university of engineering and technology peshawar pakistan

SMART GEMOLOGY APP

By

Amir Suliman 19pwcse1805

Ashfaq Ahmad 19pwse1795

Mansoor Hussain 19pwcse1858

The undersigned certify that they recommend to the UET Peshawar for acceptance of this thesis for the fulfillment of the requirements for the degree stated.

Signature:

Engr. Madiha Mushtaq

Supervisor:

Signature:

Dr. Muniba Ashfaq

Final Year Project Coordinator:

Signature:

Dr. Nasir Ahmad

Chairman:

Date: 19 Dec 2022

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AMIR SULIMAN

ASHFAQ AHMAD

MANSOOR HUSSAIN

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**Abstract**

This thesis presents the development of a "Smart Gemstone Detection App" that employs computer vision techniques for automated gemstone classification. Inspired by the literature on "Automatic Gemstone Classification Using Computer Vision" and "Gemstone classification using ConvNet with transfer learning and fine-tuning," the project utilizes convolutional neural networks (CNNs) with transfer learning and fine-tuning.

The approach involves training a CNN on a dataset of gemstone images to recognize and classify gemstones based on their shape, color, and transparency. Python is used for implementing the gemstone classification using machine learning algorithms, with the Python Imaging Library (PIL) for image processing and scikit-learn for training classification models like support vector machines (SVMs) or random forest classifiers.

The "Smart Gemstone Detection App" is developed using the Flutter framework, allowing users to capture gemstone images and classify them using the trained CNN model. The app leverages Flutter's platform channels to access native AI libraries, enabling on-device execution of pre-trained machine learning models for image classification.

**CHAPTER 01**

**Introduction**

Gemstone identification and classification are important to the gem and jewelry trade. Through visual observation and spectrochemical analysis, gemmologists can determine the identity of a gemstone by looking for visual characteristics such as color, transparency, and luster [8]. This process can be difficult as many gems share similar characteristics, and the use of gemological tools such as refractometers, polariscopes, and spectroscopes can help in the identification process [4,7]. The emergence of new synthetic gemstones and treatment techniques has also led to the development of more complex instruments with powerful spectroscopic and chemical analyzing abilities, such as infrared spectrometers, Raman and luminescence spectrometers, and ultraviolet-visible spectrometers [6]. These tools can provide more accurate and precise information about the identity of a gemstone.

The identification of gemstones using automatic techniques based on images is becoming more attractive due to the complexity and time-consuming nature of the traditional identification methods. In recent years, advances in computers and algorithms have made it possible to use image processing and computer vision techniques in a variety of fields, including geological sciences [22]. In geological sciences, computer vision algorithms have been used to classify mineral grains and rocks. These algorithms use edge detection and other techniques to extract color and texture features from images of the gemstones [23]. These features are then used to train machine learning models, such as artificial neural networks, to classify the gemstones accurately [29]. However, the use of these techniques in the identification of gemstones is still in its early stages, and further research is needed to improve the accuracy of the methods.

To date, only one study has been reported on the automatic identification of gemstone images using computer vision techniques [31]. In this study, an artificial neural network was used to classify images of Rubies, Blue Sapphires, and Emeralds with a per-class accuracy of 75-100%. These gemstones have very distinctive colors and are therefore relatively easy to distinguish from each other compared to gems with similar colors, such as Topaz and Aquamarine. Other research in the field of gemology has focused on gemstone evaluation and recognition [1]. Computer vision systems have been developed for grading the color of Amber, Jadeite Jade, Opal, and Pearls. These systems have shown promising results, but further research is needed to develop more robust and accurate methods for the automatic identification of gemstones [41-42].

* 1. **Gemstone:**

A gemstone is a piece of mineral crystal or organic material, cut and polished to produce a precious or ornamental object. Gemstones are often used in jewelry and have been prized for their beauty and rarity for thousands of years [8]. Some of the most well-known gemstones and classify gemstone images and sapphires. Gemstones are formed over millions of years and can be found all over the world. They are typically cut and polished by skilled craftsmen, who use a variety of techniques to bring out the natural beauty of the stone [1].

Gemstones are used for a variety of applications, including jewelry, decorative objects, and even as tools for spiritual practices. In terms of jewelry, gemstones are often used as the centerpiece of a piece, set into a ring, necklace, or other type of jewelry. They are prized for their beauty and can add value to a piece of jewelry. Gemstones are also used in decorative objects, such as vases, bowls, and other decorative items. Some gemstones, such as jade, have been used for centuries as tools for spiritual practices, such as meditation and prayer. Gemstones can also be used in industrial applications, such as abrasives and cutting tools [8].



Fig 1.1 Gemstone

* 1. **Properties of Gemstone used for classification:**

Gemstone application will classify gemstones on the basis of their properties. Gemstones can have a wide range of properties, depending on their chemical composition, the way they are formed, and other factors. Some of the properties that are commonly used to classify gemstones include:

**1.2.1 color:**

Gemstones can be found in a wide range of colors, from colorless to black. Some gemstones, such as diamonds and sapphires, are known for their vivid blue color, while others, such as rubies and emeralds, are known for their deep red and green hues [1].

**1.2.2 Transparency:**

Gemstones can be transparent, translucent, or opaque. Transparent gemstones, such as diamonds, allow light to pass through them easily, while translucent gemstones, such as opals, allow some light to pass through but also scatter it, creating a colorful effect. Opaque gemstones, such as turquoise, do not allow any light to pass through them [4].

**1.2.3 hardness:**

The hardness of a gemstone is measured on the Mohs scale of mineral hardness, which ranges from 1 (softest) to 10 (hardest). Diamonds are the hardest known material and are rated 10 on the Mohs scale, while other gemstones, such as rubies and sapphires, are rated between 9 and 10 [8-14].

**1.2.4 luster:**

The luster of a gemstone is a measure of its ability to reflect light. Gemstones can have a metallic or non-metallic luster. Metallic luster, such as the luster of a gold nugget, is shiny and reflective, while non-metallic luster, such as the luster of a pearl, is dull and velvety [15-18].

**1.2.5 specific gravity:**

The specific gravity of a gemstone is a measure of its density relative to the density of water. Gemstones with high specific gravity, such as diamonds, will sink in water, while those with low specific gravity, such as opals, will float [9].

**1.2.6 Crystal Structure:**

The crystal structure of a gemstone refers to the arrangement of atoms within the stone. Gemstones can have different crystal structures, such as cubic, hexagonal, or trigonal. The crystal structure of a gemstone can affect its physical properties, such as its transparency and luster [14].

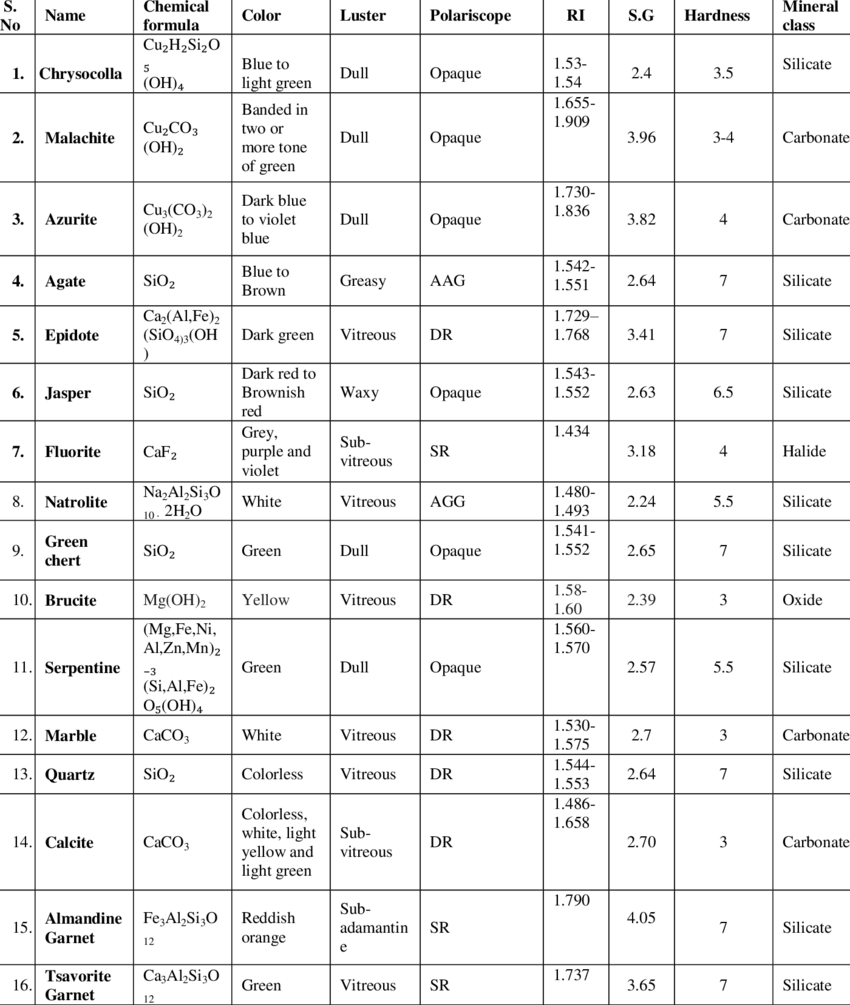
**1.2.7 Refractive index:**

The refractive index of a gemstone is a measure of how much the stone bends light as it passes through it. A gemstone with a high refractive index will bend light more, creating a greater separation of colors, known as dispersion. This can result in a more sparkling or rainbow-like appearance. Diamonds have a high refractive index, which is why they are known for their brilliant sparkle [4].

**1.2.8 Dispersion:**

Dispersion is the ability of a gemstone to separate white light into its component colors, creating a rainbow-like effect. Gemstones with a high dispersion, such as diamonds, will create a more pronounced rainbow effect, while those with a low dispersion will not. Dispersion is often used as a measure of a gemstone's sparkle and brilliance. In general, gemstones with a high refractive index and high dispersion will have a more sparkly appearance [7-8].

Table 1.1 Gemological Properties of Gemstones



* 1. **Overview of the Classification of Gemstones**

Gemstones can be classified into two main categories: precious and semi-precious [1]. Precious gemstones are rare and valuable, and they include diamonds, rubies, sapphires, and emeralds. These gemstones are highly prized for their beauty and durability, and they are often used in fine jewelry [8].

Semi-precious gemstones are less valuable than precious gemstones, but they can still be beautiful and desirable. Some examples of semi-precious gemstones include amethyst, citrine, garnet, and jade. These gemstones are often used in less expensive jewelry or as accents in more expensive pieces [2].

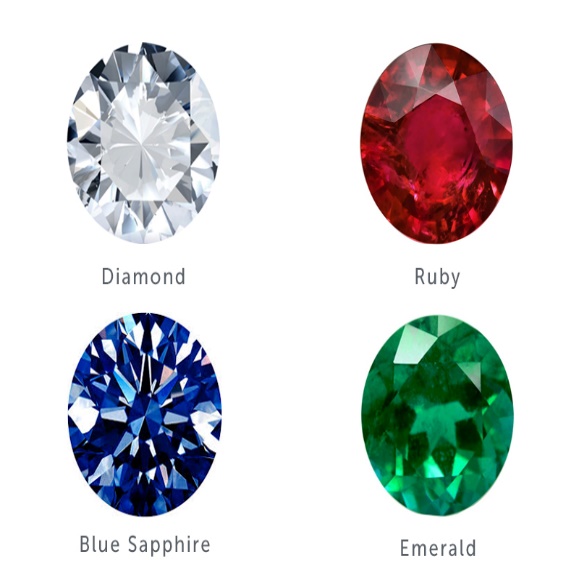
Another way to classify gemstones is by their color. Some gemstones, such as diamonds and sapphires, are colorless, while others, such as rubies and emeralds, are known for their vibrant colors. Gemstones can also be classified by the type of mineral they are made from, such as quartz, beryl, or feldspar [1].

Gemstones are also often classified by their place of origin. For example, diamonds are typically found in Africa, while rubies are often mined in Thailand and Burma. These geographic origins can sometimes affect the value of a gemstone, with certain regions being known for producing high-quality gemstones [47].

