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Master's Thesis
Academic Year 2020

A Study on Jadeite Defect Recognition and Segmentation Based on Convolutional Neural Network

Keio University
Graduate School of Media Design

Yingjun Hu

A Master's Thesis
submitted to Keio University Graduate School of Media Design
in partial fulfillment of the requirements for the degree of
Master of Media Design

Yingjun Hu

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Abstract of Master's Thesis of Academic Year 2020

A Study on Jadeite Defect Recognition and Segmentation Based on Convolutional Neural Network

Category: Science / Engineering

Summary

This study focuses on how to improve jadeite processing by using semantic segmentation technology to realize the intelligent recognition of defects of jadeite stone slice. It starts from the background research of current jadeite processing situation in China. During the background research, it is found that low level of intelligent production is obviously shown as one of the main obstacle for China's jadeite industry to further improve the production efficiency.

It is one of the most important procedures in the processing of jadeite to design and draw samples on stone slices, in which, designers need to determine the product type, size and position of the product samples according to the features of the stone slices (mainly based on the color field and defective parts of the stone). Through the study of fieldwork research, it has found that the sample drawing is currently accomplished completely manually, so that the quality and efficiency of the sample drawing is limited by the professional ability of practitioner. Therefore, image recognition by semantic segmentation based on deep learning has been decided as the methodology of this study. The aim of this research is to find out the possibility of applying image recognition by semantic segmentation in automatic recognition of the flaws of jadeite stone slices, so as to improve the quality and efficiency of the product designing step in jadeite processing.

Keywords:

Jadeite smart processing, Semantic Segmentation, Convolutional neural network

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Chapter 1
Introduction

In this chapter, the background of the research will be firstly introduced. Then the problem statement which based on the research background is made and followed by the hypothesis and research purpose. The contribution of this research will be given as well.

1.1. Research Background

Jadeite culture has a history of thousands of years in ancient China, and the processing technology of jadeite has been developing and improving in this long history of industry development. But today, in the era of rapid development of modern science technology and global economy, the development of Chinese jadeite industry, as one of the important representatives of national traditional cultural industry, has also reached a bottleneck stage. This research is to seek a possibility to innovate the current processing methods of jadeite processing. So the research background will be introduced in two parts: 1. The significance and the market prospect of jadeite industry; 2. Overview of the jadeite processing situation.

1.1.1 Significance and Market Prospect of Jadeite Industry

In China's long history of development, jade culture owns a significant historical position. As a symbol of beauty, happiness and good luck, jadeite has become people's favorite jade. Nowadays, although times have changed, social culture, economy, and other aspects of our life have undergone great changes, the "jadeite complex" of Chinese people and culture is visible in our today's life. Jadeite culture is still the classic of Chinese culture. In the atmosphere of "consumer society", Chinese jade industry has gradually developed into one of the most representative traditional Chinese cultural industries.

With the increase of per capita disposable income of Chinese residents, the purchasing power of residents for luxury goods has also been greatly improved, which makes the domestic demand for jadeite in China reach an unprecedented level. The demand for jadeite jewelry of mainland China's residents is increasing. People also have higher quality requirements for jadeite jewelry [1]. And China is a country with a population of more than 1.3 billion, which means that a huge jewelry consumption market still exists, and Chinese have their unique love and enthusiasm for jadeite. China's Jadeite market still has huge consumption potential and development prospect. And because of the influence of Chinese people's great love for jadeite and the excellent quality of jadeite itself, jadeite jewelry and culture are gradually accepted by western people. For example, in recent years, more and more western celebrities start to wear jadeite ornaments at large-scale international events, such as the Oscars. Jadeite is no longer limited to Chinese and Asian market, but is stepping into a wider international stage.

As one of the representative of traditional culture industry, jadeite industry can play a big role in the broader international stage to enhance the national identity and cohesiveness and meet the growing cultural needs of people by promoting the industry's transformation, maintaining the characteristics, overcoming the limitations and adapting to the modern transition [2]. Nonetheless, we are required to discover a path to successful jadeite industry transformation. In order to meet people's diversified needs in the new era of information, in this paper, we aimed to seek a new method that can help innovate the traditional production and processing mode of China's jadeite industry. Before talking about the technologies that I used in the research for the purpose of increasing the production efficiency and quality of jadeite products, current situation of jadeite industry processing will be introduced.

1.1.2 Jadeite Processing Overview

An uncut gem goes not sparkle. From original jadeite stones to end products, a series of processing procedures are needed. Chinese people have unique technology and experience in the processing of jadeite. Chinese jade carving can make full use of raw materials, by giving full play to the characteristics of raw materials, and achieving the most perfect artistic effect on the basis of material saving. The processing methods vary according to different regions and different masters, but they are basically the same. Generally speaking, the following is the main jadeite processing procedure:

1. First cut of the jadeite raw stone, according to the observation of the stone surface;
2. Product type positioning and slicing, based on the analysis of first cut section;
3. Sample drawing on the stone slices, considering the features of the slice (mainly the colors, defective parts such as cracks and impurities);
4. Cutting and carving according to the sample drawing;
5. Polishing.

Figure 1.1 Product design scene from fieldwork

The uniqueness of each jadeite material determines the particularity of jadeite product processing. The design and production of each jadeite product should be specially considered according to the actual situation of raw material characteristics. How to maximize the use of high-valued rare colors and high permeability parts in raw materials and weaken the influence of imperfections, such as impurities and cracks are the key issues for jadeite designers to consider. Also because of the complexity of jadeite features, the product designing (to determine the cutting and engraving scheme), as the basis of jadeite processing, is still completely finished manually, based on their manual recognition results of the features of jadeite raw materials. With the appearance of automatic cutting and engraving machine used in jadeite industry, the jadeite cutting and engraving can be operated automatically under the guidance of the design scheme which is made according to the jadeite feature recognition result.

We can conclude that the jadeite product processing is based on the jadeite feature recognition, which completely depends on manual observation and judgement. That is also the most important reason why the fully-automatic processing in jadeite industry hasn't been achieved. It is obvious that the manual recognition of jadeite features which depends on the professional experience of the processors, leads to the problems of low production efficiency, unstable processing quality and higher production cost that mainly caused by the gradually higher labor cost.

1.2. Problem Statement

Based on the background research of jadeite processing, it is found that with the development of the processing equipment, the cutting and engraving operations in jadeite processing can be done automatically, but the cutting and engraving schemes still have to be determined manually, because the jadeite features can only be recognized manually. The recognition of stone features is the foundation of all the subsequent processing steps.

In other words, only by realizing the automatic recognition of jadeite raw material features, especially the jadeite defects, can the cutting and engraving scheme be automatically generated, which can guide the fully-automatic jadeite processing. The inability to recognize the features of the raw stone intelligently has become the main obstacle to realize the automatic production of jadeite, to further improve the production efficiency of the industry.

1.3. Image Recognition and Semantic Segmentation

Image recognition refers to the technology of using computer to process, analyze and understand the image, so as to recognize the target and object of different modes. The traditional recognition process can be mainly divided into four parts: image acquisition, image preprocessing, feature extraction and image recognition. For the image recognition technology of earlier time, the steps of image preprocessing and feature extraction can only be operated manually [3]. However, with the appearance and development of deep learning, computers have grasped the ability to extract and classify the required features without the disturbance from useless noise pixels. The latest image recognition technology is based on convolutional neural network of deep learning.

Image semantic segmentation is a typical task in computer vision. When processing visual information, human can easily distinguish the target object and get the contour and position information of the target object. The computer conducts the classification of target objects in the image information and the segmentation of the object out of other element area, which is called image semantic segmentation technology. At current stage, the image semantic segmentation technology is to abstract the image into different levels of features, then classify each pixel according to these feature levels, and finally the region of the target object can be segmented from the whole image. Earlier computer vision technology can only recognize lines, curves or color transformation, but image semantic segmentation technology based on deep learning algorithm has been able to provide image understanding of pixel level according to human perception (Figure 1.2).

(a) Original image

(b) Prediction image

Figure 1.2 Prediction result of semantic segmentation

1.4. Hypothesis

Different thickness and volume of stone lead to different difficulty level for stone feature recognition. Because of its thinner thickness, the characteristics of the stone slices (in Step 3. Sample drawing) can be displayed clearly enough through 2D image. According to the background research on jadeite processing situation and inspired by the achievements in the field of semantic segmentation technology (which will be further explained in the Chapter 3), I propose the hypothesis of my research, based on Step 3. Sample drawing: By applying semantic segmentation technology, the intelligent recognition of defects of jadeite stone slice can be realized.

1.5. Research Purpose

The aim of this research is to discuss a potential method of intelligent recognition of jadeite raw material flaws to provide the basis for guiding the fully automatic processing of jadeite, so as to reduce the processing time without lower or even improve the processing quality, and the manufacturing cost of jadeite industry can be reduced as well. Through the analysis and evaluation of the experience results, the significance of intelligent recognition technology of jadeite raw stone flaws to promote jadeite automatic production is obtained.

Basically, to realize the intelligent recognition technology of jadeite raw stone flaws is the foundation to advance the automatic production in jadeite industry, for the reason that first of all, we have to achieve the automatic information collection (which here means features of jadeite stone) and then we can automatically create a cutting or designing project to guide final mechanized and automated production. This study focuses on how to realize the automation of jadeite defect information collection in jadeite processing procedures, so as to create basic condition for promoting the automatic manufacturing of jadeite industry.

1.6. Research Contribution

Before starting the research experiment, some basic researches have been done for making sure the uniqueness of my study: Applying semantic segmentation to intelligent recognition of jadeite raw material defects.

1.6.1 Innovation to Jadeite Industry

I did interview with some representative practitioners of jadeite production industry based in Foshan Pingzhou Jade Distrct, which has the largest production and sale volume of jadeite products in China. The interviews are done to confirm the significance of this research to China's jadeite industry.

From the interview, we can have the following conclusion. The research will be the first time to realize the intelligent recognition of jadeite defects, which will be a milestone in the development of jadeite industry. The processing method of jadeite industry have been standing still and ceased to make progress. The intelligent recognition of jadeite features hasn't been realized before.

The recognition of jadeite defect is the biggest challenge in jadeite processing but the most important basis of the whole manufacturing process. The complexity and variousness of the defect structure of jadeite raw stone makes it difficult to recognize accurately jadeite defects. However, the achievement of intelligent jadeite flaw detection makes the fully automatic jadeite manufacturing possible.

1.6.2 Improvement to Semantic Segmentation

Semantic segmentation hasn't been used in jadeite industry before this research. According to related works, certain new attempts of semantic segmentation application can be found. But the practical application range of semantic segmentation technology is still limited, it is mainly used in the domains of automatic driving and image and video processing. It is rarely used in traditional craft industry.

Since it is the first attempt to apply semantic segmentation technology to jade processing, no open source data set of jadeite images can be found in the field of semantic segmentation. For training the semantic segmentation network to be able to identify the jadeite raw stone defects, it is the first time to collect jadeite image data set in the field of semantic segmentation.

To optimize the semantic segmentation network to recognize the minor crack which takes the least pixel proportion in the image data. In this study, data balancing method is used for network optimization, which solves the problem of weak training results caused by unbalanced pixel proportion of different categories in semantic segmentation.

Chapter 2
Fieldwork on Jadeite Processing

The fieldwork results on jadeite processing will be given into three parts: 1) introduction of jadeite processing procedures; 2) the main reasons that force to advance jadeite intelligent processing; 3) some new technologies being used in jadeite processing.

2.1. Traditional Jadeite Processing Procedures

In order to find the starting point of research direction, it is necessary to understand the production process in detail for which I was honored to visit a jadeite manufacturer and a jadeite carving factory, and to observe the processing process. Great thanks have to be shown to two enterprises: Yingheyuan Jadeite, and Jingbo Jade Factory.

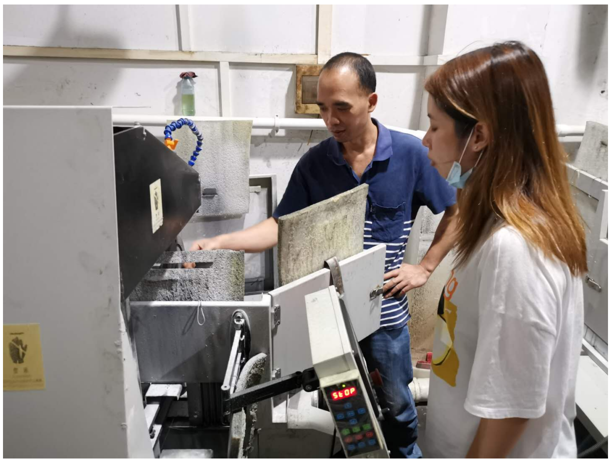


Figure 2.1 Processor is introducing the cutting machine

Firstly, by talking to the processors I got to know the formation and main component of the jadeite imperfections for better distinguishing the jadeite feature categories. The external form of jadeite is similar to that of common rocks. It is usually surrounded by a common rock shell. Myanmar Jadeite is a gem-graded hard jade produced by magmatic rocks in the geological structural zone under the condition of low temperature, high pressure and strong compression. After billions of years of collision and sedimentation, the original jadeite stone, like other rocks, generally have some cracks. In addition, impurities caused by the inhomogeneity of internal materials during the formation process are also common in jadeite raw stone.

The core requirement of jadeite processing lies in avoiding the defective parts of the original stone and making good use of areas with better color, purity and fineness. At present, the production process of jadeite is mostly semi mechanized. The defects are identified manually, and cutting is operated with the equipment such as grinding wheel cutting machine and wire cutting machine. Details of jadeite processing are shown as below (Figure 2.2):

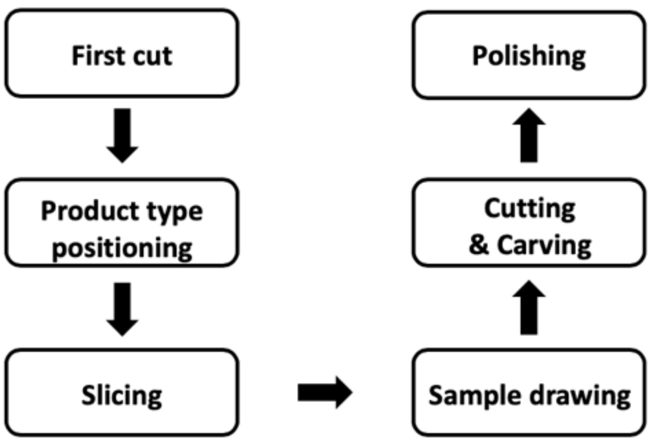


Figure 2.2 Jadeite processing procudres

1. First cut of jadeite stone

   In order to better observe the stone, and also for selling the jadeite raw stone at a better price, (jadeite producers generally purchase the raw stone after the first cut), the first cut of stone is very important, known as the window of stone (Figure 2.3).

