep learning techniques to improve the accuracy and efficiency of gemstone classification and counting under controlled imaging conditions. The OpenCV library is used to adjust brightness, reduce noise, and detect object edges, while a Convolutional Neural Network (CNN) is used to learn gemstone features such as color, brightness, and texture. Moreover, the HSV color model is applied to reduce the effect of lighting and shadows that can affect classification accuracy. Experimental results show that the proposed method provides better classification and counting performance than the compared methods, achieving an accuracy of 99.70%. The results indicate that the proposed system can effectively reduce human-related errors and processing time, and it demonstrates potential applicability as a laboratory-scale, proof-of-concept solution for automated gemstone inspection.

Image processing, gemstone classification, gemstone counting, HSV, CNN, OpenCV

I. Introduction

The gemstone industry is one of Thailand's high-value business sectors, especially in manufacturing and export. Diamonds and colored stones are essential materials that enhance both the value and appearance of jewelry [1]. However, the counting and classification of gemstones are still mostly done by hand. Operators typically spread the stones on a flat surface and count them by visual inspection, sometimes using tools such as tweezers or magnifying lenses. This manual process requires experience, takes a significant amount of time, and is vulnerable to fatigue-related errors, including double-counting or missing stones. These issues become even more likely when the gemstones are small or have similar colors. Moreover, commercial diamond-counting devices are relatively expensive and are built specifically for diamonds, which limits their ability to handle other types of colored gemstones.

From previous research, we found that image processing and machine learning techniques have been applied to support gemstone classification. For example, the work by Khanyai [20] used HSV color conversion to classify the color grades of pink and blue gemstones. While this approach helped reduce sorting time, its accuracy was limited when the colors were similar or when reflections appeared in the images. The method also required the gemstones to be arranged neatly under consistent lighting conditions to achieve good results.

The study Color Detection System for Diamond Sorting Using Machine Learning [21], used the RGB color model together with machine learning techniques to identify diamond colors, achieving an accuracy of up to 95%. However, this work focused only on color classification and could not detect shapes or count gemstones, making it unsuitable for practical counting tasks in the industry.

Another study, Gemstone Classification using Convolutional Neural Network (CNN) [3], applied a CNN model and achieved a classification accuracy of 98%. Nevertheless, the method required a large dataset and controlled imaging conditions with consistent lighting and background. When applied to real-world images, the method still faced limitations in accuracy and processing speed, especially when gemstones had similar colors or surface textures.

Overall, previous research indicates that no existing system can effectively classify and count gemstones under real operating conditions, especially when gemstones vary in color, size, and are placed randomly.

Therefore, this research aims to develop a gemstone detection and classification technique using image processing combined with deep learning. OpenCV is employed to adjust lighting, reduce noise, and detect object edges [2], providing suitable preprocessed images for classification. A CNN model [18] is then used to learn distinctive gemstone features such as color, gloss, and surface texture, enabling accurate classification and counting of gemstones.

The objective of this study is to develop a deep learning model capable of classifying and counting gemstones with high accuracy and speed, thereby reducing human counting errors and enhancing the potential for practical application in Thailand's gemstone industry in the future.

II. RELATED WORK

Computer-based gemstone detection and classification has received considerable attention in recent years. Techniques have progressed from traditional image processing methods to the application of deep learning approaches, aimed at improving accuracy and reliability in gemstone identification.

A. *Round and pear shape Gemstones colored grading with image processing*

Khanyai [20] introduced an image-processing method for grading the color of blue and pink sapphires, using round and pear-shaped gemstones as examples. The dataset consisted of JPEG images captured with a digital camera under controlled lighting. The gemstones were arranged and color-sorted by experts to provide ground truth for evaluation.

The process began by converting RGB images to the HSV color space, where the Hue channel was used to analyze color levels. Canny edge detection was then applied to separate the gemstones from the background. Morphological operations, such as closing and filling gaps, were used to improve the shapes of the stones and remove small noise regions. Objects smaller than 400 pixels were removed to ensure that only real gemstone areas remained. Each gemstone was labeled, and features such as area and centroid were calculated to compare with the expert grading.

The results showed accuracies of 91.67% for pink round stones, 100% for blue round stones, and 88.89% for pink pear-shaped stones. These outcomes indicate that the method can produce grading results close to those of human experts and help reduce sorting time.

However, the method still has limitations. It is sensitive to lighting variations and reflections during image capture. In addition, edge detection becomes more difficult when many gemstones appear in the same image, which can reduce classification accuracy in practical use.