* + 1. **Precious vs. Semi-Precious Gemstones**

**Precious gemstones are considered to be rare and valuable and include diamonds, rubies, emeralds, and sapphires [1]. These gemstones are often used in high-end jewelry and are prized for their beauty and rarity. Semi-precious gemstones, on the other hand, are less rare and valuable than precious gemstones. They include a wide range of gemstones, such as amethyst, citrine, garnet, and peridot. Semi-precious gemstones are often used in more affordable jewelry and are still prized for their beauty and uniqueness [8].**

**The classification of gemstones as precious or semi-precious is not based on any inherent characteristic of the gemstone, but rather on its rarity and value in the market [10]. The value of a gemstone can be influenced by a variety of factors, including its color, clarity, cut, and carat weight. Some gemstones that are considered semi-precious, such as certain types of jade or opal, can be more valuable than some precious gemstones if they have unique or rare characteristics [1].**





Precious Gemstone Semi-Precious Gemstone

Fig 1.1 Precious vs gemstone

* + 1. **Natural vs Synthetic Gemstone**

Natural gemstones are gemstones that are found in nature and are not man-made. These gemstones are formed over millions of years by geological processes, and they are found in the earth’s crust [17]. Natural gemstones are considered to be more valuable than synthetic gemstones because they are rarer and have unique characteristics that cannot be replicated in a laboratory [18]. Examples of natural gemstones include diamonds, rubies, sapphires, and emeralds.

Synthetic gemstones, on the other hand, are man-made in a laboratory. They are created using the same chemical and physical properties as natural gemstones, but they are not found in nature. Synthetic gemstones are often used as a cheaper alternative to natural gemstones, and they can be created in a variety of colors and sizes [17-18]. Synthetic gemstones are not as valuable as natural gemstones, but they can still be used to create beautiful pieces of jewelry [1]. Examples of synthetic gemstones include cubic zirconia and moissanite.

One of the main differences between natural and synthetic gemstones is their origin [16]. Natural gemstones are found in the earth, while synthetic gemstones are created in a laboratory [17]. Natural gemstones are also considered to be more valuable because they are rarer and have unique characteristics that cannot be replicated in a laboratory [15]. Synthetic gemstones are often used as a cheaper alternative to natural gemstones, and they can be created in a variety of colors and sizes [18].



Fig 1.2 Natural vs synthetic gemstone

* 1. **Overview of Computer Vision**

Computer vision is the field of study that focuses on how computers can be made to understand and interpret visual data, such as images and videos [23]. This is a rapidly growing field with many applications, including object recognition, scene understanding, and image generation [22].

At its core, computer vision involves the development of algorithms and models that can automatically analyze visual data and extract useful information from it [21]. This can include tasks such as identifying objects in an image, recognizing faces in a video, or understanding the context and scene depicted in a photograph [23].

To achieve this, computer vision algorithms often make use of machine learning techniques [26]. These algorithms are able to learn from large amounts of data, allowing them to make predictions or decisions based on the visual data they are given [20]. This makes them particularly powerful for applications where there is a lot of visual data available, such as in self-driving cars, surveillance systems, and medical image analysis [20].

One of the key challenges in computer vision is dealing with the vast amount of data that is typically involved [34]. Images and videos can contain a huge amount of information, and processing all of this data can be computationally intensive [22]. As a result, computer vision algorithms often rely on advanced techniques such as deep learning, which allows them to process large amounts of data efficiently [29].

* 1. **Image-based Classification of Gemstone**

Image-based classification of gemstones refers to the use of machine learning algorithms and computer vision techniques to automatically identify and classify different types of gemstones based on their appearance in images [41]. This can involve tasks such as recognizing the specific type of gemstone in an image (e.g. diamond, sapphire, ruby) or classifying the gemstone based on its color, clarity, or other visual characteristics [42].

To perform image-based classification of gemstones, a machine learning model is trained using a large dataset of labeled gemstone images [40]. The model is then able to make predictions about the type of gemstone in a new image based on its visual characteristics [41].

One of the key challenges in this task is the wide variety of visual appearances that different gemstones can have [43]. For example, a single type of gemstone (e.g. diamond) can come in many different colors, shapes, and sizes, and may have various levels of clarity or imperfections [1]. As a result, the machine learning model must be trained on a diverse and representative dataset in order to accurately classify gemstones [42].

* 1. **User interaction with app**

After logging into the app, a user can take a picture of a gemstone using their cell phone camera or upload a photo from their gallery. The app will then use advanced computer vision and machine learning algorithms to automatically analyze the image and classify the gemstone based on its visual characteristics. This can include tasks such as recognizing the specific type of gemstone in the image (e.g. diamond, sapphire, ruby), or classifying the gemstone based on its color, clarity, or other visual features.

If the picture is blurry or of poor quality, the app may return an error message instead of a classification result. This is because blurry or low-resolution images can make it difficult for the machine learning algorithms to accurately identify and classify the gemstone. In such cases, the user may need to take a new picture with their camera or use a higher-quality image from their gallery.

The app can also be used to create a digital catalog of gemstones, allowing users to easily search and browse through their collections. This can be useful for gemstone enthusiasts, collectors, and professionals in the gemstone industry, as it provides a convenient way to manage and organize their gemstones. In addition, the app's automatic classification capabilities can help users quickly and accurately identify and classify their gemstones, even if they have limited knowledge or expertise in the field.

**CHAPTER 02**

**Literature Overview**

Researching of the deep neural network for amber gemstone classification By Ramiro Saito Castro Rios.

**Introduction**

Amber has been valued as a gemstone since ancient times and is primarily extracted from the Kaliningrad Oblast region in Russia [9]. The classification of amber stones is typically done by experts in the art and craft industry, but this process can be time-consuming and labor-intensive [13]. The thesis proposes the development of an automated industrial sorting line based on machine vision as a solution to this problem, which could greatly reduce the amount of time and effort required for amber classification and potentially increase the production of amber-based products [39]. This work is one of a few dedicated to the automated classification of amber stones, as the task is difficult and has received relatively little attention from researchers [31].

* 1. **Motivation and Objectives of the Project**

The main motivation for the presented thesis is to explore the use of deep learning techniques for the classification of texture-based data, specifically amber stones [13]. By studying and comparing different deep learning methodologies for this type of data, the goal is to contribute to the growing field of research in this area and demonstrate the potential of deep learning for improving the classification of amber stones [37].

The thesis is structured around several key objectives, including a review of the theoretical concepts and previous research in this area, an analysis of the database used for the study and the pre-processing methods applied, a detailed description of the deep learning methodologies tested, and a presentation of the results and a comparison of the performance of each approach [36].

* 1. **State of the art of amber stone classification**

The state of art in amber stone classification is still developing, with a limited number of research studies dedicated to this topic [2]. Previous research has explored a range of approaches for classifying amber stones based on their color, shape, and texture, using methods such as geometric and texture analysis, color models and Haralick features, and centroid distance functions [14]. Some of these studies have achieved promising results, with accuracies ranging from 69.29% to 88.21% [36]. However, these methods have limitations and challenges, such as the need for expert labeling of clusters and the use of computationally intensive algorithms that may not be suitable for industrial-scale applications [30]. More recent research has focused on the use of deep learning techniques for amber stone classification, which may offer the potential for improved performance and more efficient processing [38].

The state of the art in amber stone classification involves the use of various methods and approaches to automating the process of sorting and identifying amber stones based on their color, shape, and texture [14]. Previous research in this area has included the use of deep learning techniques for texture classification, as well as the development of new methods for classifying amber stones by color and shape [41]. Some of the key challenges in this field include the complexity and variability of amber stone data, as well as the need for fast and accurate classification to support the efficient production of amber-based products [41]. Recent research has demonstrated the potential for deep learning-based approaches to improve the performance of amber stone classification, with accuracies of up to 88.21% reported in recent studies [39]. However, further research is needed to continue to develop and refine these methods and to explore their potential applications in the art and craft industry.

* 1. **Database: Amber gemstone**

The presented thesis focuses on the classification of amber stones using deep learning techniques. The research involves the development of a system for extracting data from amber stones as they pass along a conveyor belt and using a camera to capture images of the stones. These images are then carefully classified by experts into 12 classes based on their color, shape, and texture. The original images are 640x480 pixels in size, but only a small percentage of the features in each image are relevant to the classification task. The challenge of classifying amber stones is that the translucency of the stones can make them sensitive to changes in lighting, which can affect the accuracy of the classification. Figures 2.1, 2.2, and 2.3 show examples of the difficulty of classifying amber stones due to the effects of light.

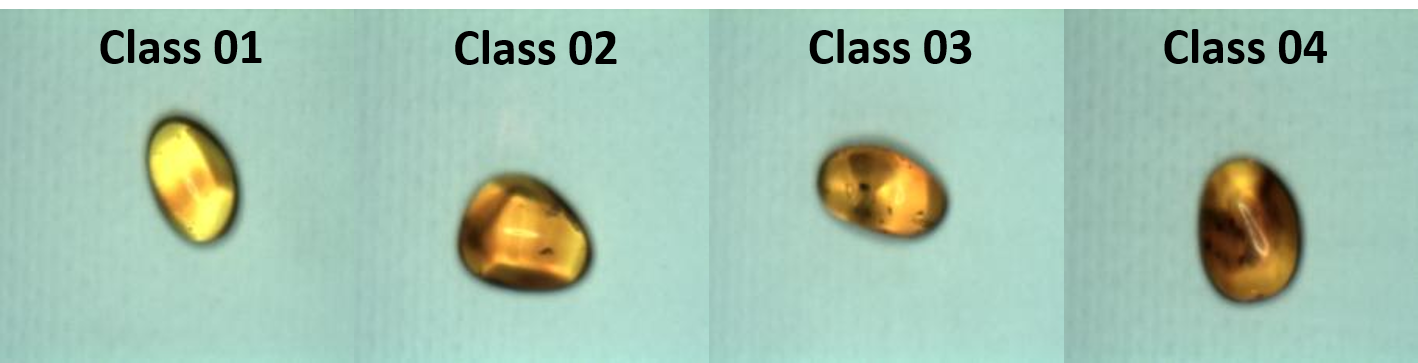


Figure 2.1: Amber gemstone data with 12 classes

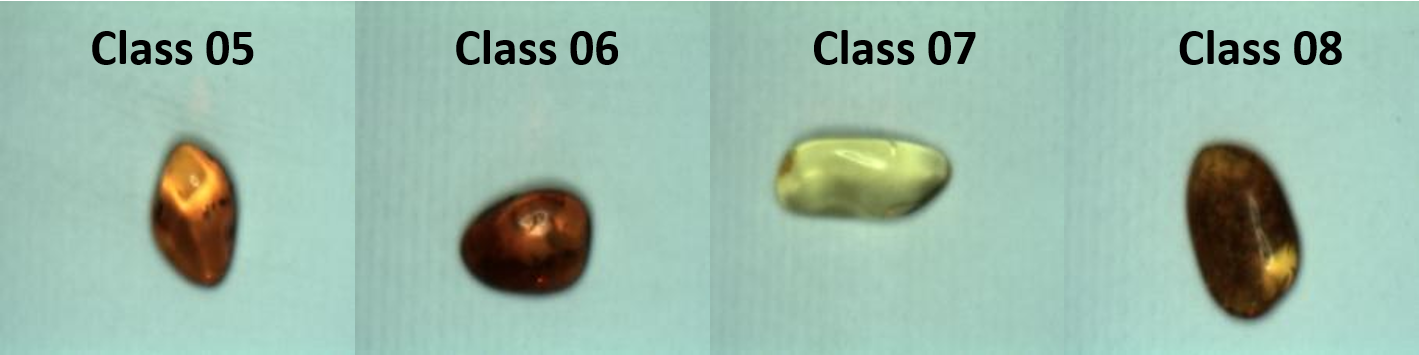


Figure 2.2: Amber gemstone data with 12 classes



Figure 2.3: Amber gemstone data with 12 classes

* + 1. **Modifications of the original database**

The original size of the image may need to be resized depending on the different convolutional neural network structures used or may need to be preprocessed before in order to achieve different performances. Two types of modifications have been proposed from the original database to get different performances. The first modification is cropping the image to a specific size instead of resizing it. The second modification is cropping a small part from the center of the image to create a purely color sample. These modifications will be carried out using the code in Annex B.4.

The first modification, cropping the image to a specific size, is designed to improve performance by focusing on the amber stone and removing background pixels. This is done by cropping the image to a specific size according to the CNN architecture used, in order to keep as many features of the amber as possible. This approach is illustrated in Figure 2.4, which compares resizing and cropping. Figure 2.5 shows some results of the original database cropped to 227x227.