Figure 2.3 Jadeite raw stone after first cut being sold in form of public bid

First, according to the surface characteristics of the original stone, the interior of the original stone is analyzed:

- Analysis of the color types of jadeite: green, purple and yellow are the most common color found in jadeite stone, in which green is seem to be the most valuable;
- Analysis of jadeite defects: observe whether there are cracks and other impurities;
- Analysis of feature distribution: observe the distribution relationship between the color of jadeite and defects.

The observation steps above are all finished by naked eye with the aid of flashlight. According to preliminary analysis, the first cut of raw stone is determined.

2. Product type positioning and slicing

Through the section of the first cut, we can more clearly and intuitively observe and speculate on the distribution of the colors and flaws, as well as the permeability of raw materials and other important characteristics. According to the observation results, the product type can be determined (Figure 2.4), and then stone will be cut into slices.

Figure 2.4 Product type positioning of the stone

The principle of slice-cutting is not to destroy valuable color areas and weaken or avoid defective parts. Try to make end products with large volume and high quality as much as possible, because the larger the volume and the higher the quality of finished products, the more rare it is, the higher the value will be. Grinding wheel cutting machine and wire cutting machine are usually used for slice-cutting of original stone.

3. Sample drawing

   Sample drawing on stone slices (Figure 2.5), considering valuable color parts and defective parts (mainly the cracks, impurities) and also other important characteristics like permeability of the raw material .

   Sample drawing is actually to determine the product design scheme of the stone slice: what is the product type that will be produced, which position of raw material stone slice will be used to produce the products, so that value of stone slice can be maximized.

   In this step, designers' careful observation is very important, because some defects can not be easily found. Designers need accurate product value

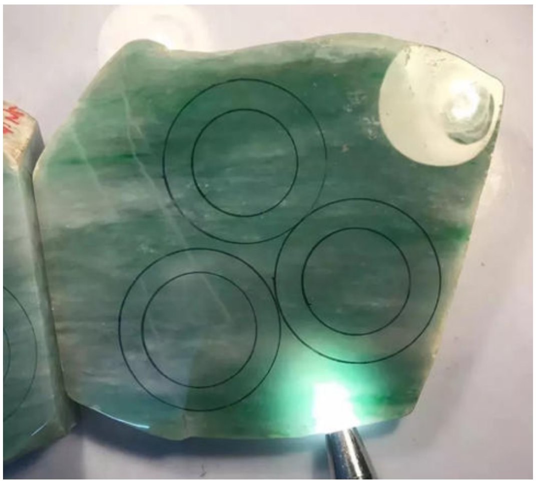


Figure 2.5 Sample drawing of jadeite bangle on stone slice

judgment to finish the product design scheme on the slice.

4. Cutting and engraving according to sample drawing and polishing

   According to the sample drawing in the previous step, cut out the outline of the jadeite products. Then the carving product needs to be engraved, and finally polished until the surface is bright and smooth.

   After thousands of years of continuous evolution, the artificial processing of jadeite has already reached a mature stage. With the continuous improvement of processing equipment, especially that of the cutting and carving machines, the accuracy of jadeite cutting and carving technology is constantly improved. With constant accumulation of professional technique and experience, people have a deeper understanding of the nature and rule of jadeite's internal patterns, which has always been the basis of jadeite processing and design. However, how to transform manual pattern recognition, especially defect identification, into automatic recognition with the help of artificial intelligence technologies, will be a fundamental reform of the whole industry processing system.

(a) cutting

(b) Engraving

Figure 2.6 Cutting and engraving according to sample drawing

2.2. Reasons of Advancing Jadeite Intelligent Processing

For having a deeper knowledge on the jadeite processing background, especially the main problems that jadeite manufacturing is facing with. I did the interviews in person and on social media Wechat with some representative practitioners based in Pingzhou Jade Industry District. Here I would like to express my great appreciation to three persons as the interviewees:

- Mr. Huanglin Liang, Permanent Honorary President of Pingzhou jewelry and Jade Association
- Ms. Mingyan Wu, General manager of Foshan Pingzhou Jade Culture Communication Co., Ltd
- Mr. Jingbo Hu, Permanent member of Pingzhou jewelry and Jade Association

Figure 2.7 Interview with the practitioner

2.2.1 Low Production Automation Level

In the past two decades, remarkable progress has been made in jadeite processing technology in China, and the manufacturing equipment has also been being constantly improved and updated. Production efficiency has been improved to some extent. However, during the background research, it is found that the processing of jadeite still largely depends on human resources, and that the production level is mainly determined by professional ability of the processing personnel. In other words, the automatization of jadeite processing still remains at a low level. For example, in the processing step 2 (Cutting raw stone into slices), it's the most important is to determine how to cut the stone by the skilled workers, depending on their own technical experience. Then professional stone cutting machine is used for precise cutting according to the determined cutting scheme. Take the processing step 3 (Sample drawing) as another example, designers are required to recognize totally manually the color parts and defective parts (mainly the cracks, impurities) for making a product designing scheme. Therefore, it is difficult to further improve the efficiency and accuracy of jadeite manufacturing and processing.

On the other hand, based on the incomplete statistics, nearly 3 million people are engaged in jadeite industry in China. However one of the most prominent situations is that the education level of these practitioners is generally low. Very few of them have college degree or above, most of them are high school or below [4]. They have concentrated the outstanding traditional qualities of Chinese working people, which are hard-working, dare to challenge, and diligent in practice. But limited by their lower education level, practitioners have uneven professional and technical ability, which leads to different working efficiency. Average educational level of jadeite industry practitioners is too low to update the processing technologies and innovate the production mode.

2.2.2 Shortage of Jadeite Raw Materials

In recent years, the old jadeite mines in Myanmar have gradually dried up, and very few jadeite mines were newly discovered. The Myanmar government started to implement protective policies for jadeite raw material. Since 2004, the military government of Myanmar has restricted the exploitation of jadeite and banned the export trade of non-governmental jadeite. The customs of Myanmar has constantly controlled the export of high-grade jadeite raw stones, which has resulted in the shortage of jadeite raw materials supply.

Some details about quantity of jadeite raw stone appeared in each Myanmar Jade and Gems Emporium are shown in the chart below (Figure 2.8). In 2011, the total quantity of raw materials in Myanmar Jade and Gems Emporium (a jadeite raw materials trade conference held by the Myanmar government in the form of open bidding; jadeite raw materials can only be traded out of the country through Myanmar Jade and Gems Emporium, and other trading channels are all regarded as illegal) was 38426 pieces. In 2017, it was only 13246 pieces, a full two-thirds reduction [1].

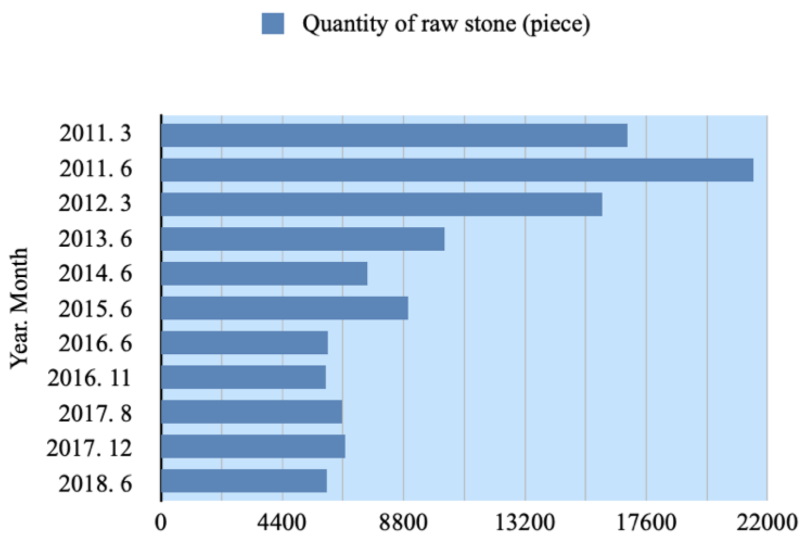


Figure 2.8 Piece amount of raw stone in Myanmar Jade and Gems Emporium, 2011-2018 [1]

Therefore, in the severe situation of the shortage of jadeite raw materials, we urgently need to improve the processing technology of raw materials, so as to improve the utilization rate of raw materials, and further realize the maximum value of raw materials.

2.2.3 High Production Cost

At present, the cost composition of jadeite products is mainly a calculation mode of “raw material cost + transportation cost + processing cost”, shown as below (Figure 2.9).

In terms of raw material cost, the raw material upstream of the jadeite industry chain is completely dependent on the import from Myanmar, while the Myanmar government controls the mining and export volume of jadeite raw stone, coupled with the long-term high export tariff of Myanmar Jadeite raw stone and the import tariff of China’s jewelry and jade, the cost of jadeite raw material is high.

In the transportation sector, from the perspective of the spatial distance of the jadeite industry chain, Myanmar Jade and Gems Emporium moved to Naypyidaw, which is only 100 kilometers away from Ruili port, Yunnan Province. However, the high tariff rate makes the jadeite raw materials go by water, transfer several times, to Guangdong Province (90 percent of China's imported jadeite raw materials are processed in Guangdong Province, and the finished products are wholesaled to other regions for sale), the transportation distance is forced to be lengthened, and also considering that the jadeite raw materials are high-value commodities, the transportation cost keeps high [5].

In terms of processing cost, since jadeite production fails to realize industrialized and standardized flow production line, only time-consuming and labor-intensive manual methods can be used, and lots of money and time are necessary for fostering a killed operator, so the processing cost accounts for about 20% - 30% of the commodity cost.

Facing the increasing production cost, the issue of how to improve production efficiency and increase product profit is urgent to be solved.

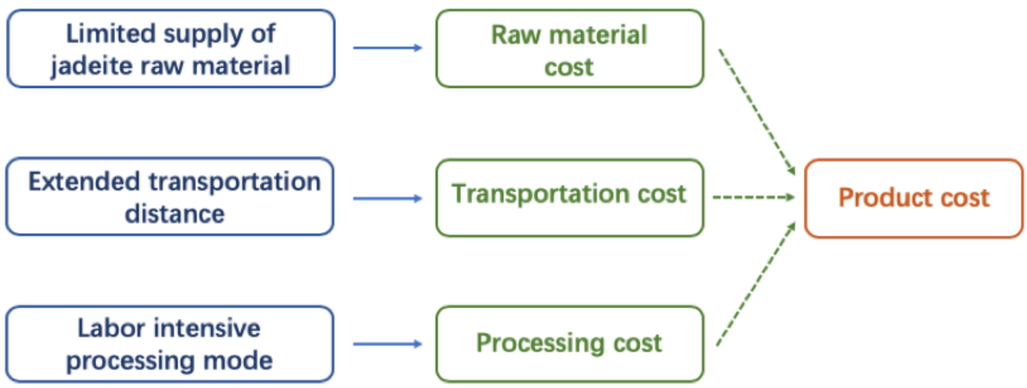


Figure 2.9 Main components of product cost

2.3. Fieldwork on CNC Jadeite Processing Machine

For making progress in jadeite processing technologies, I have to do research on the latest manufacturing technologies and equipment being used in this industry. For this purpose, besides the visits to the jadeite production company and jadeite engraving factory, introduced by Ms. Mingyan Wu, I was grateful to visit Guangzhou Yubang Automation Control Equipment Co., Ltd, so that I had more professional and comprehensive understanding on the automatic processing equipment. This fieldwork research focus on the existing CNC jadeite processing machine, which shows the highest automation degree so far in jadeite processing domain. Guangzhou Yubang Automation Control Equipment Co., Ltd, is one of the representative equipment companies that produce the CNC automatic jade processing machine.

CNC (Computer Numerical Control), is the automated control of machining tools by means of computer technology [6]. For traditional machining, equipments are controlled by manual operation with the help of some other simple tools. For example, the accuracy of products is measured by eyes and calipers. However, with the development of computer technology, the modern industry has long used the computer digital control machine tool for manufacturing.

A CNC machine processes jadeite raw material to meet specifications by following a coded programmed instruction and without a manual operator. In modern CNC systems, the mechanical part and its manufacturing program are highly automated. The part's mechanical dimensions are defined using CAD (computer-aided design) software and then translated into manufacturing directives by CAM (computer-aided manufacturing) software. The resulting directives are transformed (by "post processor" software) into the specific commands necessary for a particular machine to produce the component, and then are loaded into the CNC machine [7]. CNC is a vast improvement over non-computerized machining that must be manually controlled.

Jadeite carving is one of the oldest carving techniques and has become an important part of Chinese traditional culture. In the traditional carving, it has long been dominated by handwork. In recent years, with the continuous improvement

(a) CNC wire cutting machine

(b) CNC engraving machine

(c) Control panel

(d) Material installation

Figure 2.10 CNC jadeite processing equipment of numerical control technology, CNC carving technology has gradually entered the jadeite carving industry. The operation procedures of jadeite carving with CNC carving technology is as below (Figure 2.11):

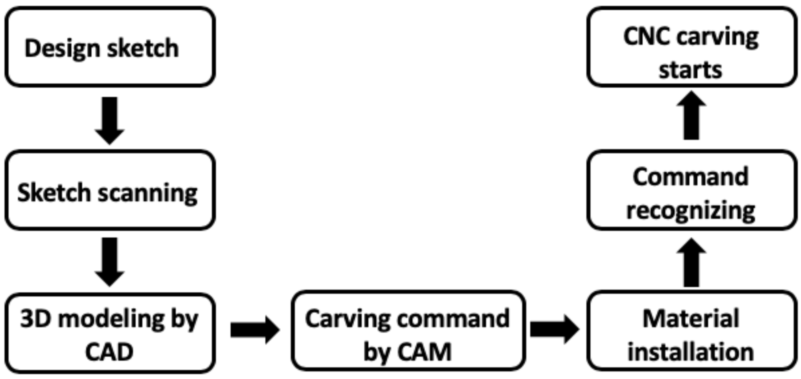


Figure 2.11 Operation procedures of CNC carving machines

CNC technology is a typical example of introducing modern advanced technology into jadeite processing, which changes the inherent mode of jade carving design and processing: a fully mechanized processing method contributes to precise processing and high integrity; carving and cutting cost is greatly reduced, when labor-saving machine works with a higher working efficiency; not only being applied to the mass production of jadeite, CNC jadeite processing, especially CNC jadeite carving, but also makes it possible to conduct customized processing, with the convenience of 3D modeling by CAD software, which helps promote the market upgrading of jadeite industry.

2.4. Summary

Through the analysis of the operation program of the CNC engraving machine, it can be found that the automatic engraving or cutting realized by the machine is still based on the hand-painted design plan, which here can be seen as sample drawing. Different from its subsequent automatic carving process, sample drawing remains in traditional manual production mode: confirm the position and direction of the features (mainly colors and flaws) of jadeite raw materials based on personal professional technical experience and observation, as the essential foundation of product design scheme. In other words, look back to the main problem we brought to our research: Only by realizing the automatic recognition of jadeite features, especially defects, can the cutting or design scheme be automatically generated, which can guide the fully- automatic manufacturing. That is why we need to look for a new path that leads to realize automatically recognizing jadeite features, and only in this way can we promote automatic product design.

