

Zhao Weiyu

by Weiyu Zhao

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Master's Project (COMPUTING)

Shovel tooth fall detection system designed for mining shovels

Name: Zhao Weiyu

Student code: 2203629

Tutor: Mike

Department: Software Engineering

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Chapter 1 Introduction

1.1 introduction to problems

In the operation of large electric shovels during excavation work, the primary loading task is carried out by the bucket. In this process, the motion of the bucket is controlled by wire ropes and the dipper handle. The electric shovel operator manipulates the extension and retraction of these wire ropes and the dipper handle to perform lifting and pushing operations. During the excavation operation of the electric shovel, the bucket and bucket teeth penetrate into the interior of the ore material under the control of the operator, leading to continuous and intense collisions and friction with the ore material. Additionally, due to variations in the composition and blasting effects of different ore materials, the size of the crushed ore chunks can differ significantly. This directly affects the tooth tip position of the bucket teeth in direct contact with the ore material.

Under the combined effects of significant impact forces, frictional forces, and compressive forces, the tooth tips of the bucket teeth experience severe wear and can even develop cracks and fatigue fractures. Furthermore, as large electric shovels operate intensively in harsh working environments and under complex conditions for extended periods, the working lifespan of the bucket teeth is typically around two to three weeks. Therefore, the primary failures occurring in the electric shovel bucket are related to the bucket teeth and can be classified into the following two types of failures:

(1) Fracture

When the electric shovel encounters high-hardness ore during excavation work, the bucket teeth can experience excessive impact forces that exceed their toughness threshold. In such cases, the bucket teeth may fracture. Typically, the structure of large electric shovel bucket teeth is fixed, and the structure at the corner where the tooth tip connects to the tooth root is a hollow structure. Consequently, many external forces may concentrate on this particular area, as illustrated in Figure 1-1[1], [2].

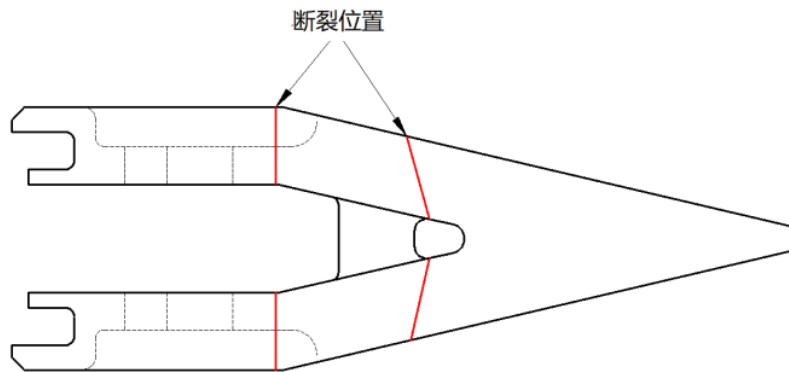


Figure 1-1 Fracture-prone areas of shovel teeth

Furthermore, considering the influence of factors such as the casting process of the bucket teeth and the operational habits of the operators, these areas are highly susceptible to bucket tooth fracture incidents.

Another situation that can lead to similar accidents is when there is uneven and prolonged force acting on the upper and lower sides of the bucket teeth during the excavation work. This unequal force distribution results in more severe wear on one side of the bucket teeth. Moreover, when subjected to bending moments during the excavation process, the bucket teeth may also be at risk of fracturing.

(2) Shedding

The shedding of electric shovel teeth means that the whole teeth fall off from the bucket due to external force. The teeth of electric shovel are connected with the main body of the bucket by the card slot through the pin. Due to too harsh working environment and complex working conditions, under the influence of fatigue stress and impact load, the connection between shovel teeth and bucket is easy to loosen, so the pins may be deformed or broken, when the pins are deformed or broken, the pins will lose their fixed role, which will directly lead to the separation of the shovel teeth from the bucket and fall off[3].

1.2 Aim

The main purpose of this project is to build a set of large electric shovel tooth shedding intelligent detection system by combining machine vision and software development, so as to realise the

application of existing computer technology to actual production. The detection software can monitor and judge whether there is any abnormality in the teeth of large electric shovels in real time during the working process. When the system detects that the teeth of electric shovels have fallen off or broken, the system will instantly send out alarms to remind operators to deal with the situation, so as to minimise the damage caused by the falling of shovel teeth. Given the time and practicality of the project, it was not possible to achieve the goal of developing a complete system, so this project will focus on the core functionality of the project. It can detect the lack of shovel teeth by collecting and automatically segmenting the teeth in the field. In this way, it ensures that the staff can be alerted when the teeth of electric shovels fall off or break, so that timely remedial action can be taken to reduce the economic losses caused by this.

1.3 Objectives

The objectives of the project are as follows:

- Current status of the research field, to understand the working status of mines and the working environment of electric shovels, and to search the literature on electric shovel detection and gather progress in the field.
- Algorithm selection, collect algorithm literature, understand the target detection algorithm and determine the algorithm used in the system.
- System design, carry out the detection system requirement analysis and divide the system function, draw the system flow chart.
- System implementation and deployment, develop the main functions of the system and deploy the algorithmic model, after completion install the equipment to the field and then carry out trials and experiments to obtain the test results.
- Analyse the results to determine the system effectiveness, analyse the results from the system operation to determine whether the system can achieve the effect of detecting safety accidents.