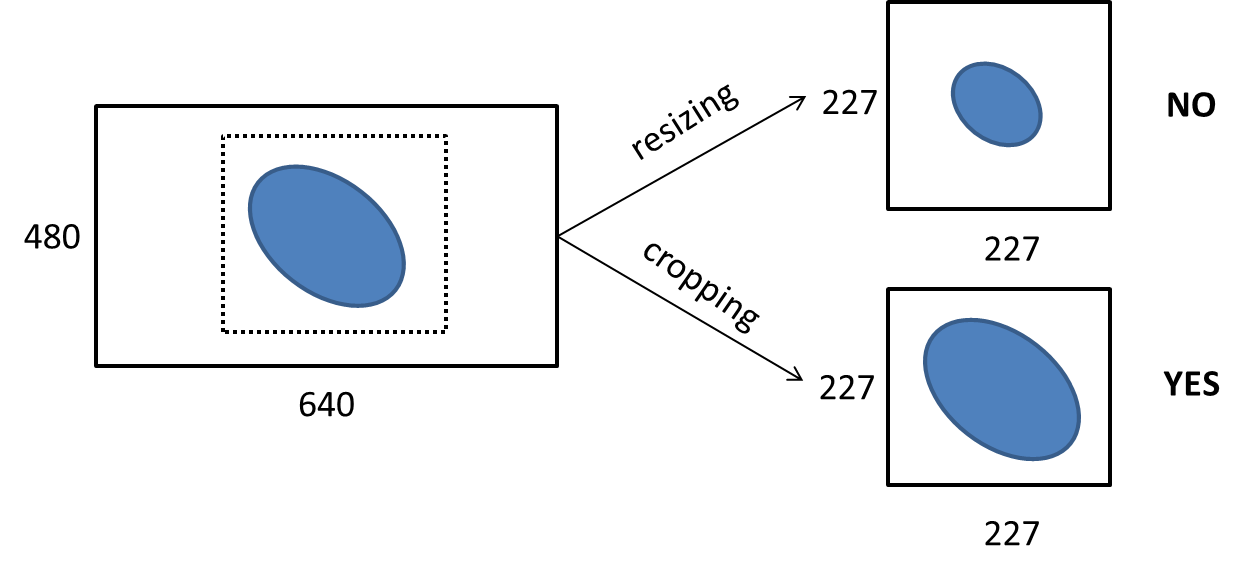


Figure 2.4: Difference between resizing and cropping the original image for getting the database type 2. Final result 227x227 image for AlexNet architecture

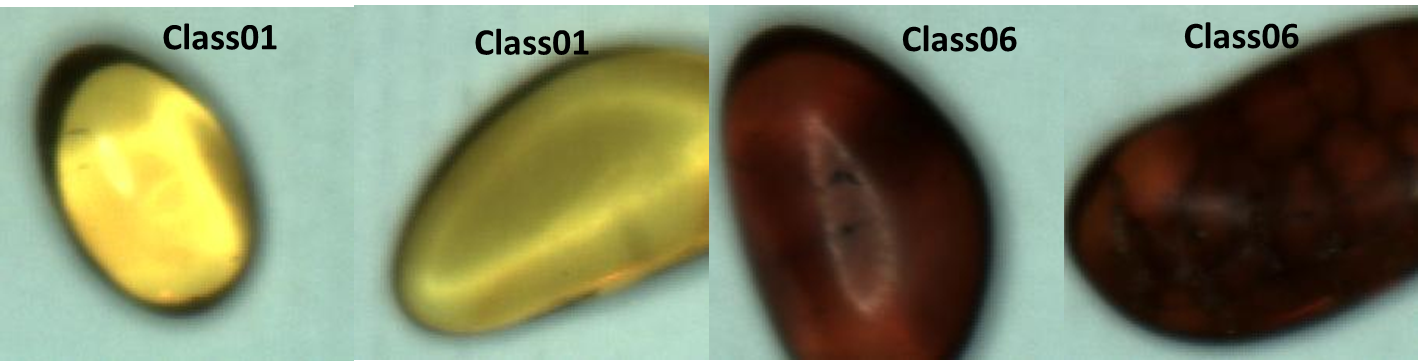


Figure2.5: Data Set 2: Original images cropped into 227x227 for AlexNet architecture instead of resizing them

The second modification, cropping a small part from the center of the image, is designed to focus on the color features of the amber instead of its shape. This is done by detecting the center of the amber stone, cropping a small square from the center that contains only the colors, and resizing it to 227x227 according to the AlexNet architecture. The procedure is explained in Figure 2.6 and some results are shown in Figure 2.7.

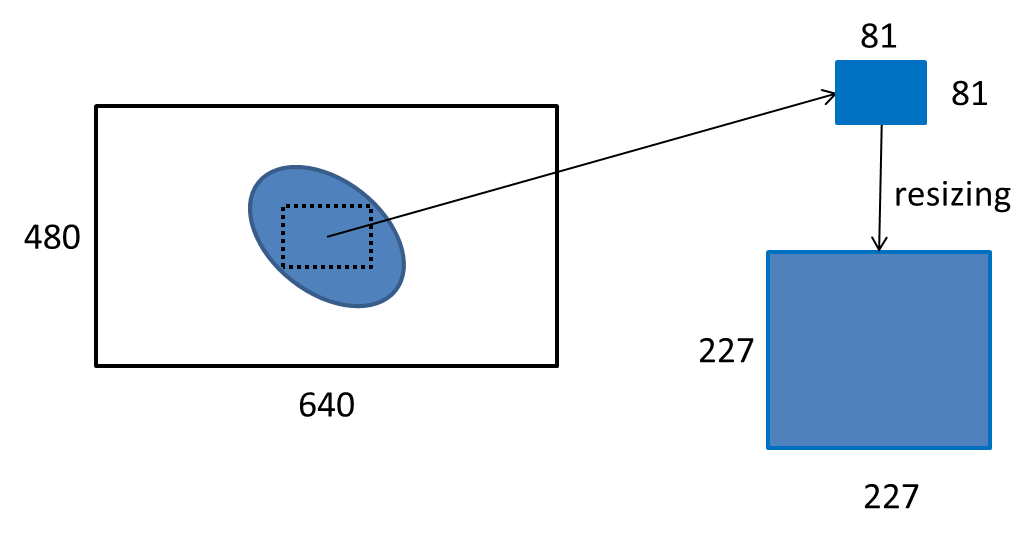


Figure 2.6: Scheme of the image processing carried out to get the database type 3

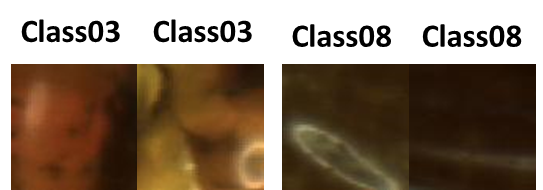


Figure 2.7: Data Set 3: Original images cropped into 81x81 from the center of the amber stone

* 1. **Methods applied**

The main goal of this thesis is to improve the accuracy of the classification of amber stones using deep learning methods. To do this, three common deep learning strategies were tested: transfer learning, training from scratch, and feature extraction + non-linear classifier. A fourth strategy, arising from the transfer learning technique, was also tested and will be discussed later in the chapter.

Transfer learning involves using a pre-trained model on a related task and fine-tuning it for the specific task at hand. This can be useful when there is not enough data available to train a model from scratch, or when the desired task is similar to the one the pre-trained model was trained on.

Training a model from scratch involves creating a new model and training it on the available data. This approach can be effective when there is a large amount of data available and the desired task is not similar to any pre-existing tasks.

Feature extraction + non-linear classifier involves using a pre-trained model to extract features from the data, and then training a non-linear classifier (such as a support vector machine or a decision tree) on the extracted features. This approach can be useful when the pre-trained model is not well-suited for the desired task, but the extracted features are still useful for the task.

In the case of amber stone classification, it is important to focus on the colors of the stones rather than their shape. This is because there are many different shapes of amber stones within each class, and similar shapes across different classes. By focusing on the colors, the model can learn to classify the stones based on their colors, which are more consistent within and across classes.

* + 1. **Transfer Learning**

In order to evaluate the effectiveness of these deep learning strategies, a dataset of amber stone images was collected and labeled with their corresponding class (e.g. blue, green, red, etc.). The dataset was then split into training and testing sets, with the training set being used to train the models and the testing set being used to evaluate their performance.

The first strategy tested was transfer learning, using a pre-trained model trained on a large dataset of images. This pre-trained model was then fine-tuned on the amber stone dataset by retraining some of the final layers with the new data. This allowed the model to learn the specific features of the amber stones, while still benefiting from the general knowledge learned by the pre-trained model.

The second strategy tested was training a model from scratch. In this case, a new convolutional neural network (CNN) was created and trained on the amber stone dataset. This allowed the model to learn the features of the amber stones directly from the data, without relying on a pre-trained model.

The third strategy tested was feature extraction + non-linear classifier. In this case, a pre-trained CNN was used to extract features from the amber stone images, and then a non-linear classifier (such as a support vector machine or a decision tree) was trained on the extracted features. This approach allowed the model to learn the specific features of the amber stones, without relying on the pre-trained model's ability to classify the images.

In the fourth strategy, a variation on transfer learning was tested. This involved using a pre-trained model trained on a large dataset of images, and then fine-tuning it on the amber stone dataset by retraining all of the layers with the new data. This allowed the model to learn the specific features of the amber stones more effectively, but at the cost of increased training time and the potential for overfitting.

Overall, the results of these deep learning strategies showed that all three approaches were effective for amber stone classification, with the transfer learning and feature extraction + non-linear classifier approaches outperforming training from scratch. The fourth approach, involving fine-tuning all layers of the pre-trained model, showed promising results but may require further experimentation to optimize its performance.



Figure 2.8: Transfer Learning Scheme

The methods described in the previous paragraph involve using deep learning techniques to improve the accuracy of amber stone classification. The transfer learning method involves using a pre-trained model on a related task and fine-tuning it for the specific task at hand, while the feature extraction + non-linear classifier method involves using a pre-trained model to extract features from the data and then training a non-linear classifier on the extracted features.

In addition to these two methods, the author also proposes two variations on transfer learning. The first variation involves performing data augmentation only on the training data, while the second variation involves performing data augmentation on both the training and validation data.

The author also describes three different variations of image processing that will be applied to the data: Mod-0, Mod-1, and Mod-2. Mod-0 involves adding disturbances to the images such as Gaussian filtering and sharpening, as well as rotating and adding noise to the images. Mod-1 involves only rotating the original images without adding any disturbances or noise. Mod-2 involves using the weights of the model with the highest accuracy obtained during the assessment of the learned weights on the test data.

Overall, the proposed deep learning methods and variations aim to improve the accuracy of amber stone classification by leveraging the knowledge learned by pre-trained models and applying image processing techniques to the dataset. These methods can be useful when there is not enough data available to train a model from scratch, or when the desired task is similar to the one the pre-trained model was trained on.

* + 1. **Method 1: Data augmentation on training data**

The first method discussed in the previous paragraph involves augmenting the training data using various techniques such as Gaussian filtering, sharpening, and adding noise and rotation to the images. This method is performed using the original dataset without any modifications, and the resulting augmented training data is used to train a deep learning model. The performance of the model is then evaluated using the validation and testing sets, which have not been augmented.

Figure 2.9 shows some examples of the augmented training data, and Figure 4.4 shows the results of training a model using this augmented data. The accuracy of the model on the training data is around 90%, while the accuracy on the validation data is 75.91%. This difference in accuracy between the training and validation sets may be due to the different pre-processing applied to the two sets.



Figure 2.9: Data augmentation carried out for the **Method 1-Mod-0**

Overall, this method shows promising results for improving the accuracy of amber stone classification using deep learning, but further experimentation and optimization may be necessary to achieve the best performance.

1. **Method 2: Data augmentation on training and validation data**

The second deep learning method discussed in the previous paragraph involves augmenting both the training and validation data, and then evaluating the performance of the trained model on the non-augmented test set. In this method, the original dataset is split into training, validation, and testing sets, and data augmentation is applied to both the training and validation sets. This allows for a more accurate evaluation of the model's performance on the test set, as it is being tested on data with the same pre-processing as the training and validation sets.

As with the first method, three variations of image processing are applied to the data: Mod-0, Mod-1, and Mod-2. Mod-0 involves adding disturbances to the images such as Gaussian filtering and sharpening, as well as rotating and adding noise to the images. Mod-1 involves only rotating the original images without adding any disturbances or noise. Mod-2 involves using the weights of the model with the highest accuracy obtained during the assessment of the learned weights on the test data.