Also under the more severe industry environment of low production automation level, less raw material supply and gradually higher production cost, if the traditional method of artificial identification of jadeite defects can be replaced by intelligent identification, the most fundamental problem to achieve full automation of production can be solved. The breakthrough will become a milestone in the whole industrial development process. The introduction of intelligent production into traditional jadeite processing conforms to the trend of the times, improves production efficiency and effect, reduces production costs, and better meets the changing requirements of the market.

Chapter 3

Related Works on Semantic Segmentation

In this chapter, some literature reviews related to semantic segmentation technology, especially those on the application cases of semantic segmentation technology will be introduced.

3.1. Development of Semantic Segmentation Technology

In 2006, Geoffrey Hinton and Ruslan Salakhutdinov formally put forward the concept of deep learning. They proposed using un unsupervised learning method to layer by layer train model and using supervised back-propagation algorithm to optimize the model, which allows the gradient disappearance problem of traditional neural network and back-propagation algorithm to be effectively solved. In 2012, Alexnet, a DCNN network jointly developed by Professor Wu Enda of Stanford University and Jeff Dean, computer expert, made amazing achievements in the field of image recognition. In the evaluation of Imagenet, with DCNN network, the error rate was successfully reduced from 26% to 15%, much better than other machine learning algorithms [8]. The RESNET algorithm proposed by he Kaiming, Sun Jian, in ImageNet Classification with Deep Convolutional Neural Networks, 2005, makes the convolutional neural network have a deeper depth, while with an accuracy stably improved, which helps avoid the problem of gradient disappearance in the deep neural network [9].

Before deep learning is applied to computer vision, researchers generally used Textonforest or RandomForest to build classifiers for semantic segmentation, but the accuracy of classification is not very satisfied. With the rapid development of deep learning, convolutional neural network is gradually applied to the field of image semantic segmentation. In 2014, Long et al. of the University of California, Berkeley, proposed a full convolutional network (FCN), which uses CNN structure to make pixel intensive prediction without full connection layer. The network is divided into two parts: the down-sampling and the up-sampling. When DCNN performs the down-sampling of pixel classification, the deconvolution is used for the up-sampling to restore the predicted segmentation results to the original image size [10]. In 2015, Ronneberger et al. proposed the U-Net network structure, which simply spliced the encoder's feature map into the up-sampling feature map of each stage decoder, thus forming a U-shaped structure. U-net achieved the best result in the ISBI Cell Tracking Challenge 2015 and the segmentation speed is very fast [11]. During 2015-2018, network series, Deeplab were proposed by Liang Chieh Chen et al. of Microsoft Research Institute. The network structure uses techniques such as Atrous Convolution and Spacial Pyramid Pooling to enable the encoder to extract image features of different receptive field sizes, making the edge of segmentation results more smooth [12] [13] [14].

3.2. Semantic Segmentation for Cell Segmentation

ISBI Cell Tracking Challenge is a competition of automatic detection of cell edge. In this competition, the official only provides very few training and testing data, and the participants need to find an efficient algorithm and use the provided data for cell edge detection. In 2015, Ronneberger and his team proposed the structure of U-Net network, and participated in the ISBI Cell Tracking Challenge using this segmentation network. The structure of the network they used in the Challenge is shown in an "U" shape, so it's called U-net.

Figure below shows U-Net network structure(Figure 3.1). Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. The arrows denote the different operations.

During the process of down-sampling, the extracted features are directly mapped to the process of up-sampling on the right side. In this way, with the classification of down-sampling, the algorithm can get the feature map of different scales and depths, the degree of feature refinement is gradually improved, and the accuracy of segmentation is guaranteed.

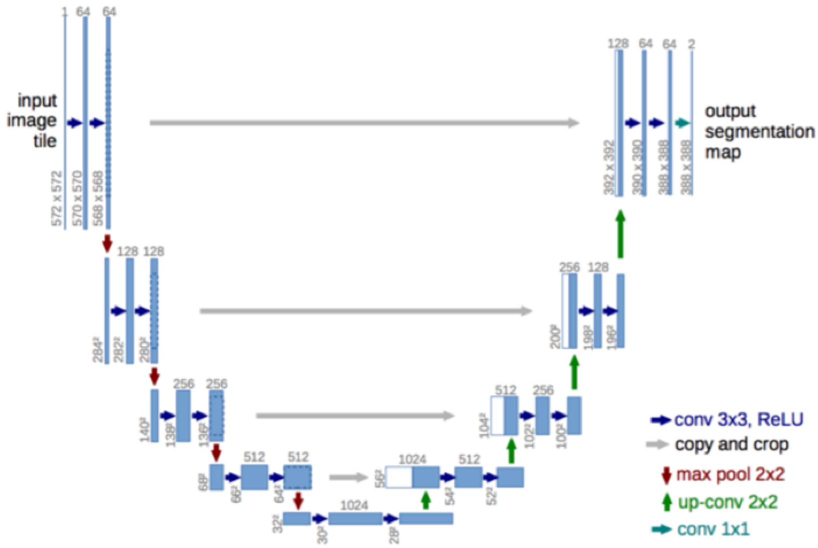
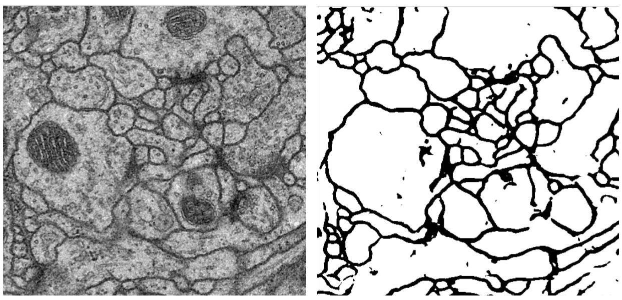


Figure 3.1 U-net structure (example for 32x32 pixels in the lowest resolution) [11]

Finally, in ISBI Cell Tracking Challenge 2015, the score of 0.9203 IOU segmentation is far higher than other competitors. The prediction image of cell segmentation with U-net is shown in the figure below (Figure 3.2).



(a) Original image (b) Prediction image

Figure 3.2 Prediction output of cell segmentation with U-net [11]

3.3. Semantic Segmentation for Concrete Crack Detection

In 2019, Donghan Lee et al. proposed a concrete crack detection network based on semantic segmentation network (Figure 3.3).

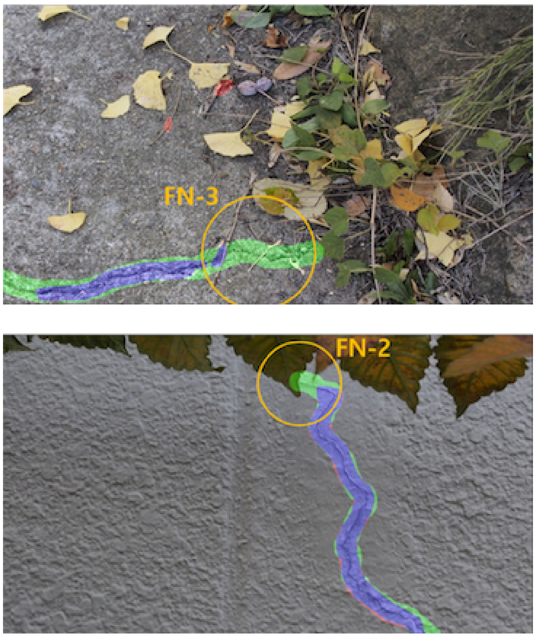


Figure 3.3 Prediction images of concrete crack detection [15]

This network can use the overall information of the image to detect the cracks in the pixel set [15]. A crack generation algorithm based on two-dimensional Gaussian kernel and Brownian motion process is proposed, which overcomes the problem of small number of data sets in reality and obtains a recognition network with high robustness and accuracy for complex images. Because of the similarity between concrete cracks and rock cracks, and the crack structure of jadeite belongs to the category of rock cracks, we can use similar methods to identify the cracks of jadeite stone intelligently, and the data enhancement method in this study is worth our trying.

3.4. Summary

According to the literature reviews, semantic segmentation technology is mainly applied in automatic driving and image and video processing, but some other new attempt is done in academic domain to make it be used in wider application range because of the outstanding image recognition and segmentation outcome of semantic segmentation technology. From the two application researches introduced above, we can learn that semantic segmentation algorithm can be used to recognize the very minor object, such as the cell membrane image segmentation. Therefore I came up with an idea: Semantic segmentation algorithm can be used for the detection of the defect of jadeite stone slice. And the crack generation algorithm used in concrete crack detection network also inspired me to consider a data amplification method to solve the problem of insufficient data amount. But on the other hand, because there are essential differences for the permeability and color between jadeite and concrete, the network we built needs to be optimized to meet our experimental requirement.

Also, two problems are found in these correlation studies:

- When the amount of data is insufficient, the recognition effect is not good for the parts that are covered or alternating between light and dark in the image. In the case of concrete crack recognition, when the cracks appear in the fallen leaves, the recognition error is significant.

- These two studies are to segment small objects from the image, but when a large pixel proportion difference exists among the target objects, the segmentation effect of small objects will be weak.

We will also encounter the similar problems in jadeite defect recognition. The jadeite stone slice may show different visual performance due to the uneven thickness and pigment distribution, which will have a great impact on the prediction results when the data set is small. The flaw of jadeite jade is mainly divided into two parts, crack and mineral impurity, the mineral impurity tends to have larger pixel proportion in the image, and since the crack is linear, its area proportion is small, the difference between the two objectives is very big, this is also the problem to be solved in this study.

Chapter 4
Data Set Preparation

This chapter is mainly about the preparation of image data set that will be used for network training. The data set preparation will be explained in the order: 1) Data collection; 2) Data annotation; 3) Data grouping.

The research principle follows the concept of deep learning which means an algorithm in the field of machine learning to learn the rules and characteristics from sample data. In other words, the algorithm is trained by the sample data to grasp a new ability. So in the experiment procedures, the first step is to prepare for the data set that is used to train and test the algorithm.

4.1. Data Collection

Semantic segmentation algorithm is a typical computer vision task based on deep learning. In the deep learning experiment, the quality of data set is an important basis for the training results of algorithm model, and there are two main sources of data collection: open source data set and personal data set. Open source data refers to the data set that has been collected and sorted out in other research experiments, which is convinient to use.

However, since this is the first time that semantic segmentation technology is applied in jade processing, the open source data set of jadeite image cannot be found in the deep learning related data. Therefore, in this study, all image data can only be collected by personal acquisition, which means that the whole data set used in this experiment is collected by the author. In the deep learning algorithm model training, large amount of data set is usually requested to have a good network training result, so how to collect and sort out a sufficient number of data set is one of the most important problems in this study.

4.1.1 Connection with Jadeite Production Enterprise

For completing the task of image data collection, I would like to express my appreciation to Pingzhou jewelry and Jade Association and the jadeite enterprises, Yingheyuan Jade and Juyuanda Jade, for their generous help given to my research. The research cannot be completed without their assistance and guidance.

When I first went to Pingzhou Jade Street for field investigation, I found that the jadeite industrial zone was completely integrated with the city block, covering a large area and a huge number of businesses. Therefore, for the goal that the research work can be carried out in a more targeted and efficient way. First of all, I visited Pingzhou jewelry and Jade Association based in Pingzhou Jade Street.

I first learned about the current situation of processing and production of jadeite industry in the visit of Pingzhou jewelry and Jade Association. Due to the diversity of physical properties of jadeite materials, different categories and grades can be found according to different classification standards. Through the discussion with people in the Association, they showed a great interest in my research because it is the first attempt to apply technology in the field of artificial intelligence to jadeite raw material defect recognition which can solve the most essential problem of jadeite processing.

With the recommendation of Pingzhou jewelry and Jade Association, I then visited two different representative jadeite enterprises in Pingzhou Jade Street, Yingheyuan Jade and Juyuanda Jade which produce and sell different types of jadeite products. Different types of jadeite products have different requirements with the jadeite raw material that is used to product the end product. So the types of jadeite raw materials vary between them. That is the reason why people in the Association introduced these two enterprises for my research, so as to ensure the variety and universality of jadeite raw material as the research object.

4.1.2 Jadeite Stone Slice Image Collection

The functional principle of semantic segmentation technology is to identify and segment the image information. Therefore, in order to achieve the result of intelligent recognition of jadeite defects, it is necessary to visualize the texture features of jadeite stone as much as possible, that is, it is required that the images obtained by photography of the stone slice can show the characteristics of the original stone as completely as possible, a semantic segmentation network model with better recognition performance for jadeite stone defects can be obtained. The main process of image data collection is described as following:

- Communicate with the professional technicians and determine the characteristic requirements of the materials needed for data collection;
- Locate the qualified raw material slices from the raw material stock according to the requirements;
- The selected jadeite stone pieces are placed on a white-lighted LED board, so that the characteristics of the stone pieces can be clearly distinguished;
- The jadeite stone pieces on the white-lighted LED board are photographed (Figure 4.1), and ensure that the image can accurately and clearly display the characteristics of the stone pieces;
- Arrange the collected jadeite stone images into data set.

Figure 4.1 Image collection

When observing jadeite stone slices, because of the translucency of jadeite material, processors usually use lighting to make the internal characteristics of jadeite more clearly displayed. But all along, people have been using the point light source equipment such as desk lamp or flashlight for lighting. However, in the process of collecting the experimental data set, the light sheet source of white-lighted LED board is used instead of the original point light source, which makes the stone slice can transmit light evenly, so as to effectively avoid the problem of insufficient light transmission at the edge of the stone slice due to the small range of light emission of the point light source. The use of white light instead of yellow light can make the images better restore the color of the original jadeite slices and reduce the color difference, which is very important for image recognition. The use of white light sheet source instead of yellow light point source provides a seemingly subtle but important improvement idea for the mechanized and fully automated jadeite production in the future.

In order to make the image data better display the grain characteristics of the original stone pieces, it is necessary to select the jadeite pieces with thin thickness and good transparency. At the same time, I try to contain different types of defects in the image data set collected to make the data features more comprehensive. Totally 330 original images of jadeite raw stone slice are collected as the data set (Figure 4.2).

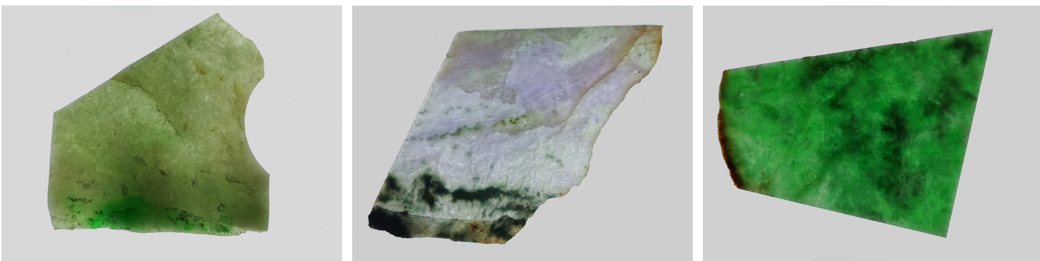


Figure 4.2 Original image samples in the data set

4.2. Data Annotation

The research follows the experiment method of supervised learning that is commonly used in deep learning research. According to the principle of supervised learning, to make the semantic segmentation network model learn the object features from the sample data, the target objects in the image data need to be labeled before being input to train the network.