B. *Color Detection System for Diamond Sorting Using Machine Learning*

Afor et al. [21] proposed a color detection system designed to support diamond sorting. It uses the RGB color model together with machine learning techniques to identify and classify diamond color shades from images. For data handling, the system uses the Pandas library and applies the Euclidean distance function to measure the difference between the color values of a diamond and a reference dataset of 865 colors stored in a CSV file. These reference colors include several common diamond shades, such as white, light gold, yellow, and light purple.

The system process starts with reading the image and converting it into the RGB format using OpenCV. The pixel values are then separated into the R, G, and B channels. After that, the system calculates the distance between the diamond's color values and each color in the reference dataset to find the closest match. The detected color name, its code, and the color intensity are then displayed in real time on the image.

The results show that the system can detect and identify diamond colors with an accuracy of around 95%, which is considered effective compared with traditional color analysis methods. However, this approach focuses only on color classification and cannot distinguish between different gemstone types. In addition, the system is sensitive to lighting changes and reflections, which may affect the accuracy when applied in real-world environments.

C. *A Study on Synthetic Diamond Quality Evaluation Using an Enhanced YOLOv8n-based Algorithm Named YOLOv8n_adamas*

Zhang et al. [15] developed an improved algorithm called YOLOv8n_adamas to enhance the detection and quality evaluation of synthetic diamonds. The method is based on the original YOLOv8n architecture, but it is adjusted to improve accuracy in identifying both the shape and quality characteristics of the diamonds.

The model uses the ConvNextV2 architecture as the backbone to strengthen image feature extraction. In addition, a Dynamic Detection Head is added to improve multi-scale object detection, supported by several attention mechanisms, including scale-aware, spatial-aware, and task-aware modules. These components help increase detection precision and reduce redundant bounding boxes.

The dataset for the experiment consists of 627 high-resolution microscope images of synthetic diamonds. The data is divided into 80% for training and 20% for testing. All images are labeled with attributes such as shape, clarity, and imperfections. The results show that the improved model achieves an accuracy of 92.8% and a recall of 97.5%, which are both higher than the original YOLOv8n model.

Although the method performs well in detecting diamond location and characteristics, it mainly focuses on identifying objects and evaluating internal quality. It does not aim to classify different types of gemstones. In addition, the training process requires detailed labeled data and relatively high computational resources, which may limit its convenience for general gemstone classification tasks.

D. *Gemstone Classification Using Convolutional Neural Network*

Judixon and Shivaraman [3] presents a gemstone classification method using deep learning with a Convolutional Neural Network. The goal is to enable the system to automatically learn and identify gemstone characteristics from images. The experiment uses more than 24,000 gemstone images, covering 12 gemstone types: Amethyst, Ametrine, Black Spinel, Blue Sapphire, Citrine, Diamond, Emerald, Pearl, Peridot, Rose Quartz, Ruby, and Smoky Quartz. The dataset is divided into 70% for training, 20% for validation, and 10% for testing. Data augmentation techniques including rotation, flipping, and scaling are applied to improve data variety and reduce overfitting.

The experimental results show that the CNN model is able to classify gemstones with 98% accuracy, while the average precision and recall range from 97.8% to 98.5%. This indicates that CNN provides strong performance in distinguishing gemstones with similar visual characteristics. However, the dataset used in this study was collected under controlled lighting conditions and contains only single-gemstone images. Therefore, the model may not perform as accurately in real production environments, where gemstones are often mixed together and affected by reflections or background surfaces.

III. PROPOSED WORK AND METHODOLOGY

This research proposes a method that combines image processing techniques using the OpenCV library together with a CNN model to improve the detection, classification, and counting of gemstones. The results from this method are compared with two other techniques, which are OpenCV + Pandas Tools [12], [21] and YOLOv8 [14], [15], to evaluate the accuracy and overall performance.

A. *Overview of the Proposed Technique*

It can be observed that most existing studies still face limitations when classifying gemstones that have similar colors or surface textures, especially when multiple gemstone types appear within the same image. Therefore, this research proposes an approach that applies image processing using OpenCV together with a Convolutional Neural Network to improve accuracy and reduce errors in gemstone classification and counting. In addition, the proposed method is compared with OpenCV + Pandas and YOLOv8 in order to evaluate its overall performance.