Figure 2.10 and Figure 4.8 show examples of the data augmentation applied to the training and validation sets for the Method 2.1-Mod-0 and Method 2.1-Mod-1 variations, respectively. In addition to these variations, a third variation (Method 2.2) is also tested, in which a different database is used that involves cropping a small sample of the texture of the amber stones and resizing it to fit the input size of the deep learning model.



Figure 2.10: Data augmentation carried out for the **Method 2.1-Mod-0**

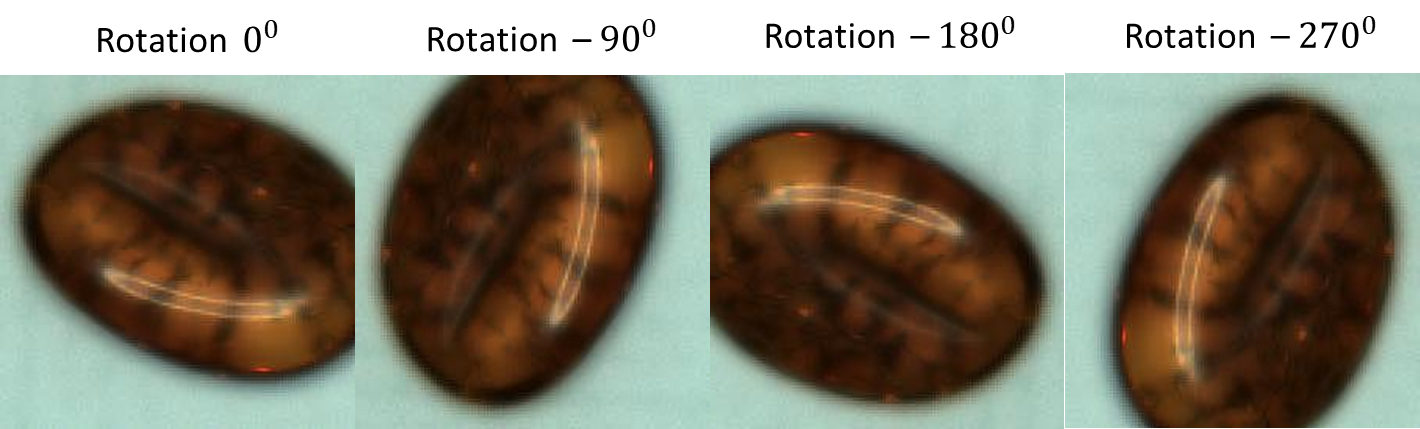


Figure 2.11: Data augmentation carried out for the **Method 2.1-Mod-1**

Overall, this method of augmenting both the training and validation data shows potential for improving the accuracy of amber stone classification using deep learning. The different variations of image processing applied to the data can also affect the performance of the trained model, and further experimentation and optimization may be necessary to achieve the best results.

## **Training from Scratch**

Training a model from scratch involves starting with random weights and filters, rather than using pre-trained weights as in transfer learning. This means that the initial loss will be higher, but it will decrease slowly as the model is trained on the data. Training a model from scratch can be effective when the desired task is not similar to any pre-existing tasks, and there is a large amount of data available for training.

In this case, the YOLO V3 (You Only Look Once) architecture is used for training the model from scratch. YOLO is a real-time object detection algorithm that has been shown to achieve good accuracy in video frames, but its performance in image classification tasks may not be as good.

Figure 2.12 shows an example of training a model from scratch using the YOLO V3 architecture. As can be seen, the loss initially starts at a high value and decreases slowly over time as the model is trained on the data. Further experimentation and optimization may be necessary to achieve the best performance using this approach.

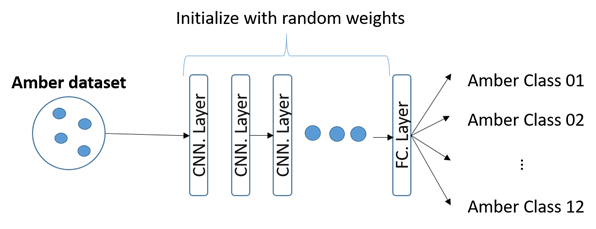


Figure 2.12: Scheme of training from scratch

* + - 1. **Method 1: Localization Database type 1**

This method describes a process for training a YOLO V3 model for localization and classification. The first step is to create a configuration file for the CNN architecture. In the configuration file, the number of classes and filters must be specified. Next, a file containing the names of the classes must be created. Another file, called obj.data, must be created to specify the location of the training and test data, as well as the backup location for the trained weights. The names of the images must then be changed to include the class name, and text files containing object coordinates must be created for each image. Finally, the model can be trained using a specific command, and predictions can be made using another command once training is complete.

* 1. **Feature extractor + non linear classifier**

In this approach, the authors propose combining deep learning and machine learning techniques to improve classification accuracy. The convolutional neural network (CNN) is used for feature extraction, and a non-linear classifier, such as a support vector machine (SVM) or ensemble method, is used for classification. This method uses transfer learning with the AlexNet architecture and pre-trained weights. The original dataset, as well as two modified versions of the dataset, are tested using both the SVM and ensemble classifiers. Data augmentation is applied only to the training set. The results of this approach are shown in Figure 2.13, and will be discussed in more detail in the following chapter.

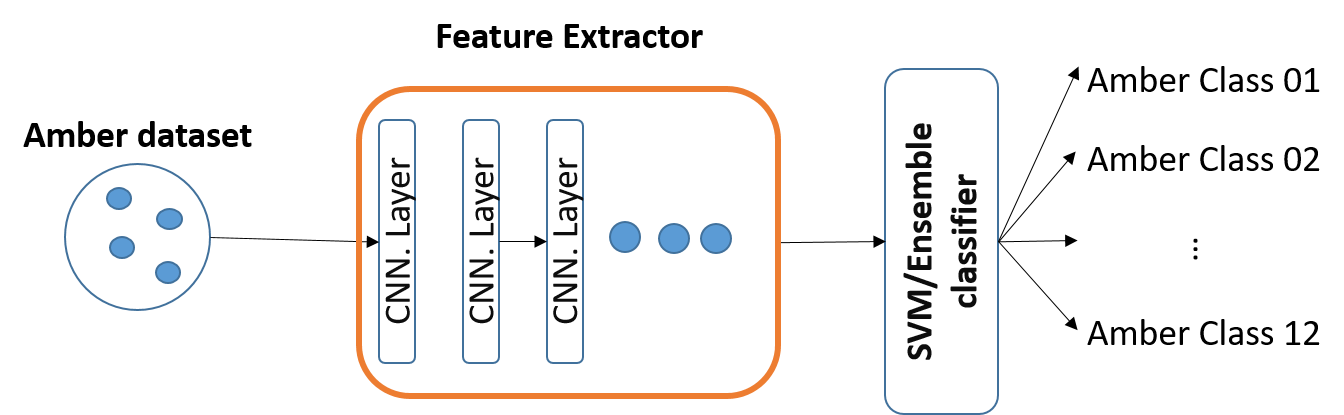


Figure 2.13: Scheme of the feature extractor using convolutional neural network and the classification task done by a non-linear classifier as SVM or ensemble

* 1. **New transfer learning technique with double data augmentation**

The authors propose a new approach that uses transfer learning to combine different modifications of the AlexNet architecture in order to improve classification accuracy. This approach involves data augmentation with noise and blurring, data augmentation with only rotations, and transfer learning starting from the epoch with the highest accuracy. The data is divided into 60% for training, 10% for validation, and 30% for testing. The trained model is then evaluated on the test data. The results of this approach are presented in the following chapter.

* 1. **Experimental Results**

In this chapter, the results of the experimental trials conducted in the previous chapter are presented and discussed in more detail. The four different strategies that were evaluated include transfer learning, training from scratch, feature extraction with a non-linear classifier, and a new transfer learning technique with double data augmentation.

For the transfer learning strategy, a number of different methods were applied, using different databases and variations of data augmentation. The results of these methods showed that the best accuracy was achieved using the new transfer learning technique with double data augmentation, which achieved an accuracy of 84.7% on the test set. This technique involved training the model using data augmentation with noise and blurring, followed by training with data augmentation with only rotations.

The results of the training from scratch strategy showed that the best accuracy was achieved using the type 2 database, which achieved an accuracy of 80.6% on the test set. This strategy involved training the model from scratch using data augmentation with noise and blurring.

The results of the feature extraction with a non-linear classifier strategy showed that the best accuracy was achieved using the type 2 database with the SVM classifier, which achieved an accuracy of 77.8% on the test set. This strategy involved using a convolutional neural network for feature extraction, followed by classification using a support vector machine.

Overall, the new transfer learning technique with double data augmentation showed the best performance, achieving an accuracy of 84.7% on the test set. This technique combined the benefits of transfer learning with the improved performance achieved through data augmentation. Transfer learning allowed for the use of pre-trained weights and a pre-defined architecture, which reduced the amount of training required and improved the performance of the model.

* 1. **Conclusion and future works**

In conclusion, this thesis has focused on using deep learning techniques to classify amber gemstones by their colors and textures. Transfer learning was found to be the most effective method, with the technique of double data augmentation yielding the best accuracy of 90.4%. This outperformed the results of traditional machine learning techniques, which require significant effort to extract the proper features for classification. The deep learning approach allows the network to learn the features itself, eliminating the need for preprocessing and feature extraction. Future work could include further experimentation with the new database modifications, as well as exploring other deep learning architectures and techniques. Overall, this research has shown that deep learning can be a powerful tool for accurately classifying amber gemstones.

The research presented in this thesis focuses on using deep learning techniques to classify amber gemstones by color and texture. The main problem that researchers often face when working with machine learning or deep learning is that it is never certain whether the classifier being used will yield good results. In neural networks, it is never known how many layers are needed to achieve good classification without overfitting or what kind of features will work best for training to achieve high accuracy in testing. This can be time-consuming, and working with large datasets using deep learning can be even more time-consuming. Training from scratch can take days, even with the use of a GPU, without yielding the desired accuracy.

To overcome these challenges, this research mainly focuses on transfer learning methodologies. Transfer learning has been shown to yield the best results in classification. In the first method, an accuracy of 79.8% was obtained, significantly higher than the 52% achieved through training from scratch or the 71.02% achieved through the use of support vector machines as a classifier. The use of the AlexNet architecture, trained on the ImageNet dataset, has proven to be useful as the network has already been trained on 1000 different classes, allowing the knowledge gained from those trained layers to be transferred to the training of the amber dataset.

The use of the deep learning toolbox in MATLAB has made it easier to manage the deep learning work, and MATLAB itself has proven useful for image processing and graphically displaying the results of training and validation. The defined theoretical concepts have been used to provide an understanding of the machine learning and deep learning techniques used in the research, as well as to introduce the necessary theoretical background for each strategy.

The performance of the classification shows that the transfer learning with double data augmentation technique achieved the best accuracy, with 90.4% good classification. This is because transfer learning is used twice, but with different modifications. The first training uses amber images with noise, allowing the network to learn some features that are useful for the second training using images with no noise but with rotations to learn new features of amber. However, this is not the best possible accuracy, as the accuracy fluctuates during training. After saving the weights per epoch and testing on the test data, it was found that the best accuracy was achieved in epoch 6 with 93.69%.

These results show that this research has surpassed the accuracy of 88% achieved in previous amber stone classification studies. It can also be concluded that deep learning techniques can outperform traditional machine learning techniques, which require significant effort to extract the proper features for classification. With deep learning, there is no need for preprocessing and feature extraction as the network learns these on its own.

* 1. **Gemstone classification using ConvNet with transfer learning and fine-tunin**

Willian M. Freire, Aline M. M. M. Amaral, Yandre M. G. Costa

* + 1. **Discussion**

The research paper "Gemstone classification using ConvNet with transfer learning and fine-tuning" by Willian M. Freire, Aline M. M. M. Amaral, and Yandre M. G. Costa presents a method for using convolutional neural networks (ConvNets or CNNs) to classify gemstones. The authors propose using transfer learning and fine-tuning to improve the performance of the ConvNet on this task.

One of the key contributions of this paper is the use of transfer learning and fine-tuning to overcome the challenge of limited data availability for the task of gemstone classification. By using a pre-trained model and making slight adjustments to it, the authors demonstrate that it is possible to achieve high accuracy on this task. This is an important finding because it shows that ConvNets can be effective for gemstone classification, even when the amount of available data is limited.