In other words, the network is trained by using the original image and the image with manual semantic annotation, so that the deep learning network can quickly grasp the feature information of the target object. The so-called annotation is to outline the contour of object and give the category information.

4.2.1 Image Preprocessing

In order to use the collected image data more accurately and more efficiently, it is necessary to preprocess the original images, which is also convenient to the subsequent manual data annotation work. Firstly, the original image is cut, blank part of the original image is removed as much as possible, so as to reduce the useless information of the image, for the reason that the image data can be processed more efficiently in the semantic segmentation algorithm.

Then we use Photoshop software to edit the cut original image, increasing the brightness, contrast, sharpness and clarity of the original images, and then adjust the shadow and highlight rate properly, so that the images can be more clear and accurate to show the features of the jadeite stone slices. The image proprocessing flow can be summarized as the figure 4.3. The image preprocessing is done for preparing for the data annotation.

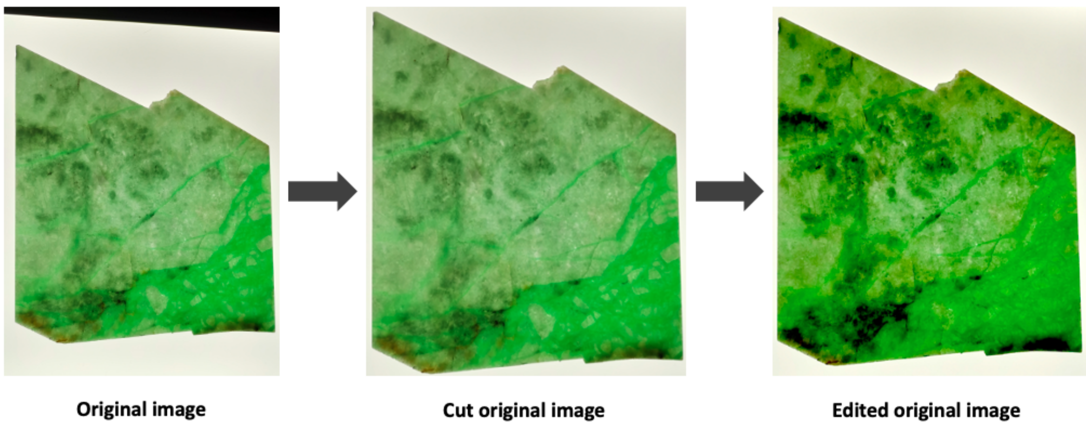


Figure 4.3 Image preprocessing

4.2.2 Annotation Tool — Labelme

Labelme is a commonly used annotation tool. Labelme is a software developed by MIT Computer Science and Artificial Intelligence Laboratory, which can be used to manually label the original image data according to the requirements of supervised learning.

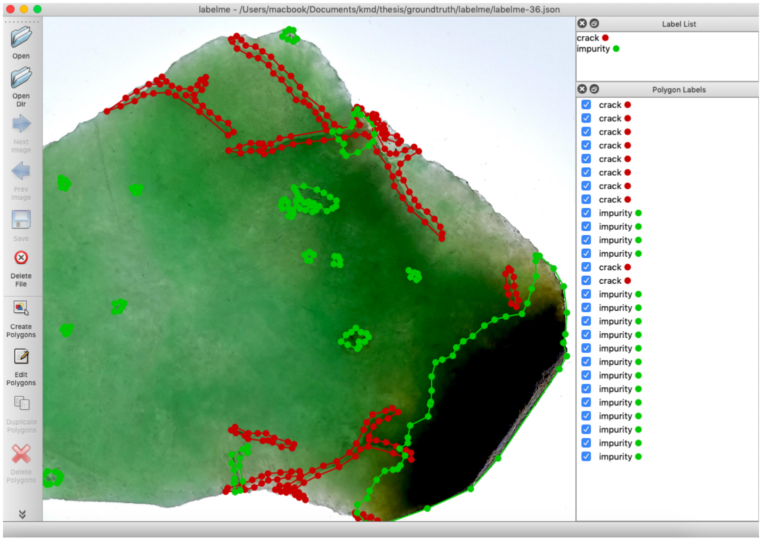


Figure 4.4 Example labeled manually with Labelme

Compared with other annotation softwares, Labelme, with gradually mature technology is easy to label classification, more convenient to operate and it can get a variety of formats of annotation files. Labelme has other advantages:

- It is designed for recognition of categories of objects according to the classification method determined by the user instead of the recognition of one single object. For example, a traditional data set may have contained images of cats in totally same size and location. In contrast, Labelme contains images of dogs in multiple angles, sizes, and locations;
- It is designed for recognizing objects embedded in arbitrary scenes instead of images that are cropped, normalized, and/or resized to display a single object;

- It contains a large number of object classes and allows to create new classes easily;
- Its diverse images from many different scenes.

4.2.3 Data Annotation with Labelme

Before starting the annotation work with Labelme, the main defect categories of jadeite raw material need to be distinguished. The imperfections of jadeite raw stone can be mainly concluded into two categories: fractures and mineral inclusions.

The most severe clarity defects in jadeite are unhealed fractures, which can have an enormous impact on value because jadeite symbolizes durability and perfection. Mineral inclusions usually are black, dark green, or brown, and white, but may be other colors. Black spots, easily visible to the eye, are basically iron deposits. Iron is what makes jadeite dark, so generally the more iron element the jadeite stone has, the darker it will be. White spots, lines or areas (pollen), also commonly seen in jadeite stone, are calcium deposit. The mineral inclusions, which can also be called impurities, severely influence the clarity of the jadeite stone, by impairing the passage of light through the stone.

Therefore, according to the main classification of jadeite defects, in the step of data set annotation, there are two label categories: crack (fractures) and impurity (mineral inclusions and spots).

The image annotation work is finished manually with Labelme, under the guidance of professional processors in the collaborative jadeite production enterprises, for more accurately and professionally distinguishing the jadeite flaws of the collected data images. In order to recognize each category of defect and find its location, we have two things to confirm:

- The size of the labeled image (groundtruth) has to be the same as that of the original image;
- The color of the same category has to be the same in all labeled images (labels of crack in red, labels of impurity in green).

First, after the manual annotation of the original image with Labelme, a json file which contains the position information of each bonding area will be generated as the result. However, the json file cannot be directly input into the network to train the network. Then the json file need to be transfered into png file which shows the labels we tagged in each original image without changing its size. The operation flow is shown as figure 4.5.

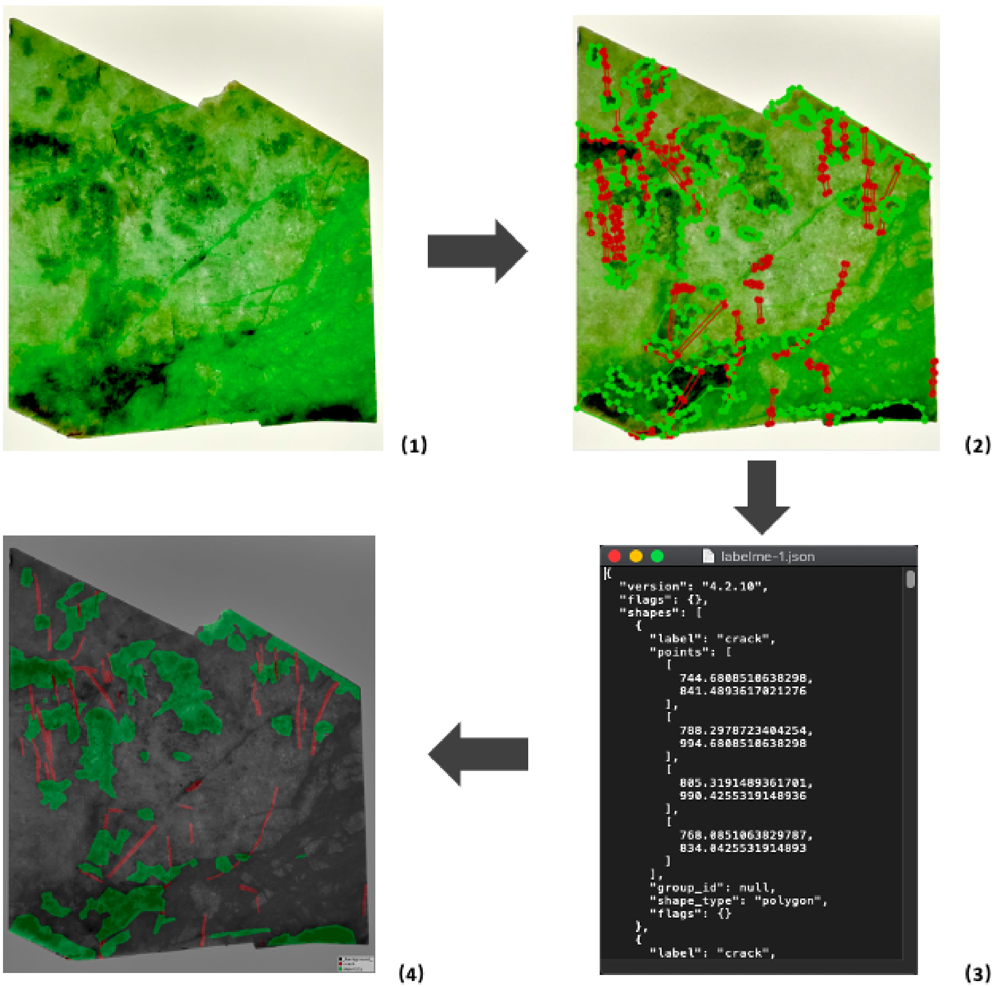
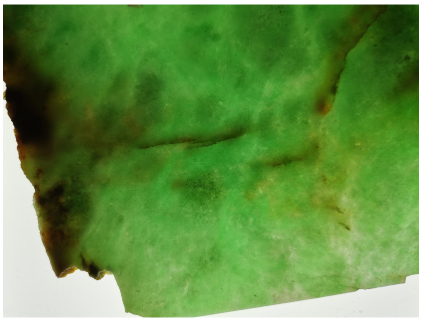


Figure 4.5 Process of labeled image generation: (1) original image; (2) image labeled manually with Labelme; (3) output json file; (4) labeled image.

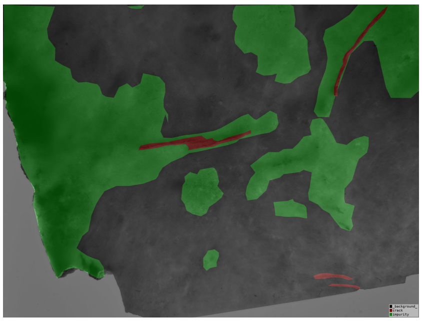
Second, to make sure the same category in all labeled images shows in the same color, the order of the label list in Labelme must be the same: 1) crack; 2) impurity. Then the label color will be consistent when the json file uniformly transferred to the png file: red for crack and green for impurity.

4.3. Data Grouping

After finishing the image annotation, one labeled image is obtained corresponding to each original image. Considering the working flow the network training, original image and its labeled image need to be imported to train the network. Therefore to set up the completed data set, one original image is paired with its corresponding labeled image as one data group in the data set (Figure 4.6).



(a) Original image



(b) Label

Figure 4.6 1 Group data: 1 original image and 1 label

Then the whole data set which contains 330 groups of images are divided into 3 parts according to the proportion of 8:1:1, which are the training set, validation set and test set (Figure 4.7), for the reason that the three different data set will be used for different purpose in experiment:

- Training set: original image and label are input to the network to train the network, the network learns the rules and characteristic from the training set;
- Validation set: it contains the totally different data images with those in the training set, original image and label are input to have network performance data, especially the accuracy rate of the network;

- Test set: it is used for testing the trained network, original image is input to get the prediction result, and the prediction can be compared with the labeled image to know the prediction effect of the trained network.

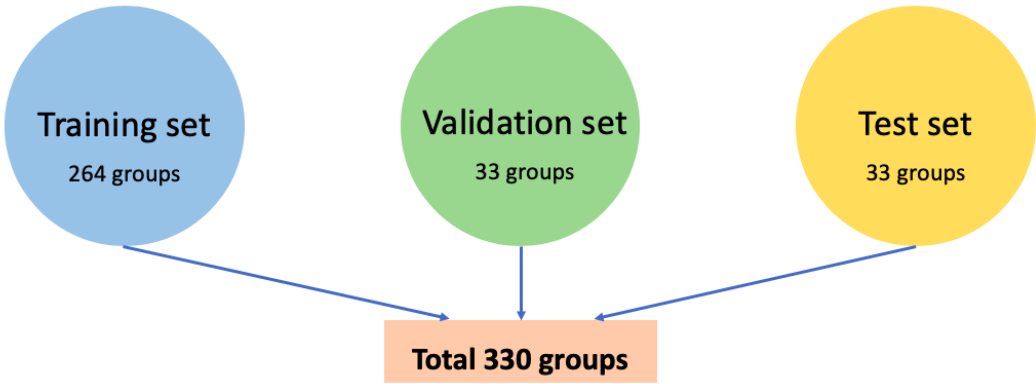


Figure 4.7 Three data sets

Chapter 5
Network Training

This chapter mainly explains the network training experiment. The content of this chapter can mainly be divided into three parts. The structure of the semantic segmentation network will be firstly introduced. Based on the main structure of semantic segmentation network, some optimization is done to make the network suitable for jadeite defect recognition, which will be the second part of this chapter. Then the network training result is given as the third part.

5.1. Structure of Semantic Segmentation Network

In this study, in order to realize the intelligent recognition of jadeite stone slice defects, we refer to the methods used in related research. And combined with the development trend of artificial intelligence in recent years, the author compared different semantic segmentation networks that have appeared in recent years. It is found that the Deeplab network series play an important role in the field of semantic segmentation, for the reason that Deeplab networks have the most excellent segmentation ability in the current semantic segmentation domain, and has excellent edge processing effect for segmented objects. At present, most of the network models are developing towards the direction to be lightweight and real-time, while the accuracy is made to be on edge. Based on the literature review on semantic segmentation technology, Deeplab V3+ network is chosen to be semantic segmentation network used in the experiment. The Deeplab V3+ code is used from open source [1].