Based on the reviewed studies, there is currently no system that can effectively detect, classify, and count gemstones under real-world conditions, particularly when gemstones vary in color, size, and are arranged in an unorganized manner. For this reason, this research focuses on developing an integrated technique that combines image processing with deep learning. OpenCV is used to enhance image quality [2], while CNN and YOLOv8 [14], [15], [17] are applied for classification and object detection, aiming to improve accuracy and reduce counting errors compared to manual inspection.

B. *OpenCV for Image Preprocessing*

OpenCV (Open Source Computer Vision Library) is an open-source framework that is widely used for computer vision and image processing. It provides a variety of functions that support image manipulation, including brightness and contrast adjustment, noise reduction, and edge detection. These processes help reduce the impact of lighting and shadow conditions while improving the clarity of object boundaries before the images are forwarded to the classification stage.

OpenCV also supports color space conversion, particularly from RGB (Red, Green, Blue) to HSV (Hue, Saturation, Value). The HSV model is considered more suitable for distinguishing gemstones with similar color tones because it separates color information from brightness components. As a result, it can reduce the effects of lighting intensity and surface reflections more effectively than RGB.

In this study, OpenCV is used for preprocessing tasks such as brightness and contrast adjustment, noise filtering, and edge detection to prepare the images before inputting them into the model. In addition, RGB-to-HSV conversion is applied to separate hue, saturation, and value components more clearly, which helps minimize lighting-related distortion and can potentially improve the accuracy of the gemstone classification results.

C. *RGB and HSV Color Spaces*

The RGB (Red, Green, Blue) color model is commonly used in digital devices because different colors can be created by adjusting the intensity of the three main color channels. However, RGB can be affected by lighting conditions, which

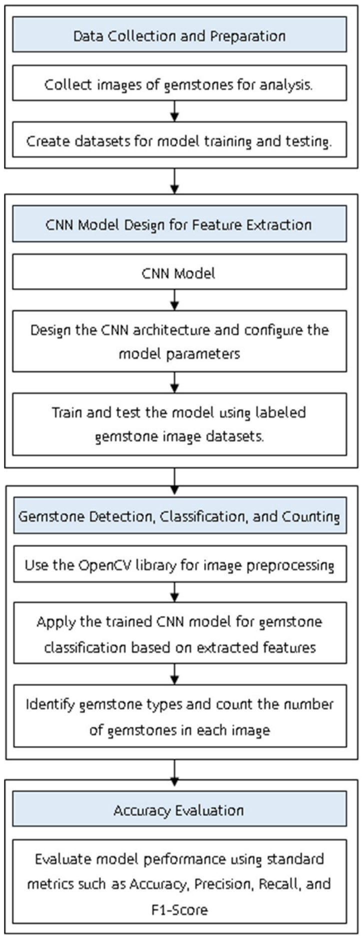

Fig. 1. the workflow of the proposed gemstone detection, classification, and counting system.

may cause the color values to change and result in lower accuracy when identifying object colors in images.

The HSV (Hue, Saturation, Value) color model represents colors in a way that is closer to human color perception. It separates the color information into three parts: Hue (color tone), Saturation (color strength), and Value (brightness). With this separation, HSV can reduce the effects of lighting and shadows and is more suitable for detecting objects with similar colors.

For this reason, this research converts images from RGB to HSV during the preprocessing stage to improve the accuracy of gemstone classification.

D. YOLOv8 for Object Detection

YOLO (You Only Look Once) is a real-time object detection technique that can identify both the location and the class of objects within an image in a single processing step. YOLOv8 is an improved version that provides better accuracy and performance by using an anchor-free structure and attention mechanisms to learn features from objects of different sizes. This makes it suitable for detecting small objects, such as gemstones, with higher accuracy.

YOLOv8 is also useful for industrial applications that require fast image processing. It can automatically draw detection boxes around each gemstone in an image. In this research, YOLOv8 is compared with the CNN model to evaluate the performance of both methods in terms of detection accuracy and processing speed.

Based on the techniques mentioned above, combining OpenCV for image preprocessing with CNN for classification and YOLOv8 for object detection is expected to improve the system's ability to identify and count gemstones accurately and quickly. This approach can also reduce the effects of lighting and shadows, which helps increase the accuracy and reliability of image processing in real-world environments.

E. Data Collection and Preparation

The process begins with collecting images of four gemstone types, which are diamond, pink gemstone, blue gemstone, and yellow gemstone. All images were captured under controlled lighting conditions and placed on a black background to improve the clarity of object boundaries. After that, the dataset was converted into two color formats, RGB and HSV, in order to compare the classification performance between both formats.

