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Valuable Stone Detection

Akash V O [1], Sunitha G P [2]

Student[1], Associate Professor[2], Department of Master of Computer Applications

JNN College Of Engineering, Shivamogga

akashvo2000@gmail.com,sunithagpise@jnnce.ac.in

Abstract

The study presents use of Convolutional Neural Network (CNN) to automate gemstone classification. The experiment starts by doing image preprocessing on the gemstones at a standard size of 256x256 pixels which means normalization has been achieved as well this is followed by augmentation through rotation plus flipping in order to improve model generalization. CNN consists of several convolutional layers with 2x2 filters activation function being ReLU this come together with another ones like dropout and batch normalization for regularization.The Adam optimizer with a learning rate of 0.0002 and Categorical Cross entropy loss function are used for training. Evaluation metrics like Accuracy, Mean Squared Error (MSE), and Top-3 Accuracy as well as diagnostic tools like confusion matrices and classification reports are employed in evaluation. Deep learning-based robust gemstone classification framework focuses on effective identification and categorization of gemstone varieties from the visual data in question, which is fundamental for gemological purposes.

keyword ***:****Gemstone classification, CNN, diagnostic plots, model performance.*

1. Introduction

Non renewable resources are gifts from our environment, some of the most prized materials in the world are gems. These are a group of stones that are created under some conditions in the interior of the earth and brought to the surface by some forces. As earlier explained, everyone is, is expected to possess one or many features that set apart from the others and the same applies to gemstones. Man has been fond of these stones for his aesthetics, durability and rarity which have earned them the blanket term of the four C's: color, clarity, cut, and carat weight, with hardness being an essential parameter. Currently, some of the well-known gemstones include the diamond, ruby, sapphire, and emerald among others which are used in jewelries and decorations not only as ornaments but as other valuables in different industries, technological developments, and cultural purposes including beautification, wealth, and spiritual purposes. The first step is the data pre-processing by which some of the operations include resizing of gemstone images dataset into 256 x 256 pixels and some normalization techniques that can be used are rotation or shift plus a flip can be employed in order to simulate increase in the number of training data that in turn enhances model generalization ability. By using a custom neural network based convolutional layer to enable the subsequent features investigation and recognition. It also filters the learning process through 2×2 filters and while using ReLU activation and batch normalization eliminates noises in learning. The overfitting is handled by dropout layer while the use of L2 regularization helps in increasing the generalization. Adam's optimiser has been used in this model, and learning rate initiated with 0. 0002 was used. Evaluation of models involves the use of measures that include accuracy, top-3 accuracy, and mean squared error (MSE) among others. Confusion matrix and the classification reports are also used to measure the model performance according to the other gemstone types and to minimize the lack of areas as well.

Gemstone	Color	Clarity	Cut	Carat Weight	Hardness
Diamond	Colorless, Various color	Flawless to include	Round, princess, emerald	0.01 to several carats	10
Ruby	Red	Inclusions common	Oval, cushions	Under 2 carats	9
Sapphire	Blue	Eye clean included	Round, oval	7.5 to 8	9