1 Deeplab V3+
`https://github.com/tensorflow/models/tree/master/research/deeplab/`

5.1.1 Structure of Deeplab V3+

The network structure of Deeplab V3+ is divided into two parts: encoder and decoder. Encoder is mainly composed of a deep convolutional neural network (DCNN) and Atrous Spatial Pyramid Pooling (ASPP), in which the convolutional neural network is used to extract the feature map from the input image. Then the extracted feature maps are convoluted by Atrous Convolution of different scales in ASPP to generate feature maps with different receptive field sizes. Finally, the feature images with different receptive field sizes are fused and then the segmentation result that is generated through 1*1 convolution kernel is transferred to the decoder.

Decoder firstly accepts low level feature transmitted from convolutional neural network, and then merges the result of feature map with different receptive field sizes that is transmitted from encoder end. These feature maps are then upsampled until they are restored to the original image size, and finally the semantic segmentation result of the original image is obtained. The figure below shows the network structure of Deeplab V3+ (Figure 5.1).

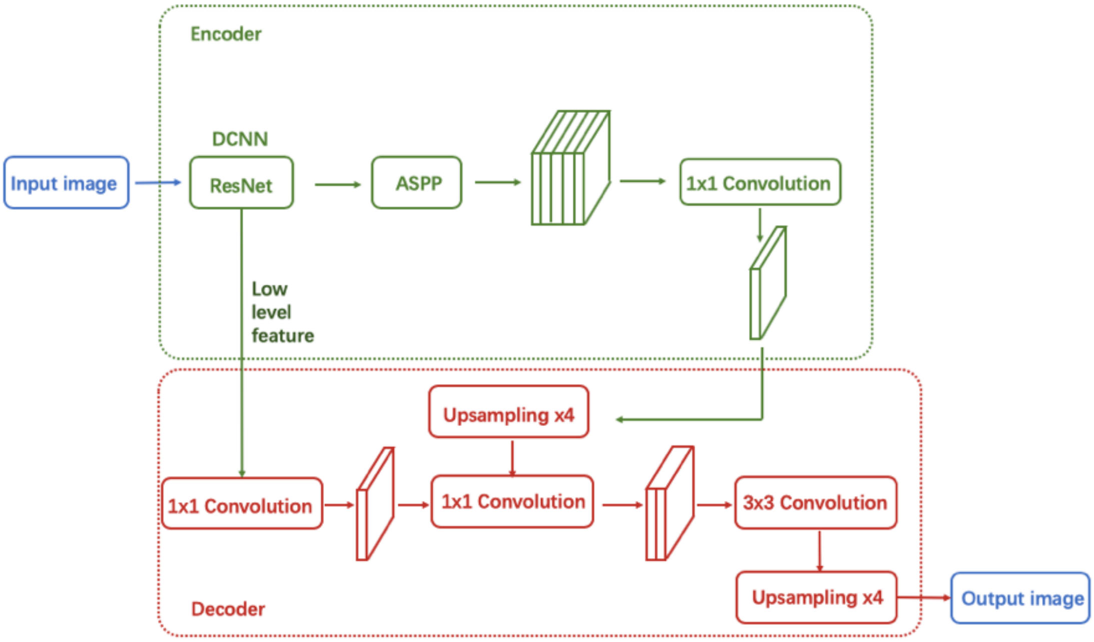


Figure 5.1 Network structure of Deeplab V3+ [13]

5.1.2 Convolutional Neural Network

As the most important part in the structure of semantic segmentation network, convolutional neural network (DCNN or CNN) is one of the representative algorithms in the field of neural network, to conduct the task of image recognition and image classification. And the object detection, biological face recognition are some of the areas in which CNN is widely used nowadays.

CNN, when operating image classification, obtains an input image, processes it and classifies it into certain categories. Computer regards an input image as array of pixels, which depends on the image resolution. The structure of convolution neural network mainly consists of input layer, convolution layer, activation function, pooling layer, fully-connected layer and output layer (Figure 5.2).

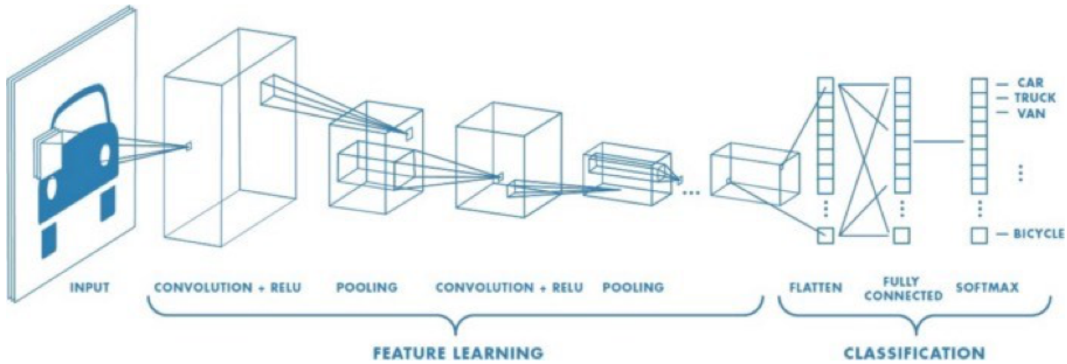


Figure 5.2 Structure of Convolutional Neural Network [11]

As the core component of the structure of convolutional neural network, convolutional kernel extracts feature from input image layer by layer. The convolution process is the sum of all kernel weights and their corresponding elements on the input image (Figure 5.3), which can be expressed as follows:

$$conv_{x,y} = \sum_{i}^{p*q} w_i v_i \tag{5.1}$$

x, y: Spatial coordinates of the input image;
p, q: Size of convolution kernel;
w: Weight of convolution.

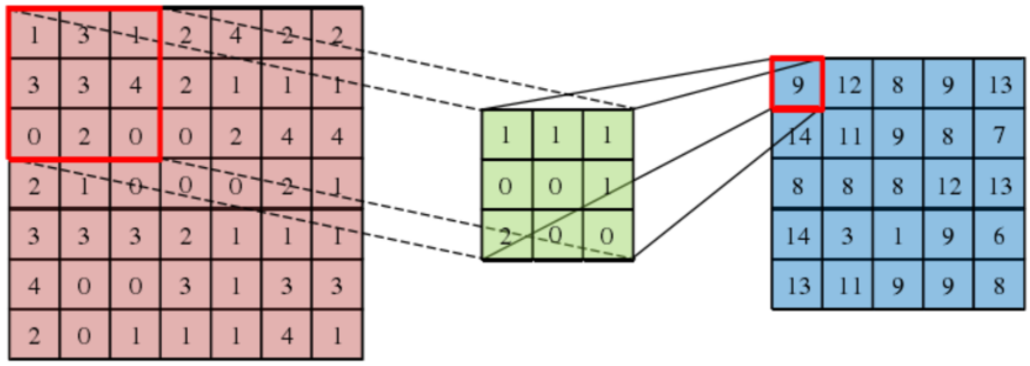


Figure 5.3 Operating principle of convolutional kernel [11]

After the above convolution, the function is a linear regression model. In order to have a stronger processing ability, the activation functions are introduced to improve the computational complexity and processing ability [16]. The main activation functions in deep learning include the formulas of ReLU and Sigmoid:

$$z_{x,y} = h\left(\sum_{i}^{p*q} w_i v_i + b\right) \tag{5.2}$$

h(): Activation function

ReLU (Figure 5.4):

$$h(z) = \max(0, z) \tag{5.3}$$

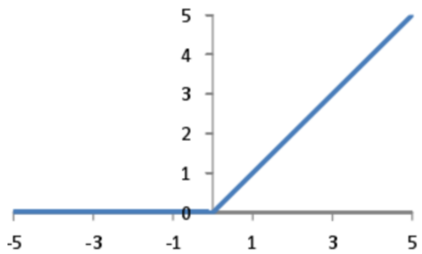


Figure 5.4 ReLU

Sigmoid (Figure 5.5):

$$h(z) = 1/\left(1 + e^{-z}\right) \tag{5.4}$$

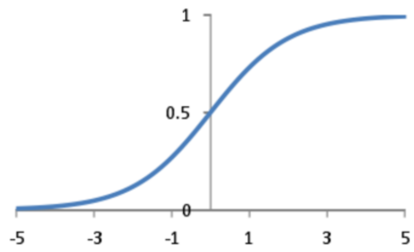


Figure 5.5 Sigmoid

5.2. Network Training Method — Supervised Learning

In the field of machine learning, there are mainly three different machine learning methods, which are supervised learning, unsupervised learning and semi-supervised learning. Among these three machine learning methods, the supervised learning is used in this research. To learn about the network training principle, we have to be clear about the definition of supervised learning.

Supervised learning refers to the process of adjusting the parameters of the classifier to achieve the required performance by using a set of samples of known categories, also known as supervised training or teacher learning [17].

Supervised learning is to infer a functional machine learning task from labeled training data. The training data includes a set of training examples. In supervised learning, each instance is composed of an input object (usually a vector) and an expected output value (also known as a supervised signal). Supervised learning algorithm is a function of analyzing the training data and generating an inference, which can be used to map on new instances.

In other words, in the task of machine learning, the labeled sample data are used to train and adjust the parameters of the algorithm, so that the algorithm can achieve the required performance. Here is an example for explaining supervised learning (Figure 5.6).

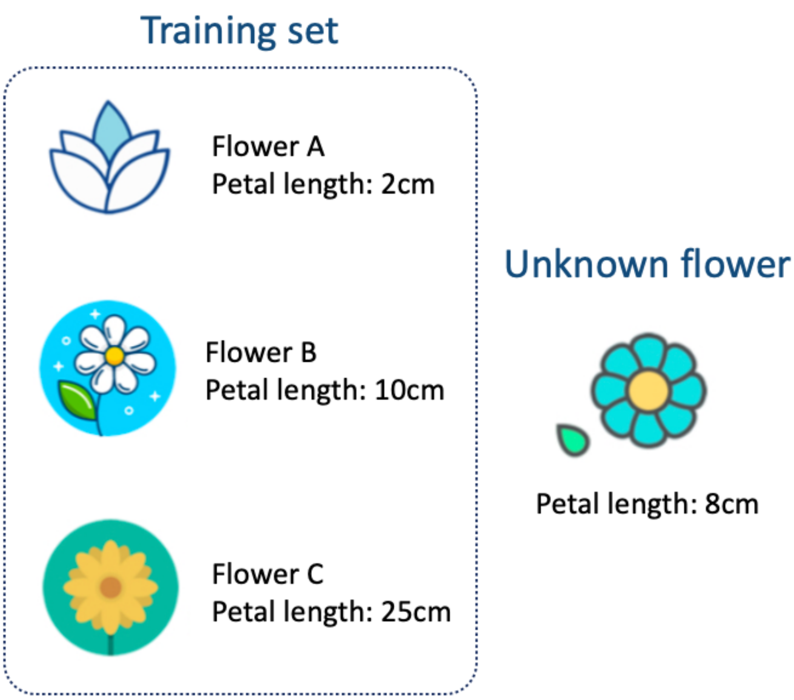


Figure 5.6 An example of supervised learning

The petal length feature of three different flowers (training set labeled feature) are given in the training data set. The 3 flowers belong to 3 species A, B and C according to the petal length. Then, for a flower of unknown species, we can judge its species according to its petal length (test set feature). In the figure above, it is more appropriate to judge the unknown flowers as class B.

The "supervision" in supervised learning is embodied in the "label" of training set. So in the whole data set described in Chapter 4, original images and labeled images are contained. In the test set which is used to train the network, both original image and labeled image are imported to the network, while the labeled image trains the network to figure out what kinds of features it needs to learn.

5.3. Network Training Environment

The experimental environment of this study is shown in the figure below (Figure 5.7).

Hardware	Parameter
CPU	Intel I9-9900k(3.6GHz)
GPU	NVIDIA TITAI Xp
Memory	32GB
Graphic memory	12GB

Figure 5.7 Experiment environment

The computer is equipped with a CPU of Intel i9-9900k. In order to carry out the training operation of high resolution RGB image, the experimental computer needs enough memory space and image operation ability. So we use the GPU of NVIDIA TITAI Xp as the main computing processor. At the same time, in order to meet the needs of large-scale photos which occupy large space of computer memory and graphic memory, un computer equipment with large memory and graphic memory is used in this experiment.

The software working environment of this experiment is shown in the following table (Figre 5.8).

Environment	Version
System	Ubuntu 18.04.4
CUDA	CUDA 10.0
Framework	TensorFlow 1.16
Language	Python 3.6

Figure 5.8 Software working environment

Due to the compatibility problem, Linux is chosen as the system environment of training network, and the version is Ubuntu 18.04.4. In order to better cooperate with the GPU, NVIDIA TITAI Xp, for artificial intelligence training, Cuda 10.0 is used. We use Python 3.6 as basic programming language. TensorFlow 1.16 is utilized as the deep learning framework. The reason why we didn't use the latest version of TensorFlow is that the development environment of Deeplab V3+ is the lower version, and numbers of running errors might happen under the framework of the higher version of TensorFlow.

5.4. Network Optimization

For the semantic segmentation network better being trained to be able to intelligently recognize the jadeite stone slice defect, certain optimization is done to improve the network performance.

5.4.1 Transfer Learning

In most tasks of deep learning, two types of situations are often encountered:

- The number of labeled training samples is limited, and the use of such limited samples often fails to make the model robust.
- The amount of training sample data so large that it takes much time for the data training and the model convergence.

In the Chapter 4 of data preparation, due to the limited amount of image data collected, only 330 original images of jadeite raw stone slice were collected, and only 264 groups of data images (1 group of data contains 1 original image and 1 labeled image), are used for network training except the validation set and test set. Under the situation of limited training data amount, simply increasing the training times of the network will make the network over-fitting, that is, it has a good performance on the training set data, but the performance is poor for other untrained data. Therefore, in this study, we use transfer learning to enhance the feature learning ability of the network.

Considering human learning behavior, human can apply previously learned knowledge to solve new problems, so that human can solve the new problems faster or achieve better results. Scientists have proposed the concept of "transfer learning" based on this principle: to learn knowledge or experience from previous tasks and apply the knowledge learnt from previous tasks to new tasks. In other words, the purpose of "transfer learning" is to extract knowledge and experience from one or more source tasks, and then apply it to a target task [18].

The transfer learning algorithm based on feature selection focuses on how to find the common feature representation between the source domain and the target domain, and then use these common features to transfer knowledge. The principle is mapping of features. The data in the source and target fields needs to be mapped from the original feature space to the new feature space. In this way, in the new space, the source domain data and the target domain data are distributed in the same way, so that in the new space, the existing labeled data samples in the source domain can be better used for classification training.

In this study, our experimental data set has 330 pictures, and the scale of the pictures can only be considered as medium. In order to speed up the experimental process, we use the transfer learning method based on feature mapping. The source pre-training model is Xception and pre-trained network on the data set of cell membrane segmentation.

5.4.2 Data Amplification

In this study, data amplification method is also used to solve the problem of insufficient training data. Since the collected image is taken by a professional camera, the resolution of the image is 2736*3648, and the distribution of defects in a single jadeite is complex and has no obvious rule. If a single image is directly imported into the network for training, the operation will be slow due to the large size of data image, and the more serious problem of graphic memory data overflow might appear when network is trained in the computer environment with small graphic memory.