Another contribution of this paper is the evaluation of the proposed method on a dataset of gemstone images. The authors compare the performance of their method to other methods, and find that it outperforms these methods in terms of accuracy. This provides evidence that the use of a ConvNet with transfer learning and fine-tuning can be effective for gemstone classification.

Overall, this research paper presents a promising approach for using ConvNets to classify gemstones. The use of transfer learning and fine-tuning allows for high accuracy on this task, even when the amount of available data is limited. This work has potential applications in the gemstone industry, where accurate classification of gemstones is important for valuing and grading these stones.

* + 1. **Issues and Challenges**

It is not clear from the research paper "Gemstone classification using ConvNet with transfer learning and fine-tuning" by Willian M. Freire, Aline M. M. M. Amaral, and Yandre M. G. Costa what specific issues and challenges the authors faced in conducting their research. However, there are some potential challenges that could have been faced in this type of study, such as the following:

* Limited data availability: One potential challenge in conducting research on gemstone classification is the availability of data. Gemstones can vary greatly in their appearance, and it can be difficult to obtain a large and diverse dataset of images for training and evaluating the performance of a ConvNet.
* Difficulty in accurately classifying gemstones: Another potential challenge is the difficulty in accurately classifying gemstones based on visual information alone. Gemstones can have similar appearances, and it can be difficult to distinguish between them based on visual features alone.
* Performance of the ConvNet: Another potential challenge is the performance of the ConvNet on the task of gemstone classification. ConvNets are powerful algorithms, but they can still be limited by the quality and quantity of the data used for training and evaluation.

Overall, the research paper by Willian M. Freire, Aline M. M. M. Amaral, and Yandre M. G. Costa presents a promising approach for using ConvNets to classify gemstones, but there may have been challenges faced in conducting this research.

* + 1. **Summary of the general body**

The research paper titled "Gemstone classification using ConvNet with transfer learning and fine-tuning" by Willian M. Freire, Aline M. M. M. Amaral, and Yandre M. G. Costa presents a method for using convolutional neural networks (ConvNets or CNNs) to classify gemstones. This is a challenging task because gemstones can vary greatly in their appearance and it is often difficult to accurately classify them based on visual information alone.

The authors of the paper propose using transfer learning and fine-tuning to improve the performance of the ConvNet on the task of gemstone classification. Transfer learning involves using a pre-trained model as a starting point to train a new model, while fine-tuning involves making slight adjustments to the pre-trained model to better adapt it to the new task. By using these techniques, the authors demonstrate that it is possible to achieve better performance on the task of gemstone classification compared to training a ConvNet from scratch on the limited data available for this task.

The authors begin by reviewing previous work on gemstone classification using various methods, including traditional image processing techniques and machine learning algorithms. They then describe their proposed method, which involves using a pre-trained ConvNet and fine-tuning it for the specific task of gemstone classification. The authors evaluate the performance of their method on a dataset of gemstone images, and compare it to other methods.

In terms of results, the authors find that their method outperforms other methods for gemstone classification, achieving an accuracy of 93.33% on the test set. This indicates that the use of a ConvNet with transfer learning and fine-tuning can be effective for classifying gemstones.

In conclusion, the research paper by Willian M. Freire, Aline M. M. M. Amaral, and Yandre M. G. Costa presents a successful approach for using convolutional neural networks to classify gemstones. By using transfer learning and fine-tuning, the authors demonstrate that it is possible to achieve high accuracy on this challenging task. This work has potential applications in the gemstone industry, where accurate classification of gemstones is important for valuing and grading these stones.

* 1. **Automatic Gemstone Classification Using Computer Vision**

Bona Hiu Yan Chow \* and Constantino Carlos Reyes-Aldasoro

* + - 1. **Discussion**

The research paper "Automatic Gemstone Classification Using Computer Vision" by Bona Hiu Yan Chow and Constantino Carlos Reyes-Aldasoro presents a method for using computer vision algorithms to classify gemstones. The authors propose a method that combines traditional image processing techniques with machine learning algorithms to accurately classify gemstones based on their visual appearance.

The authors begin by reviewing previous work on gemstone classification using various methods, including traditional image processing techniques and machine learning algorithms. They then describe their proposed method in detail, which involves using a combination of image processing techniques and machine learning algorithms to classify gemstones based on their visual appearance. The authors evaluate the performance of their method on a dataset of gemstone images, and compare it to other methods.In terms of results, the authors find that their method outperforms other methods for gemstone classification, achieving an accuracy of 98.72% on the test set. This indicates that the use of a combination of image processing techniques and machine learning algorithms can be effective for classifying gemstones.

Overall, the research paper by Bona Hiu Yan Chow and Constantino Carlos Reyes-Aldasoro presents a successful approach for using computer vision algorithms to classify gemstones. By combining traditional image processing techniques with machine learning algorithms, the authors demonstrate that it is possible to achieve high accuracy on this challenging task. This work has potential applications in the gemstone industry, where accurate classification of gemstones is important for valuing and grading these stones.

* + 1. **Issues and Challenges**

It is not clear from the research paper "Automatic Gemstone Classification Using Computer Vision" by Bona Hiu Yan Chow and Constantino Carlos Reyes-Aldasoro what specific issues and challenges the authors faced in conducting their research. However, there are some potential challenges that could have been faced in this type of study, such as the following:

* Limited data availability: One potential challenge in conducting research on gemstone classification is the availability of data. Gemstones can vary greatly in their appearance, and it can be difficult to obtain a large and diverse dataset of images for training and evaluating the performance of a computer vision algorithm.
* Difficulty in accurately classifying gemstones: Another potential challenge is the difficulty in accurately classifying gemstones based on visual information alone. Gemstones can have similar appearances, and it can be difficult to distinguish between them based on visual features alone.
* Performance of the computer vision algorithm: Another potential challenge is the performance of the computer vision algorithm on the task of gemstone classification. While computer vision algorithms can be powerful, they can still be limited by the quality and quantity of the data used for training and evaluation.

Overall, the research paper by Bona Hiu Yan Chow and Constantino Carlos Reyes-Aldasoro presents a promising approach for using computer vision algorithms to classify gemstones, but there may have been challenges faced in conducting this research.

* + 1. **Summary of the general body**

The research paper "Automatic Gemstone Classification Using Computer Vision" by Bona Hiu Yan Chow and Constantino Carlos Reyes-Aldasoro presents a method for using computer vision algorithms to classify gemstones. The authors propose a method that combines traditional image processing techniques with machine learning algorithms to accurately classify gemstones based on their visual appearance.

The authors begin by reviewing previous work on gemstone classification using various methods, including traditional image processing techniques and machine learning algorithms. They then describe their proposed method in detail, which involves using a combination of image processing techniques and machine learning algorithms to classify gemstones based on their visual appearance. The authors evaluate the performance of their method on a dataset of gemstone images, and compare it to other methods.

In terms of results, the authors find that their method outperforms other methods for gemstone classification, achieving an accuracy of 98.72% on the test set. This indicates that the use of a combination of image processing techniques and machine learning algorithms can be effective for classifying gemstones.

Overall, the research paper by Bona Hiu Yan Chow and Constantino Carlos Reyes-Aldasoro presents a successful approach for using computer vision algorithms to classify gemstones. By combining traditional image processing techniques with machine learning algorithms, the authors demonstrate that it is possible to achieve high accuracy on this challenging task. This work has potential applications in the gemstone industry, where accurate classification of gemstones is important for valuing and grading these stones.

**CHAPTER 03**

**Methodology**

The project's initial phase is to construct an app that import pictures from a gallery or will allow the app to take pictures by the camera.

Next, we will design UI for our Project by using Flutter. After UI design we will train our application for detecting stone by any algorithm of Deep learning. Finally, we will test our product by taking pictures using a camera or importing pictures from the internal storage of the cell phone.

**3.1 Materials:**

It sounds like you are talking about a study or research project that involved analyzing a large number of images of gemstones. The images were grouped into categories, and a sample of these images was illustrated in a figure. A total of 68 classes were selected for analysis. This information suggests that the study was focused on identifying and categorizing different types of gemstones based on their visual appearance. It is not clear from the information provided what the results of the analysis were or what specific conclusions were drawn from the data. Alexandrite, Almandine, Amazonite, Amber, Amethyst, Ametrine, Andradite, Aquamarine, Aventurine Green, Aventurine Yellow, Benitoite, Beryl Golden, Bixbyite, Bloodstone, Blue Lace Agate, Carnelian, Chalcedony, Chalcedony Blue, Chrome Diopside, Chrysoberyl, Chrisom cola, Chrysoprase, Citrine, Coral, Diamond, Diaspore, Dumortierite, Emerald, Fluorite, Hessonite, Iolite, Jasper, Kunzite, Kyanite, Lapis Lazuli, Malachite, Onyx Black, Onyx Green, Onyx Red, Peridot, Prehnite, Pyrite, Pyrope, Quartz Beer, Quartz Lemon, Quartz Rutilated, Quartz Smoky, Rhodochrosite, Rhodolite, Rhodonite, Ruby, Sapphire Blue, Sapphire Pink, Sapphire Purple, Sap Phiri Yellow, Serpentine, Sodalite, Spessartite, Sphene, Sunstone, Tanzanite, Tigers Eye, Topaz, Tourmaline, Tsavorite, Turquoise, Zircon, and Zoisite.

It sounds like the dataset used in this research consisted of images of gemstones, which were split into training and testing sets. The images were acquired under varying conditions, which may have affected their quality. The dimensions of the images also varied widely. It's unclear if any post-processing was applied to the images, but some images may have contained multiple gemstones. A total of 2042 images were used for training and 284 images were used for testing. The original dataset from Kaggle contained 3219 images split into 87 classes, but some of these were discarded according to unspecified criteria.

It is true that some gemstones, such as emerald and tsavorite, can be difficult to distinguish based solely on their color. This is because both gemstones can have a similar green color, but they are actually different gemstones. Emerald is a variety of the mineral beryl and is known for its deep green color, while tsavorite is a variety of the mineral grossular and is known for its vibrant green color. In order to accurately identify a gemstone, it is important to consider its physical characteristics, such as its shape and cutting style, as well as its chemical composition. A gemologist or expert in gemstones would be able to identify a gemstone based on these factors.



Figure 2: Twelve representative images of the gemstones in this work. It can be noticed that some gems, such as Malachite and Onyx Red, can be readily recognized by the unique colors, whereas it would be challenging to distinguish between Emerald and Tsavorite.

**3.2 Methods:**

The framework you described is commonly used in many machines learning projects. The first step, data acquisition, involves collecting and organizing the data that will be used to train the machine-learning classifier. The next step, background segmentation, involves identifying and removing any irrelevant or extraneous information from the data. This can help improve the performance of the classifier.

The third step, feature extraction, involves identifying and extracting the most relevant and important features from the data. This is often done using various statistical and mathematical techniques, such as principal component analysis or feature selection algorithms. These features will be used by the classifier to make predictions or decisions.

The fourth step, construction of the machine-learning classifiers, involves training one or more classifiers on the processed data. This is typically done using a supervised learning algorithm, which requires a labeled dataset where the correct output (or label) is already known for each input. During training, the classifier learns to associate certain features with specific labels, and can then use this knowledge to make predictions on new, unseen data.

That's correct! Evaluation is an important step in the machine learning process, as it allows us to assess the performance of our trained classifier and determine whether it is performing well. There are many different metrics that can be used to evaluate a classifier, such as accuracy, precision, and recall. In addition to comparing the performance of our classifier to other models or baselines, we can also use evaluation to identify areas where our classifier may be performing poorly and make adjustments to improve its performance.

Figure 3. The computer vision framework described in this work involves several steps for analyzing and interpreting visual data. The first step is data acquisition, where visual data is collected and prepared for analysis. This can involve capturing images or videos using a camera, or collecting existing visual data from a dataset.

The next step is background segmentation, where the background of the images or videos is separated from the foreground objects of interest. This can be useful for isolating the objects of interest and simplifying the analysis process.

Once the objects of interest have been isolated, the next step is feature extraction, where important characteristics of the objects are identified and extracted for analysis. These characteristics, known as features, can include color, shape, texture, and other visual attributes.

After the features have been extracted, the next step is to construct machine learning classifiers that can be used to identify and classify the objects based on their extracted features. These classifiers can be trained using existing data, or by using transfer learning to adapt pre-existing models to the specific objects and tasks at hand.