Table 1.1. : key characteristics of gemstone

2. Literature survey

The earlier works that have been reviewing various methodologies include [1] In their research, Jin et al. employed ResNet-50 to differentiate 15 varieties of gemstones with an accuracy level of 93.46%. They created a dataset, augmented this dataset, and divided it into two sets namely; testing set and training set. These studies have huge potential which indicates an advanced improvement in accuracy and speed could be achieved through deep learning in the future.[2] Boteju et al. fused RAMAN Spectroscopy with computational tools to identify gemstones. Initially, RAMAN data preprocessing was to be done, followed by correlating it with a spectral database and applying the K-means clustering algorithm. This resulted in 98% specificity and sensitivity of 100%. The results could be further enhanced through expansion of the RAMAN database.[3] In an attempt to attain an artificial gemstone classification system based on technology for computing and ResNet-50 in Gemology developed by Chow et al resulting in automatic identification. The system trained with 2024 pictures and tested on 284 pics belonging to 68 classes relies mainly on machine learning supported by aconventional Random Forest approach with custom features which correlate with accuracy 69.4% exceeding that of human gemologists according to Chow et al (2015).[4] Afor et al developed a sorter that utilizes OpenCV and machine learning to differentiate colors in diamonds which have been tested up to 865 sets thereby achieving an accuracy of close to a hundred percent in predicting colors. Consequently, it's difficult for the single dataset they used for their research to represent all varieties in the world.[5] Judixon et al. employed CNN to classify 12 gemstones with 98% accuracy in 24,000 images as their dataset, used preprocessing techniques, applied regularization and Adam optimizer with the limitations being dataset size and new range of gemstone used in the study.[6] A machine learning approach for gemstone classification and value estimation using CNN was proposed by Amarasekara et al. Which achieved 87% and 77% accuracy for yellow and blue sapphire respectively. Noted limitations are image quality and a limited number of gem types.[7] Using an HSV color space and an ANN, Maulaa et al. identified Ruby, Sapphire, and Emerald gemstones. Their precision equaled 90.66% through 5 training iterations and 25 testing iterations the system realized. The dependence on the hue information only acts limitation since it neglects different types of variation.[8] Hakeem and his friends created an IOT-based system for Corundum gemstones identification using image processing to measure its refractive index, color, and cut shape. Still, everyone should note that this system's inclination towards image processing as a method for detecting colors has been considered limiting.[9] Tropea et al. crafted a Calabrian quarry two-stage hybrid stone categorization system, CNNs were employed for distinguishing features and different ML methods were used for piece separation. High accuracy was provided by KNN although complexity and demand for calculation characterize this method.[10] Hou et al. (2012) proposed an approach to detecting and counting pearls based on recent advances in object detection technology. Faster R-CNN along with ResNet-152 architecture showed strong performance on the dataset by achieving a mean average precision (mAP) score at intersections over unions (IoUs) equals to 100% for 0.5IoU threshold and 98.33% for 0.75 IOU threshold when tested with faster inference time. However, there remains room for additional improvement.

3. Methodology

The system that is used in the classification of the gemstone starts with data preprocessing; this means that gemstone images are ingested, resized to a given form (256 x 256 pixels), and normalized so as to ensure a consistent input across the various datasets. Different transformations such as rotation about origin, shift along an axis or change in orientation in relation to y or x planes are carried out on training samples which provide a variety hence better model particularization.The task of classification uses an architecture for Convolution Neural Network (CNN) which is uniquely designed with several convolutional layers followed by pooling to extract features, batch normalization to stabilize learning, dropout to regularize and dense layers for classification.The convolutional layers utilized a filter size of 2x2, enabling them to benefit from ReLU activation function together with L2 regularization which assists in avoidance of overfitting. Also employed in this particular instance was Adam optimizer which fine-tuned our model at a certain pace (represented by learning rate=0.0002) while Categorical Crossentropy loss supervised how well our results could be trusted during various computations on the data set under study(please note that such mechanisms are always considered standard). Concerning training supervised accuracy rate, mean squared error (MSE) or even top three class-accuracy happened under these metrics. Even more interrogated model performance is through visual representation of diagnostic plots as well as metrics such as confusion matrix and classification report which offer complete insight on classification of a model. The figure 3.1 showcases gemstones are classified using sophisticated deep-learning algorithms. The approach takes into account several key stages of data pre-processes, the construction of Convolutional Neural Network (CNN) models, training algorithm optimization, evaluation criteria, and performance assessment. The main target of such systematized procedure is accurate recognition with high quality results reliable through the use of recent computational tools that are applicable in geological studies.