In order to solve the above problems and make better use of the data, the collected data are processed by data amplification code. Because of the high resolution of single image data, the image can be cut and divided into smaller multiple images (Figure 5.9). In this way, the small-scale image after cutting can better meet the requirements of network operation conditions, and can make the target feature be divided, so that the trained network has better robustness.

The after-cut image adopts the resolution of 1500*1500, which is in line with the requirement of more effective information in the central part of the image, and which improves the utilization rate of the central part of the image. After cutting, the data set is expanded by 6 times. The code for image cutting is shown in Appendix A.

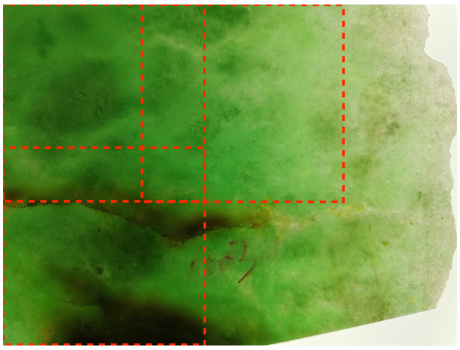


Figure 5.9 Image cutting for data amplification

After cutting, the image can be rotated to change the trend of cracks and color blocks of jadeite images, so as to obtain different feature information. In order to facilitate the data processing, the data in this study were rotated by 90°, 180°and 270° respectively, an example is shown in Figure 5.10. After the rotation transformation, the amount of data is expanded by 4 times.

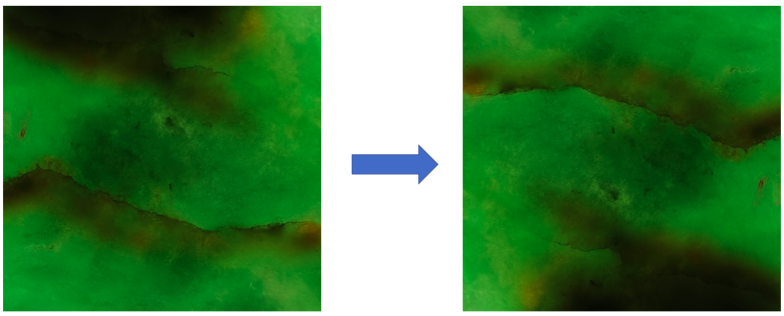


Figure 5.10 Image rotated by 180°

The flipping is also done as the transformation method. The original image is flipped according to the X or Y axis in the plane coordinate system to get a photo completely different from the original image (Figure 5.11). On this basis, the amount of data can be expanded by 4 times.

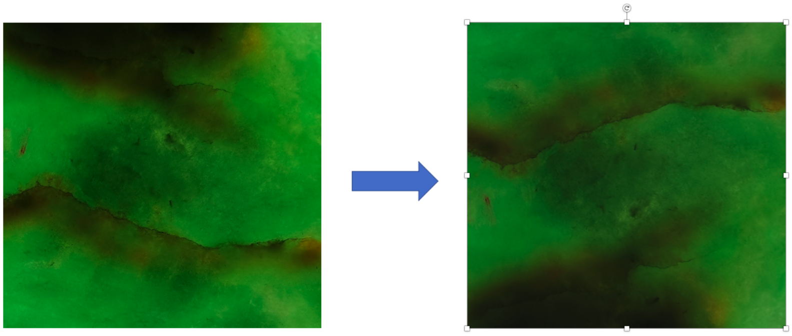


Figure 5.11 Example of image flipped by 180° along Y axis

Another transformation method different from position relation transformation is color transformation (Figure 5.12). Different colors can be found in jadeite stone. Two jadeite stones with the same color can not be found in nature. However, the experimental samples in this study are limited, so we can adjust the color of the collected samples, and expand the amount of data. Color adjustment needs to take into account the characteristics of the original jadeite stone, so we can't change the color into something that shouldn't exist in the jadeite. Therefore, we set a transformation interval based on the color of each stone, and in this interval, we extract the value once according to the random value. In this way, the original data is expanded by 2 times through this operation.

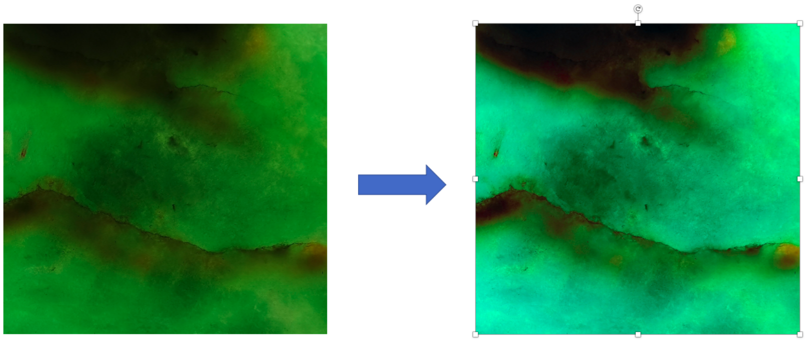


Figure 5.12 Example of image after changing color

For all data, if all the enhancement operations are carried out, the regularity of the data will be aggravated, and the possibility of over fitting training will be increased. Therefore, when data is processed, there is only 1/4 probability for each enhancement operation. The random value is randomly selected from [1,2,3,4] four integers. Only when the value is 1, the true value will be returned to the outside to guide the program to carry out transformation operation. The random event occurrence control code used for image rotation, flipping and color transformation is described in detail in Appendix B.

Since the process is controlled by random numbers and no manual operation is directly involved, the example diagram shown above are made to illustrate the transformation process and didn't participate in the experiment. So to sum up, the data can be expanded by 24 times from the original quantity. In this way, the data utilization rate has been significantly improved.

5.4.3 Data Balancing

In this study, the target object of recognition is the defective part of jadeite stone slice. The defects are divided into two categories in this research: impurity (mineral inclusions) and crack. Through a basic testing, if the data set is directly imported into the Deeplab V3+ network for training, the impurity which has a much greater pixel proportion in the image data has better recognition effect, but the crack can hardly be identified at all.

The main reason is that the proportion of pixels of the two targets is greatly different. According to statistics, the proportion of background, impurity and crack in the whole training set is 65%, 23% and 2% (Figure 5.13). When the label category with larger pixel proportion adjusts the network parameters by back propagation, it has a greater influence on the network parameters due to its large weight, so the cracks only accounting for 2% of the pixels can not be effectively extracted.

In order to solve this problem, we adjust the weight proportion of the three categories: crack, impurity, background, so that the label category with larger pixel proportion has a smaller weight, and the label category with smaller pixel proportion uses a larger weight parameter. The impact of the three types of labels on the overall network is maintained at a balanced level. Through calculation, the weight ratio of crack, impurity and background is then adjusted to be 38:3:1. The code is shown in Appendix C.

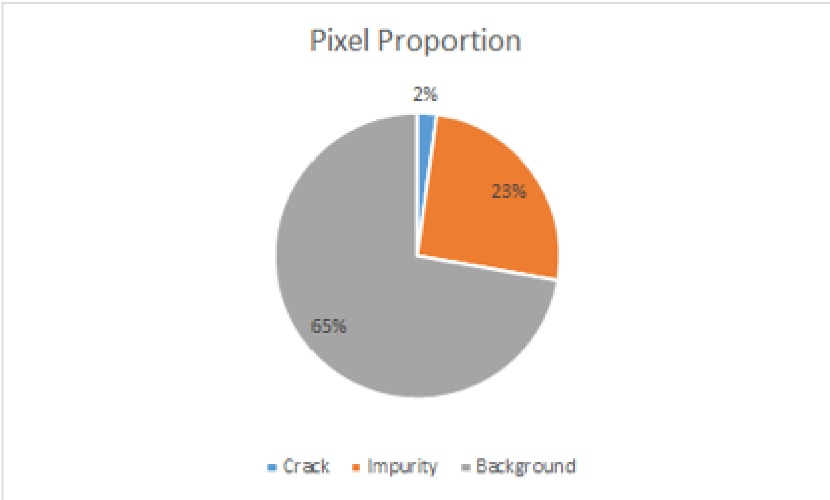


Figure 5.13 Pixel proportion of three categories of object

5.5. Network Initialization and Data Set Import

In order to enable the network to learn features quickly at the beginning and reach the fitting curve faster, we set the learning rate to 0.01 at the initial stage of training. Then, as the training progresses, the loss value of the model will drop significantly. In order to make the network have better robustness, we adjust the learning rate of the network in stages: 0.001, 0.0001.

After initializing the training network, the training data is imported for network training. After the input image passes through the network, the prediction image will be obtained, and the loss value will be calculated by comparing the prediction image with the corresponding labeled image tagged manually with Labelme under the guidance of professional processor. According to the loss value, the back propagation is carried out, and the hidden layer parameters in the network structure are automatically modified. When the network is trained once with all the training data, validation set data will be used to verify the network, to get the accuracy rate and loss value, to evaluate the real-time performance of the current network. The operation flow of network training is shown as below (Figure 5.14):

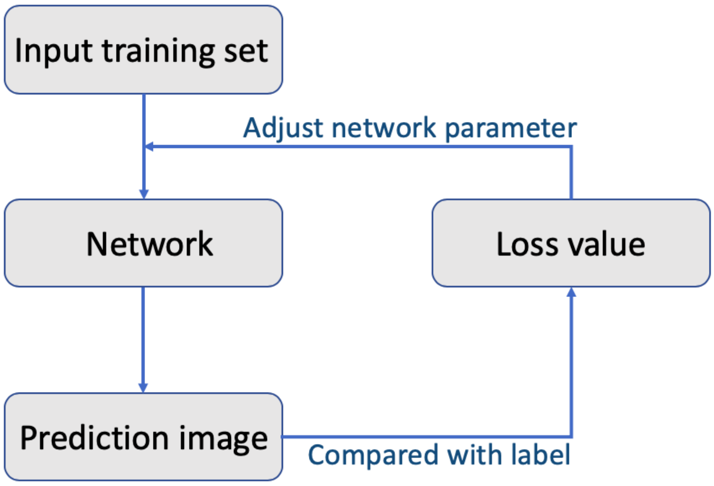


Figure 5.14 Operation flow of network training

5.6. Network Training Result and Analysis

5.6.1 Evaluation Criteria

In this paper, the objective evaluation standard of quantitative analysis is used, and the commonly used quantitative analysis evaluation standard in semantic segmentation is mean Intersection over Union (mIoU) [10], that is, the ratio of the size of the overlapping area of labels and prediction results to the size of the whole image. The formula is:

$$IoU = \frac{TP}{TP + FP + FN} \tag{5.5}$$

TP (true positive) is the positive sample of correct classification, TN (true negative) is the positive sample of incorrect classification, FN (false negative) is the negative sample of incorrect classification, and mIoU is the mean value of IoU of each category to be segmented in the image. The formula is:

$$mIoU = \frac{1}{N}\sum_{i=1}^{N} IoU_i \tag{5.6}$$

N is the total number of categories and IoU_i is the ratio of Intersection-over-Union of the ith category (Figure 5.15)

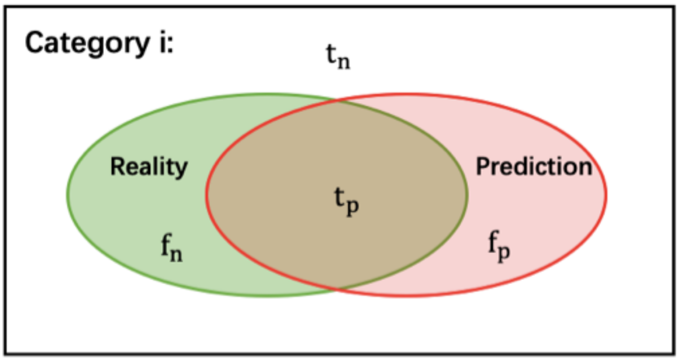


Figure 5.15 Intersection-over-Union [10]

5.6.2 Analysis of Network Training Result

After the training of 60 epoch (epoch means whole data set), up to 79 hours of training, we get the following experimental results (Figure 5.16).

Parameter	mIoU	Accuracy	Prediction time (one image)
270MB	0.69	87.82%	3.208s

Figure 5.16 Experiment result data

The loss value is obtained when the network performance is tested with validation set. As the figure of loss value (Figure 5.17), it can be seen from the change of the loss value of the network that the loss value drops significantly at the beginning phases because of the large learning rate adopted in the network (which is described in 5.5 Network Initialization and Data Set Import). With the continuous training, the loss value basically tends to be saturated and stable when approaching 40 rounds of training, the loss value no longer fluctuates greatly, and the network structure tends to be stable.

Figure 5.17 Loss value

With the network being trained, the accuracy of the network when tested with validation set data after each training epoch is shown in the figure below (Figure 5.18). With the training of network, the accuracy shows a rising trend. The accuracy rate fluctuates greatly in the early stage, and rises at a faster speed, which is basically similar to the change of loss value.