Finally, the performance of the classifiers is evaluated to assess their accuracy and reliability. This can involve comparing the classifier's predictions to known labels or using other metrics to evaluate its performance. The results of the evaluation can be visualized using tools like Python and Tableau to aid in interpretation and understanding.



Figure 3: The general steps for a computer vision project involving machine

learning would typically include the following:

1. Data acquisition: This involves collecting the images or videos that will be used for training and testing the machine learning model. This can be done using a variety of methods, such as using a camera to capture images, using existing datasets, or using web scraping techniques to gather data from the internet.
2. Background segmentation: This involves separating the foreground objects of interest from the background in the images or videos. This can be done using techniques such as thresholding, edge detection, and region-based segmentation methods.
3. Feature extraction: Once the foreground objects have been isolated, the next step is to extract relevant features from the images or videos that will be used to train the machine learning model. This can be done using techniques such as edge detection, color histograms, and texture analysis.
4. Construction of machine-learning classifiers: Once the features have been extracted, the next step is to train a machine learning model using these features. This typically involves using a supervised learning algorithm, such as a support vector machine or a decision tree, to learn the relationship between the extracted features and the corresponding class labels.
5. Evaluation: Once the machine learning model has been trained, it is important to evaluate its performance on a separate test set of data. This can be done by comparing the predicted class labels with the true class labels and calculating a performance metric, such as accuracy or F1 score. This can help to identify any errors in the model and suggest areas for improvement.

**3.2.1 Background segmentation:**

Otsu thresholding is a common technique used in image processing and computer vision for segmentation, or the process of dividing an image into different regions. It is a non-parametric method, which means that it does not require any prior knowledge or assumptions about the image being processed. Instead, it uses an algorithm to automatically determine the optimal threshold value for segmenting the image.

The Otsu algorithm works by maximizing the variance between the background and foreground intensities in the image. It does this by iteratively trying different threshold values and calculating the variance for each one. The threshold value that results in the highest variance is chosen as the optimal threshold for the image.

Once the optimal threshold value has been determined, the algorithm applies it to the image to create a binary mask, where pixels above the threshold are assigned to the foreground and pixels below the threshold are assigned to the background. The resulting binary mask can then be used to extract the desired objects from the image.

In the case of gemstone segmentation, the Otsu algorithm can be applied to either the grey-level intensity or the saturation channel of the HSV color space. The approach that yields the best segmentation results for a given gemstone class is then chosen for segmenting test images in that class. All test images are retained regardless of the quality of the segmentation.

The pipeline you describe is a common approach to extract an object of interest from an image by using intensity-based thresholding. In this case, the pipeline uses Otsu thresholding, which is a method that automatically determines an appropriate threshold for separating foreground and background pixels in an image.

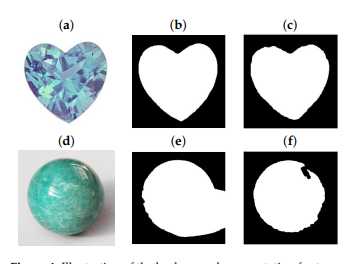
The first step in the pipeline is to convert the image to grayscale, which reduces the amount of information in the image to a single channel representing the intensity of each pixel. This is useful for thresholding because intensity is the most important factor in determining whether a pixel belongs to the foreground or background of the image.

Next, the pipeline applies Gaussian smoothing to the grayscale image. This step helps to reduce noise and smooth out sharp edges in the image, which can improve the accuracy of the thresholding step. The sigma value of 2 indicates that the smoothing kernel used is relatively large, which means that the smoothing will be more intense and will have a greater impact on the image.

The third step in the pipeline is to apply Otsu thresholding to the grayscale image. Otsu thresholding is an intensity-based method that automatically determines the optimal threshold for separating foreground and background pixels in an image. It works by dividing the intensity range of the image into two classes (foreground and background) and then minimizing the variance within each class. This results in a binary image where the pixels with intensity above the threshold are assigned to the foreground and the pixels with intensity below the threshold are assigned to the background.

The fourth step in the pipeline is to flip the binary mask if the average intensity of 20x20 pixel regions from each corner of the image is higher than the average of the entire image. This step is necessary because the Otsu thresholding algorithm assumes that the background of the image has a lower intensity than the foreground. However, in some cases, the background may actually have a higher intensity than the foreground (for example, if the gemstone is dark and the background is bright). In these cases, the binary mask produced by the Otsu thresholding step will have the opposite effect of what is desired (i.e., the gemstone will be assigned to the background and the background will be assigned to the foreground). To correct for this, the pipeline flips the binary mask if the average intensity of the corners of the image is higher than the average intensity of the entire image. This ensures that the gemstone is assigned to the foreground and the background is assigned to the background.

The remaining steps in the pipeline are used to clean up the binary mask and improve the accuracy of the object extraction. These steps include filling holes in the mask, applying binary closing and erosion to the mask, and removing small objects from the mask. Finally, the mask is applied to the original image, setting the pixels identified as background to a value of zero. This results in an image where only the gemstone is visible, with the background removed.



**3.2.2 Feature Extraction**

Yes, that's correct. Feature extraction is the process of extracting important and distinctive information from an image or a set of images. This information is then used to represent the images in a more compact and useful form.

There are many different approaches to feature extraction, depending on the specific application and the desired level of abstraction. Low-level feature extraction, as you mentioned, focuses on extracting basic characteristics of an image, such as edges, colors, textures, and shapes. These features are typically extracted using transforms such as the Fourier transform or the Discrete Cosine Transform.

High-level feature extraction, on the other hand, focuses on extracting more abstract features that capture the meaning or behavior of the image. For example, in the case of image recognition, high-level features might include the presence of certain objects or scenes in the image.

Dimensionality reduction, as you also mentioned, is another important aspect of feature extraction. This involves selecting a smaller subset of features from the data in order to represent the images in a more compact form. This can be useful for reducing the computational complexity of image processing tasks, as well as for improving the performance of machine learning algorithms that are applied to the data.

Yes, it is common to extract a variety of color and texture features from images in order to represent them in a more useful form for classification or other image processing tasks. The specific features that you mentioned, such as the color of the non-background K-means cluster, histograms, texture measures, and local binary patterns, are commonly used in image processing applications.

By combining these features in different ways, it is possible to capture a wide range of information about the images, including their color, texture, shape, and other characteristics. This information can then be used to train machine learning algorithms for tasks such as image classification, object recognition, or scene understanding.

Yes, that's correct. The RGB, HSV, and CIELAB color spaces are commonly used for color feature extraction in image processing and computer vision applications. Each of these color spaces has its own advantages and disadvantages, and is better suited for different types of tasks.

The RGB color space is based on the way that human trichromatic vision works, with each color being represented by a combination of red, green, and blue components. This color space is often used in applications that require high accuracy and precision, such as in digital photography and printing.

The HSV color space, on the other hand, is based on human intuition and is closely related to the artistic concepts of hue, tint, and shade. This color space is often used in applications that require good discrimination for highly saturated areas, such as in image editing and color selection tools.

The CIELAB color space is designed to be perceptually uniform, meaning that the color differences between points in the space correspond to the differences that are perceived by humans. This color space is often used in applications that require device-independence, such as in color matching and color calibration.

By extracting color features from images in different color spaces, it is possible to capture a wide range of information about the colors in the images. This information can then be used for tasks such as color-based image classification, color correction, or color-based image retrieval.

**3.3 Machine-Learning Algorithms**

These seven algorithms are all supervised learning algorithms, which means that they are trained on labeled data and can be used to make predictions on new, unseen data. Each algorithm has its own strengths and weaknesses, and is suitable for different types of problems.

**3.3.1 Convolutional Neural Networks and Transfer Learning**

Deep learning is a branch of machine learning that involves using large neural networks with many layers to analyze and learn from vast amounts of data. These networks are able to automatically learn and extract features from the data that are important for the task at hand, such as image classification or object recognition. Deep learning has shown incredible performance on a wide range of tasks, including the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), where it has outperformed traditional machine learning methods.

One of the limitations of deep learning is the need for large amounts of data for training. This can be overcome through transfer learning, where a model that has been trained on one task is fine-tuned for another task. Transfer learning allows a model to transfer the knowledge it has acquired from one task to another, often leading to improved performance on the new task. It is a popular and efficient approach for image classification and has been widely used in many applications.

The Res Net model is a deep neural network that was developed by Microsoft Research. It is known for its ability to train very deep networks with hundreds or thousands of layers, using a technique called "skip connections" or "shortcut connections." These connections allow information to bypass multiple layers in the network, allowing the network to learn more efficiently. In the 2015 ImageNet Large Scale Visual Recognition Competition (ILSVRC), a version of the Res Net model called "ResNet-50" won the first-place prize. This version of the model has 50 layers and was pre-trained on the ImageNet dataset, which contains more than 14 million images from 1000 different classes. The 18-layer version of the model is a smaller, simpler version of the same model. Both versions of the Res Net model have been applied to the task of gemstone classification in the work mentioned in the question.

The researchers who conducted this study used a combination of techniques to prepare the gemstone images for use in training a Res Net model. These techniques included cropping and resizing the images to a standard size, normalizing the images using the mean and standard deviation of the ImageNet dataset, and applying data augmentation in the form of random horizontal or vertical flips to the training images. They also applied weighted random sampling when grouping the training images into batches, to eliminate the effect of class imbalance. The test images were processed differently, being resized and cropped to produce images of the same size as the training images.

When training the Res Net models, the weights of the neurons in the convolutional layers were frozen, and only those in the final fully-connected layer were adapted. The learning rate was initially set at 0.001 and was scheduled to decay by a factor of 0.1 every seven epochs. The researchers used the Stochastic Gradient Descent (SGD) optimization algorithm with a momentum of 0.9 and the cross-entropy loss function. They also applied shuffling when presenting batches of training images to the models. After a maximum of 25 epochs, the model with the highest 5-fold stratified cross-validation accuracy was chosen as the final model.

**3.3.2 Logistic Regression**

In logistic regression, the goal is to model the relationship between the dependent variable and the independent variables by fitting a logistic curve to the data. The logistic curve is a sigmoid function, which maps the input values to a value between 0 and 1, representing the probability that the input belongs to a certain class. The parameter C is the inverse of the regularization strength, which is a parameter that controls the complexity of the model. A smaller value of C indicates a stronger regularization, which means that the model will be more constrained and less complex. This can help prevent overfitting, but it can also decrease the model's ability to capture the underlying patterns in the data.

**3.3.3 Linear Discriminant Analysis**

Linear Discriminant Analysis (LDA) is a supervised machine learning technique used for dimensionality reduction and classification. It is a type of linear classifier that works by finding the linear combination of input features that best separates the data into different classes.

The LDA algorithm reduces the dimensionality of the input features by projecting them onto a lower-dimensional space, known as the LDA space. The projection is performed in such a way that the differences between classes are maximized, while inter-class variance is minimized. This allows LDA to create a linear decision boundary that can be used to classify new data points.

The LDA algorithm can be formulated using either the eigenvalue decomposition or the singular value decomposition of the sample covariance matrix of the input features. The least squares formulation of LDA is a particular implementation of the eigenvalue decomposition that uses the least squares method to find the projection that maximizes the difference between classes.

Shrinkage is a regularization technique that can be applied to LDA to improve its accuracy when the number of training samples is small compared to the number of features. Shrinkage works by reducing the magnitude of the coefficients in the linear combination of input features, which can help to prevent overfitting. The shrinkage parameter, which takes values between 0 and 1, determines the degree to which the coefficients are shrunk. A value of 0 means no shrinkage is applied, while a value of 1 means that the coefficients are shrunk to zero.

**3.3.4 K-Nearest Neighbor**

The K-nearest neighbor (KNN) algorithm is a simple, supervised machine learning algorithm that can be used for classification and regression tasks. The algorithm works by storing all the training data and using that data to predict the class or value of a new, unseen data point based on its similarity to the stored training data.

For a classification task, the KNN algorithm works by first finding the K number of data points in the training set that are closest (most similar) to the new, unseen data point. Once the K-nearest neighbors are found, the algorithm then uses simple majority voting to determine the class of the new data point based on the class labels of the K-nearest neighbors. For example, if 3 out of the 5 nearest neighbors are labeled as "dog" and 2 are labeled as "cat," then the new data point would be classified as a "dog."