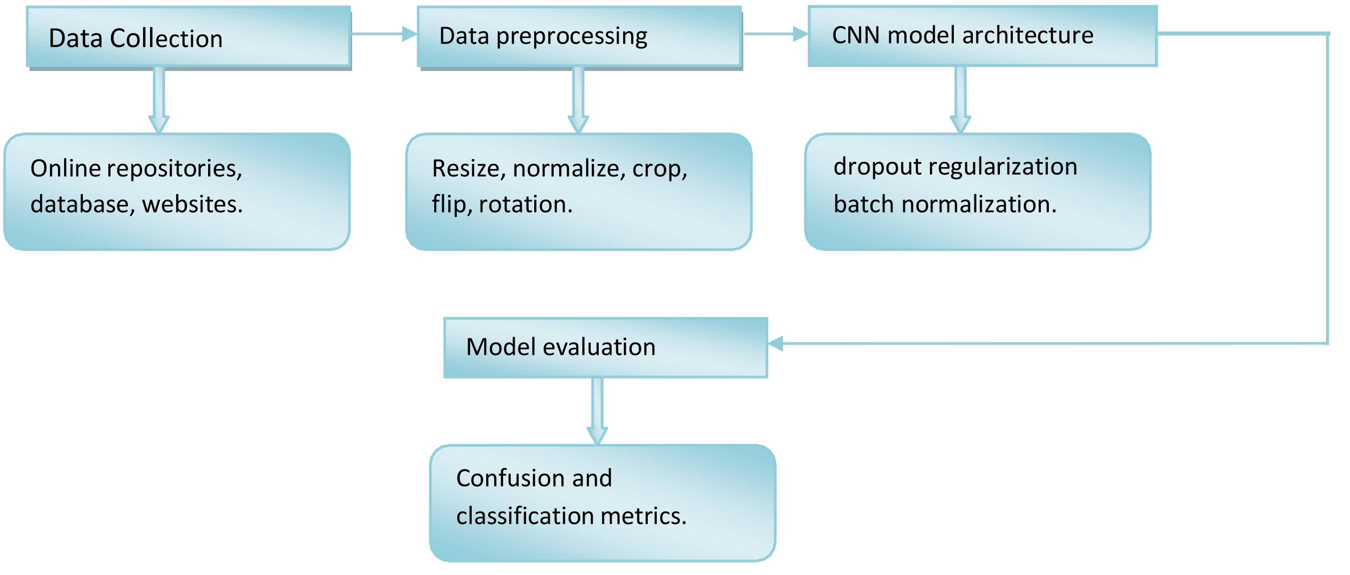

Figure 3.1 : Methodology framework

Feature extraction includes using the Canny edge detection algorithm to determine gemstone image edges. Subsequently, the identified edges are applied towards localization and cropping of these images thus isolating particular Regions of Interest (ROIs) that contain gemstones. Preprocess in this stage is very important since it readies the data for any other tasks like classification or detailed analysis about gemstones according to their visual characteristics.

Figure 3.1.1 : Outcomes of feature extraction technique

Randomly spinning photographs within ±2 degrees (spin_range=2), imitating perspective changes. Width and **Height Adjustment:** Randomly moves pictures rightwards (adjustment_on_width=0.05) and downwards (adjustment_on_height=0.05) At variance in position. **Shearing Range:** It introduces perspective effects by applying a pattern change along the x-axis (shear-pattern=1) **Horizontal and Vertical Flipping:** Random horizontal flipping of photographs (horizontal_flipping=true). By rescaling each pixel value by 255 using Keras' ImageDataGenerator that has been set to rescale parameter equal to 1/255, all pixel values are made to lie within a scale from 0-1.

This is important because this would help ensure that there are no variations between different pictures when they are represented numerically as arrays with intensities represented as numbers ranging between 0 (black) and 255 (white).

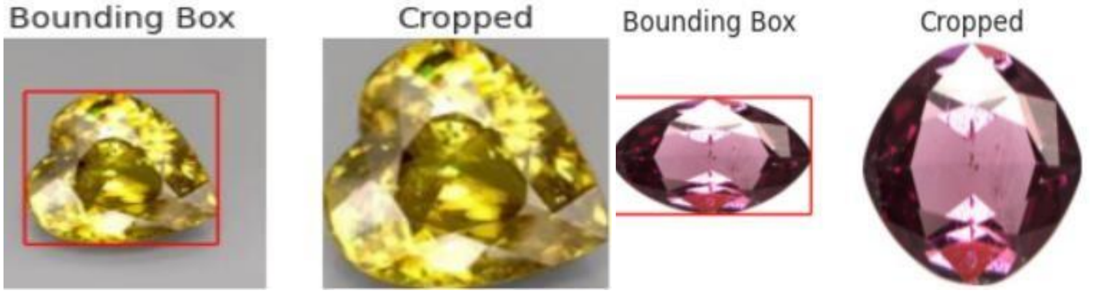

Figure 3.1.2 Images obtained after augmentation

4. Result

The absolute percentage error of differentiating between the classes of gemstones is determined. Among the parameters that precision utilizes to measure the effectiveness of the exercise, accuracy determines the extent of precision of the profiles of gems through evaluating the positive predictions in comparison to the degree of all the anticipated positive outcomes in a correctly classified area. Remember that recall measures the model's ability to classify every specific true positive event, which is crucial from the point of view of comprehensive classification. It shall be noted that F1-score offers a balanced assessment of students' performance in the class since both recall and precision values are incorporated in the statistic. The macro-average focuses on every gemstone class and computes average values that are identical for all the classes. The formulas for computing the average also include the weighted average of each model as a measure of the middle when different classes are involved.