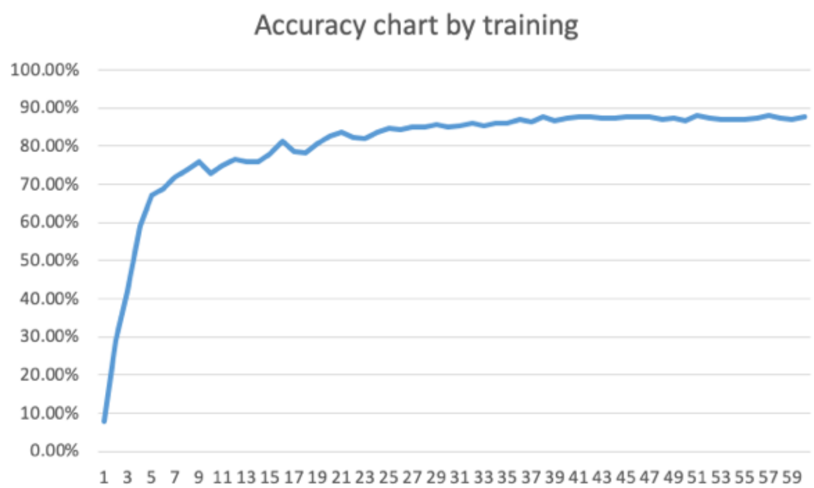
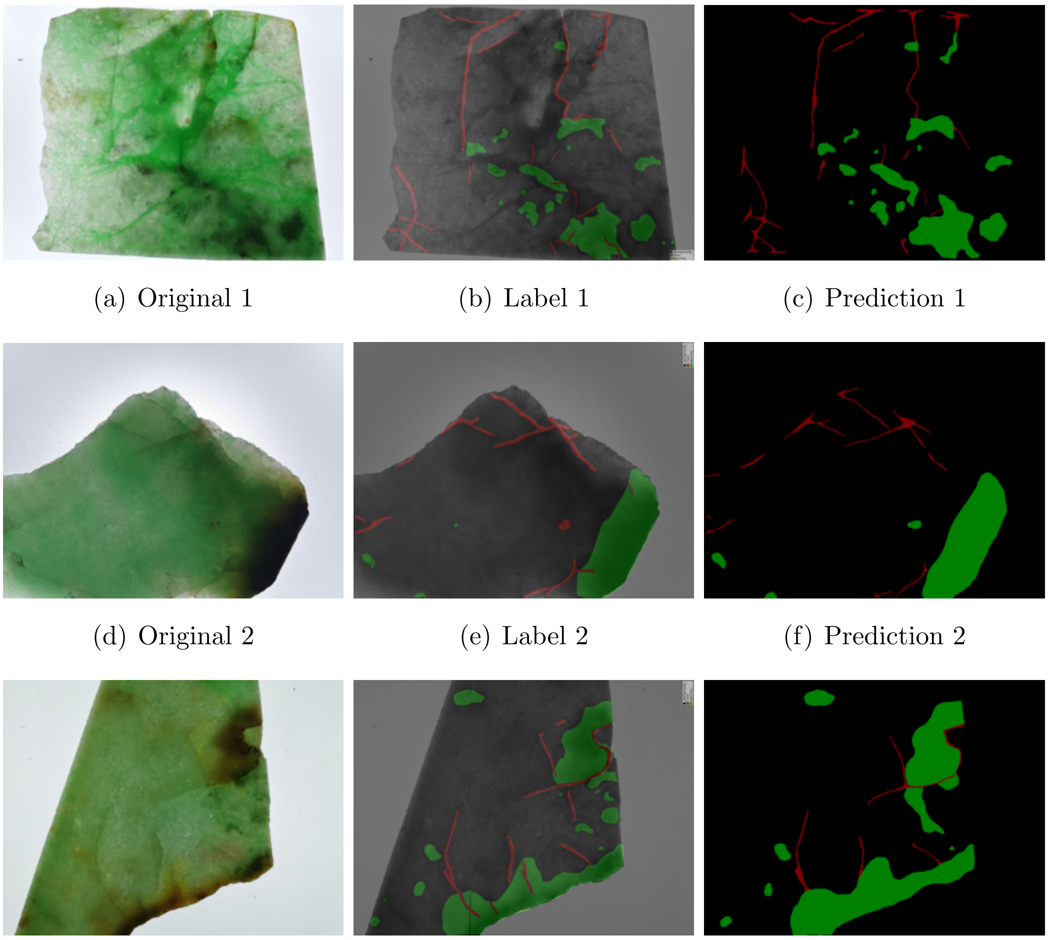


Figure 5.18 Accuracy value

On the basis of such network training effect, we use the trained network to predict the test set data, then get the prediction images. Three examples of the prediction results are shown in Figure 5.19.



(a) Original 1 (b) Label 1 (c) Prediction 1

(d) Original 2 (e) Label 2 (f) Prediction 2

(g) Original 3 (h) Label 3 (i) Prediction 3

Figure 5.19 Result of semantic segmentation in this experiment

By comparing the prediction image obtained from the trained network with the label made with Labelme, we can conclude that the mineral inclusions with large area and dark color can be easily identified, and the object range and location information of the recognition results are relatively accurate. Similarly, the thick and dark cracks in the original image can also be identified clearly.

But on the other hand, through the observation of the results of the prediction, we can find that: the network trained in the experiment is still difficult to recognize the lighter and smaller cracks and the minor impurity spots; when the color blocks appear on the stones, the junction position of the color blocks and impurities is difficult to accurately identify and distinguish, even when the color blocks are too dark, the color blocks are easy to be misjudged as defects.

The accuracy of the prediction in this experiment is 87.82%, which can help people identify most of the defects accurately. In the practical application of jadeite processing, this intelligent recognition network can be used as the basic recognition of stone defects. It can help to improve the recognition accuracy rate in the jadeite processing by combining with the manufacturer's simple recheck and verification.

Using the test data set for efficiency test, the test set data is composed of 30 images with a resolution of 2736*3648. We input these 30 test data into the network after being trained. It took totally 96.24 seconds for the network to test the 30 images, so the average prediction time of a single picture is only 3.208 seconds, and the prediction speed is fast. Therefore, using the network to recognize the defects of stone slices can reduce the time required for the defect identification of raw materials and greatly improve the efficiency of processing and design.

Finally, in order to make the trained network model guide the future automatic processing, the segmentation results need to be transformed into camera coordinate system, so that the automatic cutting or engraving machine can process according to the actual coordinates. We use the code (Code of Defect Coordinate Extraction in Apppendix D) to extract the coordinates of the defects in the segmentation results, and get the coordinates of the defects in the camera coordinate system (Figure 5.20) and crack in the camera coordinate system (Figure 5.21).

```python
from PIL import Image
import numpy as np
import os

def getAddress(image_path):
    img = Image.open(image_path)
    rgb_img = img.convert('RGB')
    i,j = 1, 1
    list_crack = []
    list_impurity = []
    print(rgb_img.size)
    width = rgb_img.size[0]
    height = rgb_img.size[1]
    for i in range(0, width):
        for j in range(0, height):
            data = rgb_img.getpixel((i,j))
            if (data[0] == 128 and data[1] == 0 and data[2] == 0):
                list_crack.append([i,j])
            if (data[0] == 0 and data[1] == 128 and data[2] == 0):
                list_impurity.append([i,j])
    return list_crack, list_impurity

list_crack, list_impurity = getAddress(r'C:\Users\napoleon\Desktop\result_128.jpg')
print(list_crack)
```

```
(3648, 2736)
[[1140, 1608], [1141, 1606], [1141, 1607], [1141, 1608], [1141, 1609], [1142, 1606], [1142, 1607], [1142, 1608], [1142, 1609], [1142,
1610], [1143, 1607], [1143, 1608], [1143, 1609], [1143, 1610], [1143, 1611], [1144, 1607], [1144, 1608], [1144, 1609], [1144, 1610],
[1144, 1611], [1145, 1608], [1145, 1609], [1145, 1610], [1145, 1611], [1145, 1612], [1146, 1608], [1146, 1609], [1146, 1610], [1146, 1
611], [1146, 1612], [1147, 1609], [1147, 1610], [1147, 1611], [1147, 1612], [1147, 1613], [1148, 1609], [1148, 1610], [1148, 1611], [1
148, 1612], [1148, 1613], [1148, 1614], [1149, 1610], [1149, 1611], [1149, 1612], [1149, 1613], [1149, 1614], [1150, 1611], [1150, 161
2], [1150, 1613], [1150, 1614], [1150, 1615], [1151, 1611], [1151, 1612], [1151, 1613], [1151, 1614], [1151, 1615], [1152, 1612], [115
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1], [1159, 1622], [1160, 1616], [1160, 1617], [1160, 1618], [1160, 1619], [1160, 1620], [1160, 1621], [1160, 1622], [1160, 1623], [116
1, 1617], [1161, 1618], [1161, 1619], [1161, 1620], [1161, 1621], [1161, 1622], [1161, 1623], [1161, 1624], [1162, 1617], [1162, 161
8], [1162, 1619], [1162, 1620], [1162, 1621], [1162, 1622], [1162, 1623], [1162, 1624], [1162, 1625], [1163, 1618], [1163, 1619], [116
```

Figure 5.20 Coordinate of crack in camera coordinate system

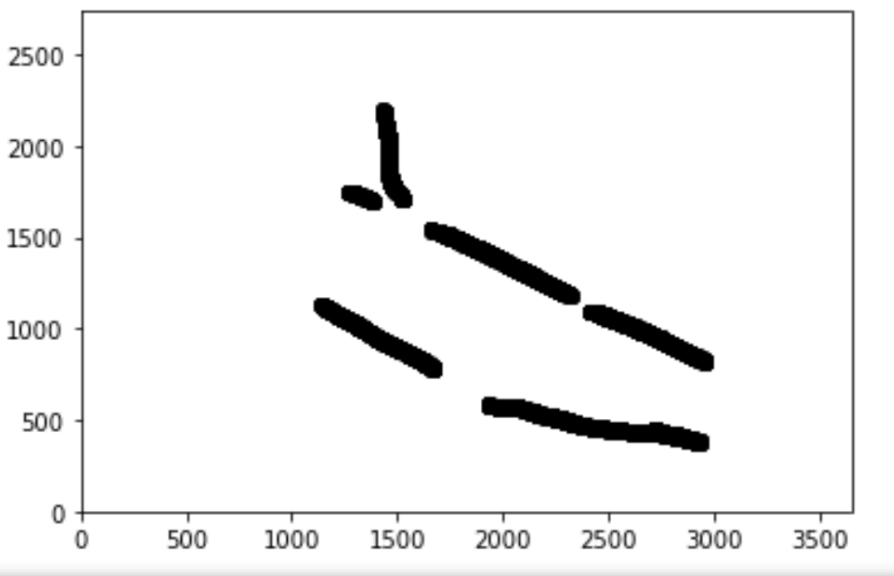


Figure 5.21 Crack in camera coordinate system

Chapter 6
Test

This chapter is mainly about the user test done to test the prediction effect of the trained network model for intelligent jadeite defect detection, according to the feedback of the target user: processors of jadeite industry.

The main purpose of the research is that the intelligent prediction results obtained by the trained network model are mainly used to guide the automatic processing of machines. But considering the experiment result in Chapter 5, the current performance of the trained network model is able to assist the manual processing work. In the user tests, through the verification of the prediction results by professional processors, the prediction effect can be tested more intuitively and professionally.

6.1. Test Setting

6.1.1 Test User

20 jadeite processors participated in the test, who work on jadeite stone cutting, jadeite carving or jadeite product design and have more than 5 years of jade processing experience, which can ensure that they have the proficient and professional jadeite defect recognition ability.

6.1.2 Limitation

Some limitations are found and need to be considered in test design. The main limitations are indicated as below:

- To run the network model has high requirements for GPU and memory of computer equipment, and author's mobile computer equipment (laptop) can not support the operation of network model, so the network test can only be remotely completed in the experimental environment (Section 5.3), and the prediction results are then transmitted to the test user.

- Since the contour of the stone slice is not labeled in the labeled images, the trained network model can not recognize the contour of the stone slice. It is difficult to accurately determine the relative position of the defects on the stone slice when the prediction effect is judged by human vision. Therefore, the prediction image generated by the trained network need to be processed before being shown to the test users.

6.1.3 Equipment

The following equipment are prepared for the user test:

- A PC providing experimental environment that was used in laboratory experiment, for running the trained network model to have prediction result.
- Another PC (laptop) equipped in the test site for receiving the prediction image transmitted from the experimental PC, and to show the prediction result to the test users.
- Internet for the remote connection between the test site and experimental PC.
- A camera for photographing the stone slices.
- Randomly selected stone slices in the test site.
- A white lighted LED board for better showing the jadeite stone slice features when photographing.
- A desk lamp used for test users verifying the prediction result.
- Snapseed APP for prediction image processing

6.2. Test Procedure

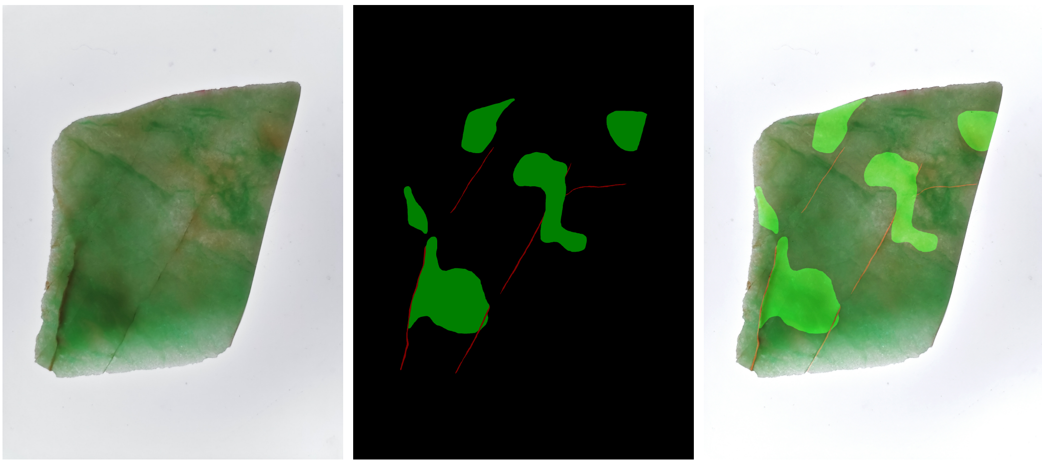
The test process is carried out in the following step:

1. Test users select the jadeite raw stone slices that will be used for testing.

2. The selected jadeite stone slice is placed on the white-lighted LED board and then test user takes photo of the stone slice. And the photo of the stone slice is sent to the laboratory (to the experimental PC).

3. The original image of stone slice received by the experimental PC is imported to the trained network model to generate its corresponding prediction image of jadeite defects. And the prediction process by the trained network is shared in real time to the test user through video meeting, so that the user can realize the prediction time.

4. The original image and the corresponding prediction image are completely overlapped by the double exposure function of Snapseed APP, then the defects recognition result in the prediction image can be directly displayed on the original image (Figure 6.1), which makes the prediction result more clear and easy for test users to understand and verify.



(a) Original image (b) Prediction image (c) Processed prediction result

Figure 6.1 Prediction result processing

5. The processed prediction image is sent to test user. The accuracy of the prediction image is verify by the test user (Figure 6.2).

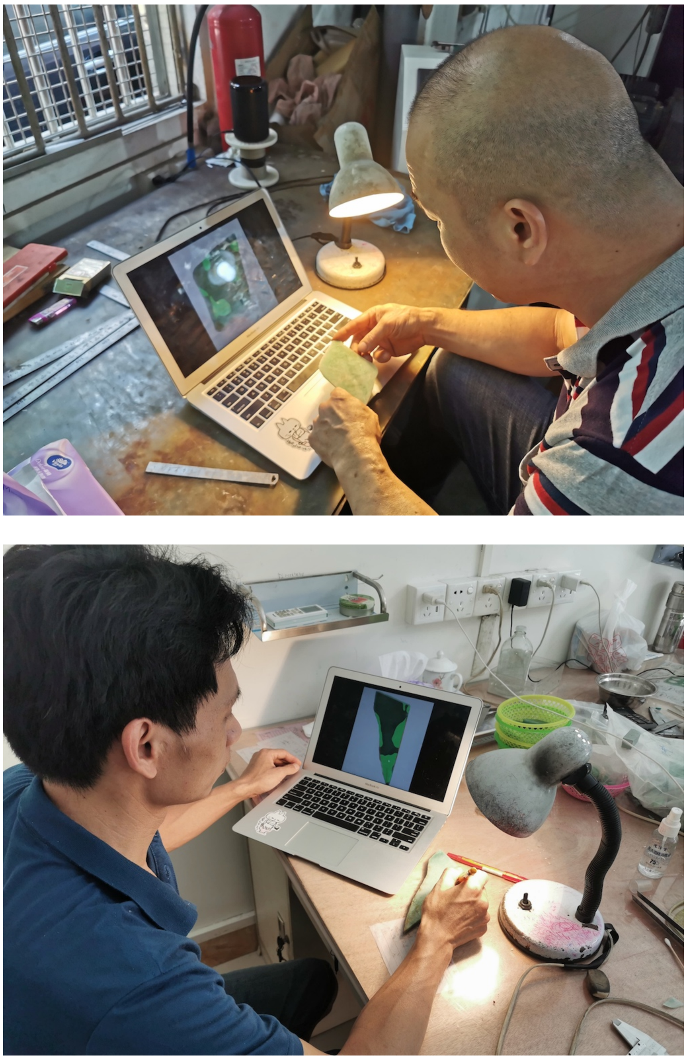


Figure 6.2 Test users checkout the prediction result

6. After the prediction result checkout, test users are asked to answer a questionnaire to know their feedback of the jadeite defect recognition network model. The questionnaire contains the following questions:

   - Do you think if the intelligent recognition of jadeite raw stone defect has a development potential?