All images were resized to 150 × 150 pixels to maintain consistency, and the dataset was then divided into 80% for training and 20% for testing. A fixed random seed was used during data splitting to ensure that the experiment can be repeated and produce consistent results.

F. CNN Model Development for Feature Extraction

In this step, a convolutional neural network was designed to classify different types of gemstones. The main structure of the model consists of the following components:

- 3 convolutional layers using 3×3 filters with 32, 64, and 128 filters, respectively

- 3 max-pooling layers for reducing the spatial dimensions of the feature maps

- A flatten layer to convert the 3D feature maps into a 1D vector

- A fully connected layer with 512 nodes and a ReLU activation function

- An output layer with 4 nodes and a Softmax activation function for four-class classification

The model was trained using the Adam optimizer with a learning rate of 0.001. The loss function used was sparse categorical cross-entropy, and the batch size was set to 32. Training was performed for 30–50 epochs with early stopping to prevent overfitting. Data augmentation techniques such as flipping, rotation, and zooming were also applied to increase the variety and robustness of the dataset.

G. Gemstone Detection, Classification, and Counting

In this step, the OpenCV library is used for initial image processing and object detection before passing each detected object to the CNN model for classification. The procedure consists of the following steps

1. Adjusting image brightness and contrast to improve visibility (alpha = 0.7, beta = 30)

2. Converting the image from RGB to HSV color space to separate color components and reduce sensitivity to lighting variations

3. Creating color masks by defining Hue ranges for each target color: pink (140°–170°), blue (90°–130°), and yellow (20°–30°)

4. Applying thresholding and morphological closing to isolate gemstones from the background and reduce noise

5. Detecting object boundaries and drawing bounding boxes to locate each gemstone within the image

The detected regions are then passed to the CNN model for classification. The model identifies key features such as color, shape, and texture to improve classification accuracy. Based on the predicted classes, the system counts the number of gemstones in each category.

H. System Accuracy Evaluation

The performance of the proposed system and the comparison methods is evaluated using standard metrics, including Accuracy, Precision, Recall, and F1-Score. The formulas are as follows:

1. Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

where TP is the number of true positives, TN is true negatives, FP is false positives, and FN is false negatives.

2. Precision

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

This metric indicates how many of the samples predicted as positive are actually correct.

3. Recall

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

This measures the system's ability to correctly detect all actual positive samples.

4. F1-Score

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (2)$$

This score represents the harmonic mean of Precision and Recall, reflecting the balance between both metrics.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The model was trained using the Adam optimizer with a learning rate of 0.001. The loss function used was sparse categorical cross-entropy, and the batch size was set to 32. Training was performed for 30–50 epochs with early stopping to prevent overfitting. Data augmentation techniques such as flipping, rotation, and zooming were also applied to increase the variety and robustness of the dataset.

To evaluate the performance of the developed system, experiments were conducted to compare three primary gemstone classification techniques:

1. Classification using OpenCV combined with Pandas Tools

2. Classification using YOLOv8

3. The proposed method: OpenCV integrated with a CNN model

Each technique was tested using both RGB and HSV color spaces to examine how color conversion affects the accuracy of gemstone classification.

A. Dataset

The dataset used in this experiment consists of 10,000 images of gemstones, covering four types: diamonds, pink gemstones, blue gemstones, and yellow gemstones , with 2,500 images per category. The dataset is balanced across all four gemstone classes. All images were captured under controlled lighting conditions and placed on a black background to make the object boundaries clear. A sample of the dataset can be viewed at: https://chaibwoot.no-ip.org/dataset.jsp

The dataset was divided into two parts: 80% for training and 20% for testing. A fixed randomization method was applied during the splitting process to ensure that the results can be reproduced accurately and to evaluate the system's performance on data it has never seen before.

B. Experimental Environment

All experiments were carried out on the Google Colab platform, which provides a cloud-based computing environment using Python within a Jupyter Notebook structure. The main libraries used in this study include OpenCV, Pandas, TensorFlow, Keras, and YOLOv8 (Ultralytics) for image processing and deep learning tasks.

C. Experimental Parameters

For the CNN model used in the experiments, the main parameters were set as follows:

Parameter	Value
Learning rate	0.001
Optimizer	Adam
Batch size	32
Epochs	30–50
Loss function	Sparse Categorical Cross-Entropy
Activation function	ReLU (hidden layer), Softmax (output layer)
Image size	150 × 150 pixels
Color space	RGB, HSV

For the YOLOv8 model, the default parameters of the YOLOv8n (Nano version) were used. The batch size was set to 16 and the input image size was set to 640 × 640 pixels.