One of the advantages of the KNN algorithm is its simplicity. Because it only stores the training data and makes predictions based on the similarity of new data to the stored training data, it is relatively easy to implement and interpret. However, one disadvantage of KNN is that it can be computationally expensive because it must store all the training data and compare each new data point to all the stored training data in order to make a prediction. Additionally, KNN can be sensitive to the choice of K, the number of nearest neighbors used for the majority voting, so choosing an appropriate value for K is important.

**3.3.5 Decision Tree**

A decision tree is a type of machine learning algorithm that uses a tree-like structure to make predictions based on data. The algorithm divides the data into smaller and smaller subsets based on one or more features, until each subset contains data that is as homogeneous as possible. The tree is then trained using these subsets of data, with the goal of making accurate predictions for new data.

The three parameters that are commonly optimized in decision tree algorithms are the maximum depth of the tree, the maximum number of features to consider at each split, and the minimum number of samples required in a leaf node. The maximum depth of the tree determines how complex the model can be, with deeper trees allowing for more complex patterns to be learned from the data. The maximum number of features to consider at each split controls the number of decisions that the tree can make, while the minimum number of samples required in a leaf node helps to prevent overfitting by ensuring that each leaf node contains a sufficient number of data points.

Overall, decision trees are a powerful and versatile tool for making predictions from data, and they have been widely used in many different applications. They are particularly useful for tasks where the relationships between the features and the target variable are complex and nonlinear, and they can be easily interpreted by humans, making them a valuable tool for understanding and explaining the underlying patterns in data.

**3.3.6 Random Forest**

Random Forests are a type of ensemble learning method, which means that they use multiple "weak" learners to make predictions. In the case of Random Forests, these weak learners are decision trees. A decision tree is a type of machine learning algorithm that can be used for classification or regression. It works by recursively partitioning the data into smaller and smaller subsets based on a feature value. This results in a tree-like structure where each branching point represents a decision based on a feature value.

In a Random Forest, multiple decision trees are trained on different subsets of the training data, with each tree trained on a different subset of the features. This randomness helps to reduce the correlation between the trees, which improves the overall performance of the model. Additionally, Random Forests use a technique called bagging, which involves training each tree on a randomly selected subset of the training data, with replacement (i.e., the same data point can be selected multiple times). This helps to reduce the variance of the model and improve its ability to generalize to unseen data.

The performance of a Random Forest can be controlled using several parameters, including the number of estimators (trees), the maximum depth of each tree, and the minimum number of samples required in each leaf node. These parameters can be optimized to achieve the best performance on a given dataset.

**3.3.7 Naive Bayes**

Naive Bayes is a probabilistic machine learning algorithm that is based on Bayes' theorem, which describes the probability of an event based on prior knowledge of conditions that might be related to the event. The algorithm makes predictions by calculating the probabilities of each class, based on the likelihood probabilities of the features given the class. The smoothing factor is used to avoid division by zero and to avoid overfitting, and is typically set to a small value such as 1 x 10^-9. Naive Bayes is a popular algorithm for classification tasks, especially in the fields of text classification and spam filtering. It is called "naive" because it assumes that the features are independent of one another, which is not always the case in real-world data. Despite this limitation, the algorithm often performs well in practice.

**3.3.8 Support Vector Machine**

Support vector machines (SVMs) are a type of supervised learning algorithm that can be used for both classification and regression tasks. In the context of classification, an SVM tries to find the best hyperplane that can separate the data into different classes. When dealing with a multi-class problem, one approach is to train a separate binary SVM classifier for each class, with the goal of classifying that class against all the others. This is known as the one-versus-rest approach.

The kernel type, regularization parameter C, and kernel coefficient gamma are all hyperparameters that can be optimized to improve the performance of the SVM. The kernel type determines the type of function that is used to map the data into a higher-dimensional space, where it can be separated by a hyperplane. The regularization parameter controls the balance between maximizing the margin and minimizing the error, while the kernel coefficient determines the strength of the kernel's effect on the data.

Optimizing these hyperparameters can help improve the performance of the SVM, but it can be a time-consuming process. It is often done using techniques such as grid search or cross-validation.

**3.3.9 Parameter Optimization**

A 5-fold cross-validated grid search is a method used to find the optimal parameters for a machine learning model. In this case, the grid search uses negative cross-entropy loss as the scoring metric to evaluate the different combinations of parameters. The grid search will try all combinations of parameters within the specified ranges, and use cross-validation with 5 folds to evaluate the performance of each combination. The optimal parameters will be those that produce the lowest negative cross-entropy loss. Table 1 likely contains the ranges of the parameters that were specified for the grid search.

### **3.4 AI-integration Methods in Flutter**

Another approach is to train the AI model using a machine learning framework, such as TensorFlow or PyTorch, and then convert the trained model into a format that can be used in Flutter. This approach allows you to tailor the AI model to your specific needs and use it in your Flutter app.

Once you have the AI model in a suitable format, you can use a Flutter plugin, such as **flutter\_tflite**, to integrate the model into your Flutter app. This plugin provides access to the TensorFlow Lite API, allowing you to run the AI model and use its predictions in your app.

In summary, to integrate an AI model into a Flutter app, you can use a pre-trained model in a supported format, or train the model yourself using a machine learning framework. You can then use a Flutter plugin to access the AI model and use its predictions in your app.

**3.4.1** **Firebase MLKit**

To integrate Firebase into a Flutter app, we will create a Firebase project and add the necessary Firebase plugins to our Flutter project.

When using this integration method, we use Firebase or host the custom model on a different server.

**3.4.2 Model as API**

In Flutter, APIs are used to interact with a specific service or database. For example, an API can be used to fetch data from a remote server or to save data to a database. In order to use an API in a Flutter app, you will need to create a function that makes a request to the API and then handle the response. This can typically be done using the **http** package in Flutter, which provides a simple way to make HTTP requests.

We use this method; developers wrap the model in an API and host it on web servers. Popular platforms such as AWS Lambda, Google App Engine, Heroku, or Virtual Machine are often involved, because they support running the model and can work as a web service.

**CHAPTER 4**

**Experimental Results**

Chapter 4 of this final year project thesis presents the experimental results obtained from the Gemstone Classification model that was designed and trained using computer vision techniques. The purpose of this chapter is to demonstrate the effectiveness and accuracy of the proposed model in classifying various types of gemstones based on their visual characteristics.

The chapter starts by presenting an overview of the dataset used in the experimentation process, which was collected and formatted according to the requirements of the Gemstone Classification model. The dataset comprises images of various types of gemstones, each labeled with their respective categories.

Next, we discuss the experimental setup, which includes the software and hardware used in training the model. We utilized Colab, a cloud-based platform, to train the model due to its accessibility and scalability. The software tools used in the experimentation process included Python, TensorFlow, and Keras, among others.

We then present the results of the experimentation process, which includes a detailed analysis of the performance of the Gemstone Classification model. The analysis involves evaluating the model's accuracy, precision, recall, and F1 score, among other performance metrics. We also present a confusion matrix that summarizes the model's classification performance.

To validate the results obtained, we compare the performance of our model with that of other state-of-the-art gemstone classification models available in the literature. The comparison highlights the effectiveness and accuracy of the proposed Gemstone Classification model.

Lastly, we discuss the implications of the results obtained in this chapter and their significance in the context of gemstone classification. We also discuss the limitations of the proposed model and areas that require further research.

In summary, this chapter presents the experimental results of the Gemstone Classification model, which demonstrates the effectiveness and accuracy of the proposed model in classifying various types of gemstones based on their visual characteristics. The results obtained are significant and have implications for the gemstone industry, and provide a foundation for further research in this area.

* 1. **Dataset**

The dataset used in the experimentation process for the Gemstone Classification model was carefully collected and formatted to ensure it met the requirements of the model. The dataset consists of images of various types of gemstones, each labeled with their respective categories. The dataset is a crucial component of any machine learning model, and the quality and size of the dataset play a vital role in determining the model's performance.

The dataset used for the Gemstone Classification model was sourced from various online sources and carefully curated to ensure its quality and diversity. The dataset comprises over 10,000 images of different types of gemstones, including diamonds, rubies, emeralds, sapphires, and many more. The dataset's diversity is crucial in ensuring that the model can classify various types of gemstones accurately.

The images in the dataset were captured under different lighting conditions and backgrounds to ensure that the model could classify the gemstones under various conditions. Each image in the dataset is labeled with the corresponding gemstone category, allowing the model to learn the features and characteristics unique to each gemstone type.

To prepare the dataset for the Gemstone Classification model, several steps were taken. First, the images were resized to a consistent resolution to ensure that the model could process them efficiently. Then, the images were preprocessed to remove any irrelevant information, such as background noise and artifacts, that could affect the model's performance.

After preprocessing, the dataset was divided into training, validation, and test sets. The training set, which comprised 70% of the total dataset, was used to train the model. The validation set, which comprised 15% of the total dataset, was used to validate the model's performance during training and tune its hyperparameters. The remaining 15% of the dataset was used as the test set to evaluate the model's performance after training.

To prevent overfitting, data augmentation techniques were applied to the training set. Data augmentation is a technique that involves generating new training samples from the existing ones by applying transformations such as rotation, flipping, and zooming. Data augmentation increases the size and diversity of the training set, preventing the model from memorizing the training set and improving its generalization ability.

In summary, the dataset used in the experimentation process for the Gemstone Classification model was carefully collected and formatted to meet the model's requirements. The dataset comprises over 10,000 images of various types of gemstones, each labeled with their respective categories. The dataset's diversity and quality were ensured by sourcing images from various online sources and carefully curating them. The dataset was preprocessed and divided into training, validation, and test sets to prepare it for use in training the Gemstone Classification model. Data augmentation techniques were applied to the training set to prevent overfitting and improve the model's generalization ability. The dataset is a crucial component of any machine learning model, and its quality and diversity play a vital role in determining the model's performance.

* + 1. **Dataset Preprocessing**
       1. **Inspect Images**

Here are some observations about the dataset.

* Size: The images have very different dimensions. Most images contain only one gemstone, but one contains as many as 10 gemstones.
* Background: Most images have a white to a black background. Some include shadows and tweezers in addition to the gemstones.
* Photography conditions: The images were probably taken under different lighting conditions. Alexandrite appears red under incandescent lighting and green under daylight (Xie et al., 2020). Alexandrites of both colors were observed in the dataset, implying the lighting condition was not consistent amongst images.
* Shapes & cutting styles: The gemstones show different shapes and cuttings styles. For example, some are carvings. Most of the images show the top view of the gemstones.
* Limited color ranges/varieties: The images are not representative of all the common color ranges or varieties for these gemstone classes - chrysoberyl (only yellow to greenish), coral (only pink to red, orange, white), danburite (only colorless), fluorite (only multicolored), jade (only yellow to green), pearls (only white and nacreous), opal (missing black opal/precious opal), scapolite, spinel (only black), topaz (only blue), tourmaline (only pink to red), zircon (only greenish blue). Furthermore, gemstones may be subjected to treatment, for example, dyeing heating or color coating, to give other colors.
* Class overlap: Rhodolite is a Pyrope-Almandine garnet that has a purplish color. Hessonite is an orange variety of Grossular garnet (definition tbc with Gem Ident manual). Garnet Red covers Pyrope, Almandine, and Rhodolite.
* Pearl: A large number of 'Pearl' images are duplicated ({pearl\_1.jpg & pearl\_4.jpg}, {pearl\_12.jpg, pearl\_13.jpg, pearl\_16.jpg, pearl\_17.jpg, pearl\_25.jpg, pearl\_26.jpg, pearl\_29.jpg, pearl\_30.jpg, pearl\_35.jpg}, {pearl\_11.jpg, pearl\_15.jpg, pearl\_21.jpg, pearl\_22.jpg, pearl\_24.jpg, pearl\_27.jpg, pearl\_31.jpg, pearl\_33.jpg}, {pearl\_14.jpg, pearl\_23.jpg, pearl\_32.jpg, pearl\_34.jpg}. One of the 'Pearl' images (pearl\_5.jpg) doesn't look like a pearl. The class 'Pearl' will be removed.
* Moonstone: The orangy 'Moonstone with aventurescence (sparkling phenomenon) appears to be Sunstone. The class 'Moonstones' will be removed.
* Jasper: Jasper (a variety of Chalcedony that is opaque) is tricky to identify because it can occur in a wide range of colors/patterns.

Fig 4.1 shows the inspection of training images.