- Do you think if the prediction speed is fast?
- Do you think if the prediction result has high accuracy?
- Do you want to use the network model to assist the processing work?
- Do you think it can help guide the fully automatic jadeite processing?

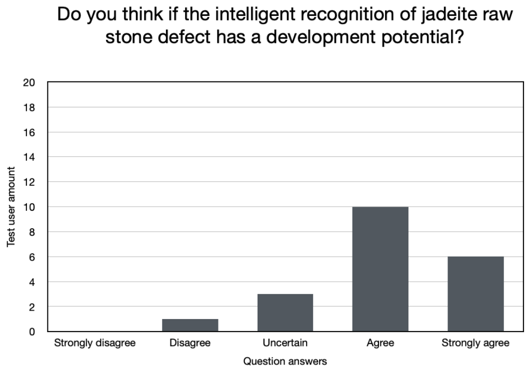
The test users are to answer the questions from the options of: Strongly disagree, Disagree, Uncertain, Agree, Strongly disagree.

6.3. Evaluation and Feedback

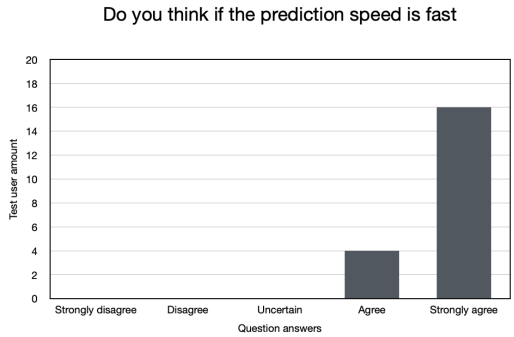
According to the results of the questionnaire survey (Figure 6.3), the study has been generally approved: the intelligent identification of jadeite defects provides a new concept and direction to solve the most basic problem in the whole process of jadeite production. Intelligent and automatic production is the general direction of industrial development. The design and production of jadeite products is based on the analysis of the features of jadeite raw materials. Therefore, in this study, the defects of jadeite can be identified by using semantic segmentation technology, which provides an important basis for intelligent guidance of automatic processing. The application and expansion of this research have great prospects.

In terms of the experimental results realized at the current stage, the test users are shocked by the prediction speed of the trained network, and the they comment that it takes much less time to identify the jadeite stone defects by the network model than by manual identification. The accuracy of the identification results can not completely replace the manual identification, but testers generally believe that with the help of network model, the processor only needs to carry out a relatively easy review work, and the work efficiency is still improved under the premise of ensuring the accuracy of identification. Therefore, most of the testers expressed their willingness to use this network to assist in their jadeite processing work.

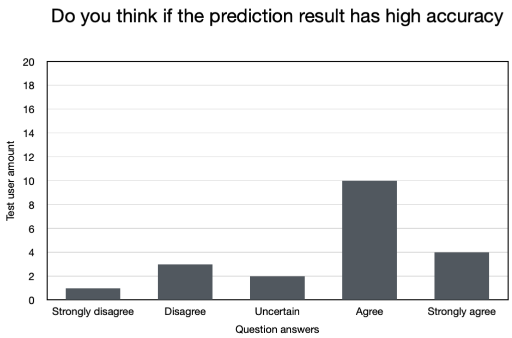
In addition to answering the questionnaire survey, the test users also provided some valuable suggestions. In order to make this technology can be truly applied to the actual production and processing, the accuracy needs to be further improved, especially for the identification of small cracks and mineral spots. In



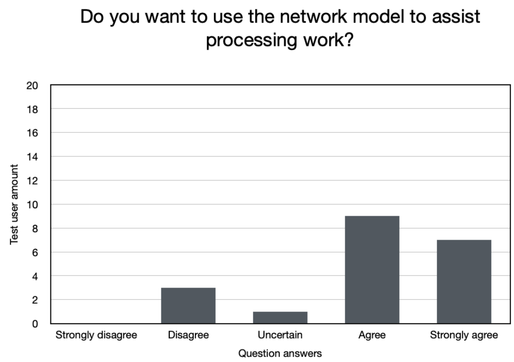
(a) Question 1



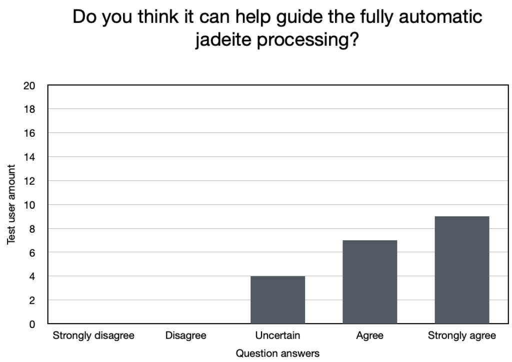
(b) Question 2



(c) Question 3



(d) Question 4



(e) Question 5

Figure 6.3 Questionnaire result

addition, the identification results of this technology need to be used in the automatic design system to realize the identification results guiding the automatic production. Therefore, it is necessary to connect the identified results with the automatic design system to maximize the value of this intelligent recognition network model for jadeite raw stone defect.

Chapter 7
Conclusion

This chapter will give a conclusion of this research based on the experiment result and user test result and then will briefly talk about the related future work of this research, for the further improvement of the study.

7.1. Conclusion

This research attempts to apply the concept of artificial intelligence (AI) to the processing of jadeite, so as to promote the intelligent and automatic production of jadeite. In this regard, inspired by the successful application of semantic segmentation technology, the topic of this study is found: through the application of semantic segmentation technology based on deep learning, the intelligent recognition of cracks and other defects of jadeite raw materials can be realized.

Through a series of experiments, it is proved that the semantic segmentation in the field of artificial intelligence can automatically identify the defects of jadeite. And the experimental results show that the trained network has an accuracy of automatic recognition of 87.82%, with a relatively fast running speed, which is 3.208 seconds. The accuracy is mainly affected by the amount of training set, which means that the accuracy can be further increased when being trained by a larger amount of training set. In addition, the running speed is also affected by the functional configuration of computer equipment. If the computer with higher GPU performance is used, the operation speed of the network will also be improved.

As the information collection step of jadeite processing, the recognition of features of jadeite raw materials is the basis of the design and processing of jadeite products. Because of the subtle and complex defects, in the traditional processing method, defect identification is the most time-consuming and labor-consuming. It usually takes about 10 to 15 minutes for a skilled manufacturer to find out the distribution of defects in a stone slice. Moreover, the effect of defect recognition varies from each individual, which is mainly influenced by the technical experience of processors. But according to the experiment result, using the semantic segmentation technology of image recognition to identify the jadeite defects, on the basis of the recognition accuracy of about 87.82%, it has reached an average speed of 3.208 seconds. Compared with the traditional manual recognition, the intelligent recognition based on semantic segmentation technology has an essential improvement in efficiency. For example, using this defect identification technology, the processors only need to carry out simple and quick recognition results review work, the production efficiency is significantly improved, with the processing quality of products guaranteed, and the utilization rate of raw materials can be improved as well. With the continuous optimization of semantic segmentation network, the accuracy of intelligent recognition will be further increased, and the realization of full-automatic recognition is just around the corner.

The intelligent recognition technology of jadeite defects is the embodiment of artificial intelligence guiding jadeite production. It can effectively improve production efficiency and liberate productivity. Manual identification of defects has higher professional and technical requirements for practitioners, and the training of professionals costs time and money. However, with the help of this intelligent identification technology of jadeite defects, the processing personnel can get started on work faster and easier. Under the social background of continuous increasing labor cost, this technology shortens the training cycle of processing personnel, thus reducing the labor cost, and reducing the production cost. Combined with the automatic modeling software, the digital model which can directly reflect the physical properties of jadeite raw materials can be automatically generated, which provides the basis for the subsequent artificial review and intelligent design and processing. It is connected with the existing CNC automatic carving machine to realize the full automation of jadeite processing.

The concept of artificial intelligence is introduced into jadeite industry, which breaks the traditional production mode of traditional cultural industry dominated by human resources. This is an attempt of Intelligent Manufacturing in the traditional jewelry industry, which provides a favorable example support for the modernization of the traditional jadeite industry, to better face the rapid development of the information age. At the same time, it also contributes to the application and promotion of artificial intelligence in traditional industries. It is a breakthrough in the practical application of artificial intelligence, and further promotes the effective combination of artificial intelligence and industrial processing production in reality.

7.2. Future work

The trained network has achieved an accuracy of about 87.82% in the network training experiment. And also according to the feedback of the test users, to achieve complete intelligent manufacturing, it is still necessary to improve the recognition accuracy of semantic segmentation network. The accuracy of the network can be improved by increasing the amount of training sets and selecting high-quality training data, using a deeper convolution neural network structure, and applying semi supervised learning to reduce the overfitting of the network.

This research mainly focuses on the application of semantic segmentation technology based on deep learning to realize the intelligent identification of jadeite defects, which is only a part of the feature and quality identification of jadeite raw materials. In addition to the defect identification, the material identification in the jadeite processing procedure also includes the identification and judgment of the characteristics such as the color, transparency and texture of jadeite. However, for the more complex feature judgment such as color and transparency, more different kinds of sensors are needed and the collection steps of data sets are more complicated. In the next stage of research, it can be further optimized to make the objects identified by semantic segmentation network more comprehensive.

Semantic segmentation technology is based on image content recognition, so in theory, it can only recognize the objects that can be imaged. Therefore, this research mainly aims at the intelligent recognition of the jadeite slices that have thinner thickness to show the jadeite features clearly enough in 2D image. The semantic segmentation technology can't recognize the internal features and structure of the jadeite original stones that can't be reflected in 2D image because of their greater thickness. This is the main limitation of the application of semantic segmentation technology in the feature recognition of jadeite raw materials. But in the future, we can get the information of the inner grain of the raw stone through more precise ultrasonic sensors and photosensitive elements, so as to break through the limitations of the inner recognition of the raw stone.

At present, this research is limited to the defect identification of raw materials, but in the future, based on the optimization of network structure and complete identification object types, it will provide accurate and comprehensive features information for the automatic modeling software. An intelligent quality and value evaluation system of jadeite products can be established based on the characteristic information. The design and processing scheme of the products is generated intelligently on the basis of the data model of jadeite, which can guide the automatic operation of the cutting and carving machine of jadeite and realize the fully intelligent jadeite processing.

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Appendices

A. Code of Image Cutting

```
import numpy as np
import matplotlib
import os
from PIL import Image

def img_seg(image_path):
    files = os.listdir(image_path)
    for file in files:
        a, b = os.path.splitext(file)
        img = Image.open(os.path.join(image_path + "/" + file))
        hight, width = img.size
        w = 2500
        h = 2200
        id = 1
        i = 0
        while (i + h <= hight):
            j = 0
            while (j + w <= width):
                new_img = img.crop((i, j, i + h, j + w)
                rename = "./pic3/"
                new_img.save(rename + a + "_" + str(id) + b)
                id += 1
                j += 1074
            i = i + 1236
```

B. Code of Image rotation, Flipping and Color Transformation

```
import numpy as np
import cv2
import os
from PIL import Image

def flip(root_path, img_name):
    img = Image.open(os.path.join(root_path,img_name))
    filp_img = img.transpose(Image.FLIP_LEFT_RIGHT)
    return filp_img

def rotation(root_path,img_name):
    img = Image.open(os.path.join(root_path, img_name))
    rotate_img = img.rotate(90)
    return rotation_img

def randomColor(root_path,img_name):
    image = Image.open(os.path.join(root_path, img_name))
    random_value = np.random.randint(0, 41) /10.
    color_image = ImageEnhance.Color(image).enhance(random_value)
    random_value = np.random.randint(10, 31) / 10.
    brightness_image = ImageEnhance.Brightness(color_image).enhance(random_value)
    random_value = np.random.randint(10, 21) / 10.
    contrast_image = ImageEnhance.Contract(brightness_image).enhance(random_value)
    random_value = np.random.randint(0, 31) / 10.
    sharpness_imge = ImageEnhance.Sharpness(constrast_image).enhance(random_value)
    return sharpness_image

def randomProcessing():
    random_num = np.random.randint(1,4,size=1)
    if random_num[0] == 1:
        ifProcessing = True
    else:
```

```
        ifProcessing = False
    return ifProcessing
```

C. Code of Data Balancing

```
add_softmax_cross_entropy_loss_for_each_scale(scales_to_logits,
                                        labels,
                                        num_classes,
                                        ignore_label,
                                        loss_weight=[1.0, 3.0, 38.0],
                                        upsample_logits=True,
                                        hard_example_mining_step=0,
                                        top_k_percent_pixels=1.0,
                                        gt_is_matting_map=False,
                                        scope=None):
```

D. Code of Defect Coordinate Extraction

```
from PIL import Image
import numpy as np
import os
import matplotlib.pyplot as plt

def getAddress(image_path):
    img = Image.open(image_path)
    rgb_img = img.convert('RGB')
    i,j = 1, 1
    list_crack = []
    list_impurity = []
    print(rgb_img.size)
    width = rgb_img.size[0]
    height = rgb_img.size[1]
    for i in range(0, width):
```

```
        for j in range(0, height):
            data = rgb_img.getpixel((i,j))
            if (data[0] == 128 and data[1] == 0 and data[2] == 0):
                list_crack.append([i,j])
            if (data[0] == 0 and data[1] == 128 and data[2] == 0):
                list_impurity.append([i,j])

def drawDefect(list_crack, list_impurity):
    list_x = []
    list_y = []
    for i in list_crack:
        list_x.append( i[1])
    print(list_x)
    for i in list_crack:
        list_y.append( i[0])
    print(list_y)

    plt.xlim(xmax=3648, xmin=0)
    plt.ylim(ymax=2736,ymin=0)
    plt.plot(list_x, list_y,'ko')
    plt.show()
```