D. Experiment

TABLE I. PERFORMANCE OF EACH MODEL IN GEMSTONE CLASSIFICATION

Technique	Test Accuracy (%)	Precision	Recall	F1 Score
OpenCV + Pandas Tools (RGB) [21]	73.10%	73.10%	100.00%	84.40%
OpenCV + Pandas Tools (HSV)	62.71%	72.50%	82.20%	77.10%
YOLOv8 RGB [15]	94.30%	84.50%	96.30%	90.07%
YOLOv8 HSV	88.72%	79.58%	98.22%	87.81%
OpenCV (RGB) + CNN (RGB)	94.50%	95.69%	98.70%	97.17%
OpenCV (HSV) + CNN (HSV)	99.70%	99.80%	99.60%	99.70%

TABLE II. PERFORMANCE OF EACH MODEL IN GEMSTONE CLASSIFICATION

Technique	Diamond	Pink Gem	Blue Gem	Yellow Gem	Total
OpenCV + Pandas Tools (RGB) [21]	72.10%	66.75%	77.25%	76.30%	73.10%
OpenCV + Pandas Tools (HSV)	35.53%	76.14%	59.22%	79.95%	62.71%
YOLOv8 RGB [15]	95.30%	92.95%	94.45%	94.45%	94.30%
YOLOv8 HSV	99.60%	85.10%	71.00%	99.10%	88.72%
OpenCV (RGB) + CNN (RGB)	99.40%	77.78%	99.40%	99.40%	94.34%
OpenCV (HSV) + CNN (HSV)	**99.85%**	**99.65%**	**99.65%**	**99.65%**	**99.70%**

The experimental results show that the proposed method (OpenCV (HSV) + CNN (HSV)) achieves the highest accuracy of 99.70%, which is higher than that of the other evaluated methods. As shown in Table I, the use of the HSV color space does not improve the performance of all baseline methods. However, the proposed CNN-based model performs better when HSV is applied. This is because the CNN can learn relevant features from HSV images, where color is separated from brightness. As a result, the model is less affected by changes in lighting and shadows, which helps when classifying gemstones with similar colors, such as pink and yellow.

As shown in Table II, the proposed CNN-based method with HSV achieves high classification accuracy across all gemstone categories. This suggests that the performance improvement is not restricted to specific colors, but is observed across different gemstone types.

For YOLOv8, the results indicate strong object detection capability and high precision, but with increased processing time due to the simultaneous prediction of object locations and class labels. In contrast, OpenCV combined with Pandas Tools is the fastest method, but its accuracy is limited, especially when dealing with uneven lighting or gemstones with similar colors.

Overall, the results show that applying OpenCV-based image preprocessing prior to CNN training improves classification performance. The CNN trained with OpenCV-processed images achieves improved feature separation in terms of color and texture, leading to an increase in accuracy from 94.50% (RGB) to 99.70% (HSV). These findings indicate that the proposed method provides a favorable balance between accuracy, stability, and processing efficiency under controlled imaging conditions, and it serves as a laboratory-scale, proof-of-concept approach for automated gemstone inspection.

V. Conclusion

This research presents a method for detecting, classifying, and counting gemstones by integrating image processing techniques with deep learning under controlled imaging conditions. The OpenCV library is used for image preprocessing, including image enhancement and edge detection, while a CNN is employed to classify gemstones based on visual features such as color, shape, and texture.

The experimental results show that the proposed method achieves higher classification performance than the compared techniques, including OpenCV + Pandas Tools and YOLOv8, with an accuracy of 99.70% and an improved F1-score. The use of the HSV color space contributes to improved performance for the proposed CNN by reducing the influence of lighting variations and shadows, although similar improvements are not observed for all baseline methods. In addition, the system is able to process images efficiently and classify multiple gemstone types within a single image frame.

Overall, the results indicate that the proposed system can effectively reduce human-related errors and processing time. The system demonstrates potential applicability as a laboratory-scale, proof-of-concept solution for automated gemstone inspection rather than a fully deployed industrial system.

Despite the promising results, this study has several limitations. The dataset was collected under controlled lighting conditions and does not yet represent the full variability encountered in real industrial environments. Future work will focus on expanding the dataset under more diverse lighting conditions and investigating advanced deep learning approaches, such as YOLOv8-segmentation and Vision Transformers, to further improve detection and classification performance for more complex gemstone scenarios.

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