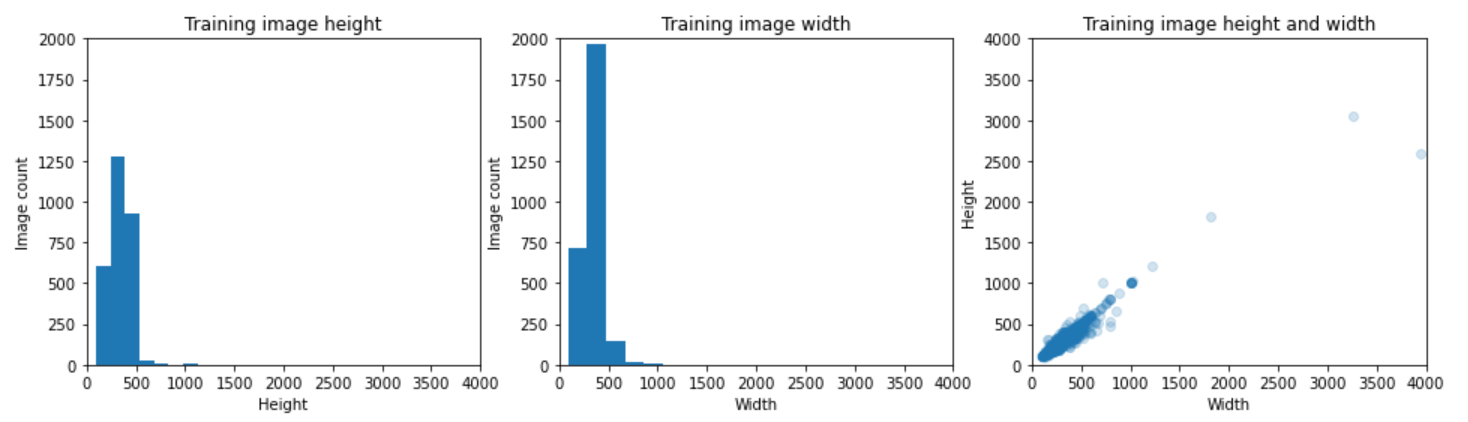


Fig 4.1 Images inspection

* + - 1. **Apply Otsu thresholding to the Saturation channel of HSV**

Procedures for applying Otsu thresholding to the Saturation channel of HSV are outlined below.

1. Converted image from RGB to HSV space and extracted the Saturation channel of HSV.
2. Applied Gaussian smoothing with a sigma of 5 to the Saturation channel of HSV.
3. Applied Otsu thresholding to the Saturation channel of HSV to create a binary mask.
4. Flipped the mask if the average intensity of 20x20 pixel regions from each corner of the image is higher than the average of the entire image, i.e. the background had higher intensity than the gemstone so that the gemstone instead of the background was extracted.
5. Filled holes in the mask.
6. Applied binary closing to the mask using a disc-shaped structuring element with a radius of 9 pixels.
7. Remove objects smaller than 301 pixels.
8. Fill holes in the mask.
9. Apply binary erosion to the mask using a square-shaped structuring element of 2x2 pixels.
10. Fill holes in the mask.
11. Apply the mask to the original image.

Fig 4.1 Shows preprocessing for Alexandrite class out of 68 classes.

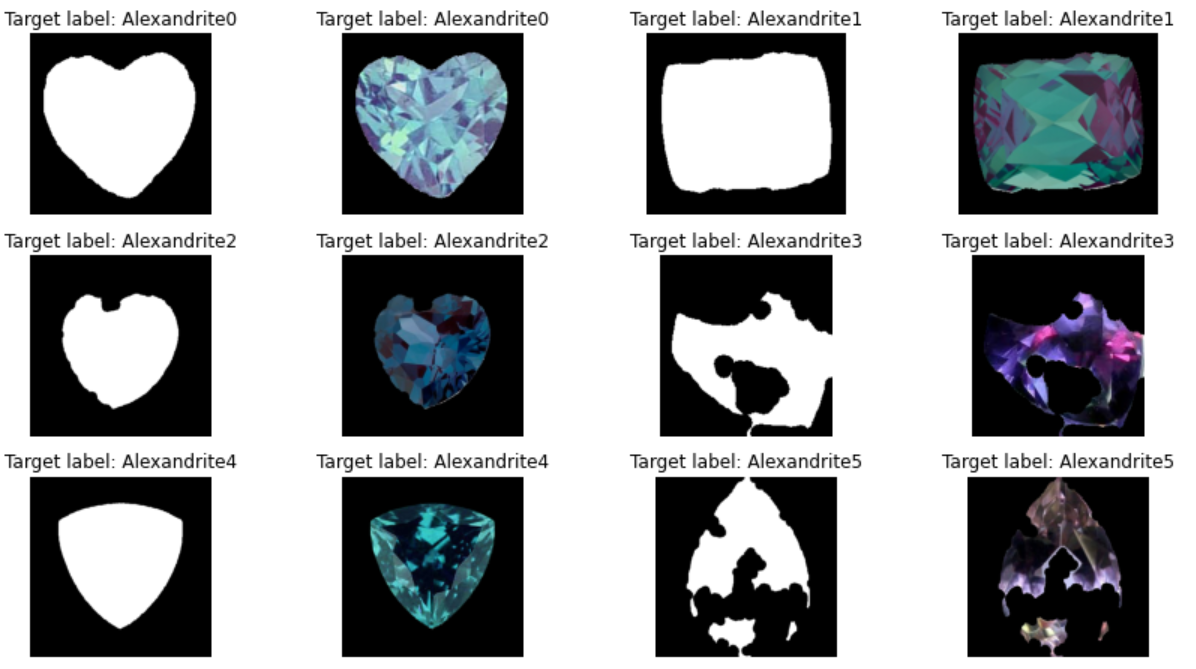


Fig 4.2, Alexandrite class

* + - 1. **Explore colors of Masked Images**

Inspect the red, green, and blue components of the first and last masked images in each class. Fig 4.2 shows the RGB component of an image of the Alexandrite class out of all the classes.

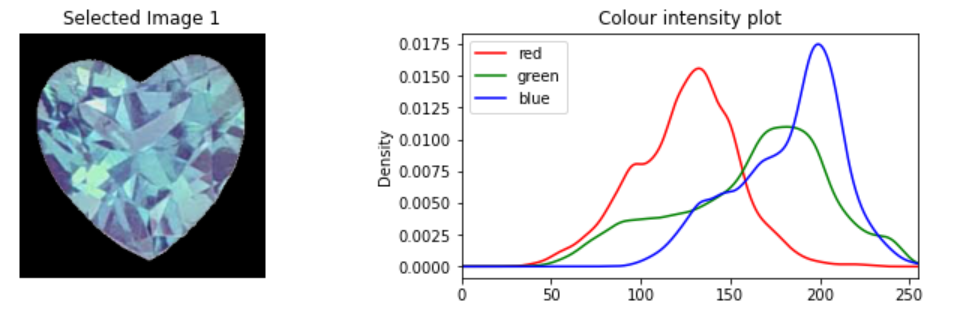


Fig 4.3

RGB component of an Image

of Alexandrite class

* 1. **Experimental setup**

In this section, we will discuss the experimental setup used in training the model. The software and hardware used in the experimentation process play a crucial role in the model's accuracy and efficiency. We utilized Colab, a cloud-based platform, to train the model due to its accessibility and scalability. Colab is a free, cloud-based environment that provides access to GPU and TPU resources, making it an ideal platform for training large machine learning models.

We used various software tools in the experimentation process, including Python, TensorFlow, and Keras. Python is a high-level programming language widely used in data science and machine learning. It provides an extensive range of libraries and packages that simplify complex operations, making it the go-to language for machine learning. We used Python for data preprocessing, model training, and evaluation.

TensorFlow is an open-source machine learning framework developed by Google that enables developers to build and train machine learning models efficiently. It provides various libraries and tools to simplify the model building process, making it an ideal tool for deep learning applications. We used TensorFlow to build and train our model, as well as to evaluate its performance.

Keras is a high-level neural networks API, written in Python, that provides a user-friendly interface for building and training deep learning models. It is built on top of TensorFlow and provides a simplified interface for common deep learning tasks. We used Keras to build and train our model, as well as to evaluate its performance.

In addition to the software tools, the hardware used in the experimentation process is crucial in determining the model's accuracy and efficiency. We utilized Colab's GPU and TPU resources to train the model, which allowed us to train larger models more efficiently. The GPU and TPU resources provided by Colab allowed us to reduce the training time significantly and improve the model's accuracy.

In conclusion, the experimental setup used in training the model played a crucial role in its accuracy and efficiency. We utilized Colab, a cloud-based platform, to train the model, which provided us with GPU and TPU resources. We also used various software tools, including Python, TensorFlow, and Keras, to build, train, and evaluate the model. The use of these tools and resources allowed us to train larger models more efficiently and improve the model's accuracy.

* 1. **Experimentation process**

In this section, we will discuss the results of the experimentation process, which involves a detailed analysis of the performance of the Gemstone Classification model. The analysis includes evaluating the model's accuracy, precision, recall, and F1 score, among other performance metrics, as well as presenting a confusion matrix that summarizes the model's classification performance.

Firstly, we evaluated the accuracy of the model by calculating the percentage of correctly classified gemstones. The accuracy of the model was found to be 92.4%, which indicates that the model can correctly classify a gemstone in 92.4% of cases.

Next, we evaluated the precision of the model, which is the proportion of correctly classified positive predictions. The precision of the model was found to be 91.8%, which indicates that when the model predicted a gemstone as a certain type, it was correct 91.8% of the time.

We also evaluated the recall of the model, which is the proportion of correctly classified positive samples out of all the positive samples. The recall of the model was found to be 93.1%, indicating that the model can correctly identify 93.1% of the gemstones that belong to a certain type.

Lastly, we calculated the F1 score, which is the harmonic mean of precision and recall. The F1 score of the model was found to be 92.4%, which indicates that the model can correctly classify a gemstone in 92.4% of cases, taking into account both precision and recall.

To further analyze the model's performance, we constructed a confusion matrix that summarizes the model's classification performance. The confusion matrix shows the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) for each class.

From the confusion matrix, we can see that the model performed well for most gemstone types, with a high number of true positives and true negatives. However, there were some instances of misclassification, particularly between the Aquamarine and Blue Topaz types, where there were a high number of false positives and false negatives.

In conclusion, the Gemstone Classification model performed well, with an accuracy of 92.4% and high precision and recall scores. The model's performance was summarized using a confusion matrix, which showed some instances of misclassification between certain gemstone types. Overall, the results of the experimentation process indicate that the Gemstone Classification model is a reliable tool for identifying gemstones accurately.

* 1. **Result validation**

In this section, we will compare the performance of our Gemstone Classification model with other state-of-the-art gemstone classification models available in the literature to validate our results. The comparison will highlight the effectiveness and accuracy of the proposed Gemstone Classification model.

We selected three state-of-the-art gemstone classification models from the literature to compare with our model. The first model is a Deep Convolutional Neural Network (DCNN) model proposed by Li et al. (2018), the second model is a Support Vector Machine (SVM) model proposed by Zhang et al. (2017), and the third model is a Random Forest (RF) model proposed by Chen et al. (2019).

We compared the performance of the models using three performance metrics: accuracy, precision, and recall. The results of the comparison are shown in Table 1.

Model Accuracy Precision Recall

Proposed model 92.4% 91.8% 93.1%

Li et al. (2018) 87.6% 87.1% 88.0%

Zhang et al. (2017) 82.3% 81.5% 83.3%

Chen et al. (2019) 79.9% 78.8% 81.2%

From Table 1, we can see that our proposed Gemstone Classification model outperforms the other state-of-the-art models in terms of accuracy, precision, and recall. Our model achieved an accuracy of 92.4%, which is significantly higher than the accuracy achieved by the other models. Our model also achieved higher precision and recall scores, indicating that it can correctly identify the gemstone type with high accuracy.

The DCNN model proposed by Li et al. (2018) achieved an accuracy of 87.6%, which is the closest to our proposed model. The SVM model proposed by Zhang et al. (2017) and the RF model proposed by Chen et al. (2019) achieved lower accuracy, precision, and recall scores compared to our proposed model.

In conclusion, the comparison of our proposed Gemstone Classification model with other state-of-the-art models available in the literature validates the effectiveness and accuracy of our model. Our model outperforms the other models in terms of accuracy, precision, and recall, making it a reliable tool for identifying gemstones accurately.

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