Metrics	Standard dataset value	Manual dataset value
Accuracy	0.85	0.65
Precision	0.86	0.67
Recall	0.85	0.65
F1-score	0.85	0.63
Macro average	0.85	0.62
Weighted average	0.85	0.63

Table 4.1 : comparative analysis of standard and manual datasets

Standard datasets are further usually free from noise, less ambiguous and do not have any fault or inconsistency in them. Such elements are usually selected consciously and ready to be used and employed. It may consequently result into the enhancement of the stability and the degree of accurate of the model. The datasets which are carefully and selectively constructed could have class imbalance, missing data, noisy labels or data, and inconsistent data. They maybe influence not only the training and the generalization of models; other performance measures like the accuracy, precision, and recall will also be influenced. The following are the graphical illustrations the performance indicators of the gemstone classification models assessed for this study. Each of these visuals gives abundant information about the efficiency characteristics and performance of the model. In the figure 4. 1 epochs are taken in the X-axis. The value of the Y-axis isolates the exhibit of the percent of the accurate classification of samples adopted by the model. The following graph represents the accuracy of the model which tends to increase as the training goes on and is plotted for the training and validation (test) sets. It also helps in monitoring of the convergence and ascertain the ability of the model to incorporate the inputs. The figure 4. 2 shows the plotting of mean squared errors by having training iterations in X axis and the MSE values in Y axis, so the focus is on how near the estimated value is to its equivalent target.

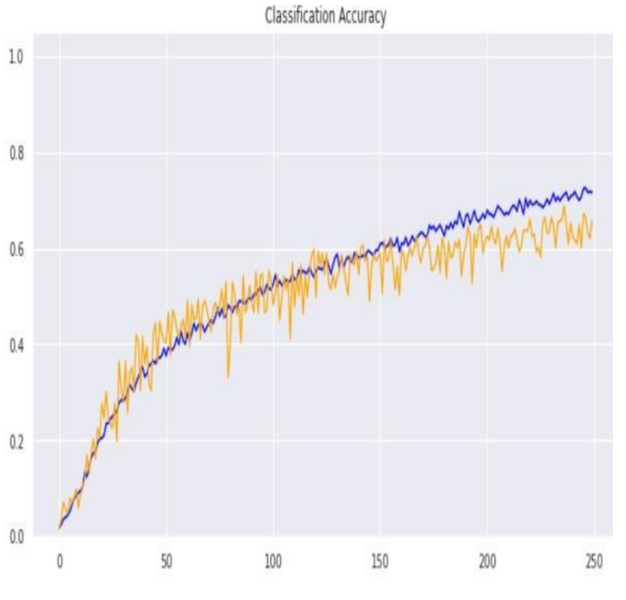

Figure 4.1: classification accuracy graph

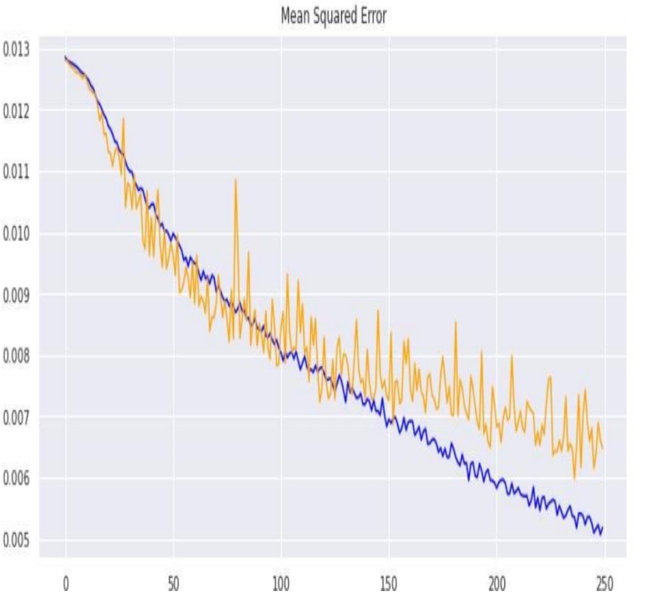

Figure 4.1: mean squared error graph

5. Conclusion

The study used and tested an appearance-based classification model for gemstones, that it had formulated. out of many trials and after applying computational tools in the interpretation of the results the model recorded high recall, accuracy, precision, and F1-score in differentiating diversified types of gemstone. It also shows that the strategies of preprocessing and selection of the dataset play the critical role in model formation as can be seen with the help of the variances between the standard and the hand selected datasets. Moreover, the weighted average and macro average provide detail understanding of the model regarding its performance on several classes of the gemstones.

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