By accomplishing these objectives it can be determined if the system is effective in protecting the safety of the electric shovel. In order to accomplish these tasks, this project requires the knowledge

of the background related to the work of mining electric shovels and the current concepts related to machine vision target detection. This chapter will already provide an introduction to the problem of tooth shedding and the design goals of the electric shovel; Chapter 2 will provide background knowledge related to the current mining electric shovels through a literature review, the existing research progress in the field and the currently available algorithms for target detection; Chapter 3 will present the research methodology used for the project (philosophy, approach, strategy, and data collection); and Chapter 4 will present the software development methodology and select one to guide this software development. Chapter 5 describes the requirements analysis and functional analysis of the project. Chapter 6 describes some of the processes of the software and the problems encountered during deployment and testing. Chapter 7 presents and analyses the test data.

Chapter 2 Literature review

In this chapter, the background knowledge related to electric shovel detection systems will be summarised based on the understanding of previous literature, including the production environment of mine electric shovels and the current safety hazards of electric shovels, as well as the progress in the field and target detection algorithms.

2.1 Electric shovel working environment and principle

The methods of mineral extraction are classified as open pit mining and underground mining. Comparing underground and open pit, open pit mining has the advantages of low mining cost, high labour productivity, high quality labour conditions, high working safety, and is not restricted by space and has a high degree of automation, so the form of open pit mining has been used in a large number of cases. The large electric shovel has the advantages of high operating rate, better adaptability to the working environment, better stability and durability, and low operating costs, so it is used as an indispensable extracting and loading equipment in the open pit mine. In the world, the current open-pit mining method is a combination of large electric shovels and dump trucks, the mode of construction flexibility, high interest rates of equipment, and the mode in the

complex terrain of the mine infrastructure process requires less cost, and construction cycle is short.

Large electric shovel working process of excavation, electric shovel bucket at the same time by the lifting force of the wire rope and the bucket bar under the joint action of the push pressure, the bucket through the shovel teeth to cut the mineral to reduce the friction inserted into the pile of ore materials, electric shovel bucket continue to exert forward and upward force, at this time, because of the upward movement of the bucket forward, the minerals were loaded into the bucket[4], and its mode of operation as shown in Figure 2-1.



Figure 2-1 Electric Shovel Working Schematic

2.2 Hazards of Shovel Tooth Loss

In the electric shovel operation, the electric shovel bucket, when pushed by the bucket rod, deeply embeds the shovel teeth in the ore material, so that the overall shovel teeth are subjected to impact, friction and other factors, which leads to the wear and damage of the shovel teeth. In addition, due to the electric shovel in shovel loading construction, the shovel teeth will be affected by the digging load and bending moment, it is easy to produce cracks, or even fracture, especially when the electric shovel is loaded with hard and large ore materials, the shovel teeth in contact with the hardness of the ore materials, will produce a huge reaction, so that the shovel teeth originally mounted on the base of the bucket is easy to be

fractured in the pin or the whole loosened[5]. When the shovel teeth are dislodged or broken, it will cause the following two situations:

(1) Shovel teeth as the primary part of the bucket inserted into the ore material layer, the teeth of the shovel fall off or broken will make the electric shovel shovel digging friction resistance increases, and the teeth of the shovel on the ore material layer of the cutting efficiency becomes low, thus reducing the electric shovel on the mining speed of the ore, and consequently reduce the efficiency of the entire surface mining operations; at the same time, the lack of teeth of the shovel, making the shovel bucket directly friction with the ore material layer, the hardness of the shovel bucket is relatively low, easy to be damaged, so it will affect the electric shovel shovel bucket and the electric shovel's life as a whole, increasing the cost of the mine on the maintenance of the equipment, and further reduce the efficiency of the entire open pit mining.

(2) More importantly, most of the electric shovel teeth are made of high strength manganese steel alloy material, and the manganese value of different shovel teeth manufacturers is different. When the electric shovel is engaged in shoveling and excavating, the operator of the electric shovel does not find out in time that the teeth are shedding or broken, and the part of the teeth that is shedding or broken is mixed with the ore materials and loaded into the mining trucks, and the mining trucks will transport the teeth and the ore materials to the crushing station directly. Then the truck will transport the broken teeth and ore materials to the crushing plant. If the broken or dislodged teeth are not detected at this time, the broken or dislodged teeth will be transported to the crusher at the same time with the ore materials through the belt transport equipment. The hardness of the teeth is high, and the broken teeth will cause serious damage to the crusher components, which will lead to the destruction of the crushing system, and the broken crushing system will also bring about a drop in the production of the entire mining enterprise, which may result in a serious shutdown of the whole crushing system, and the high cost of the crushing system, the maintenance is difficult and time-consuming, which may result in long-time production cuts or production shutdowns, which will bring about a very high level of maintenance costs. It can also cause serious and indelible consequences to the main production line of

the mine, and once the dislodged or broken part of the shovel teeth enters the crusher, there is also a significant risk to the safety of the operators of the crushing production.

Due to the pursuit of work efficiency in mining enterprises, most of the electric shovels used in open-pit mining are large electric shovels with relatively large scale, while the complex working conditions and poor working environment lead to the operators of large electric shovels not being able to check the working status of the teeth of the shovels through manual inspection, so the operators have to check and record the status of the teeth of the shovels under the shovels when the shovels stop working. This kind of checking method can't detect the tooth falling off or breaking in time, and has a delay, and it can't be repaired immediately, which greatly reduces the working efficiency, and this method of relying on manual checking requires the shovel operator to get down from the shovel to observe and record, or arrange other operators to carry out manual checking on the project site throughout the day, which is difficult for the electric shovel operator to observe for a long time. The electric shovel operator observes for a long time, and accidents and negligence will inevitably occur.

2.3 Literature in the field of tooth detection

In recent years, in the relevant professional researchers and related universities and enterprises to improve the impact caused by shovel teeth falling off, do a lot of theoretical research and practice, formed a certain result. Contact detection and non-contact detection are the two most important means.

In 2004, Luo Xiujuan[6] et al. proposed a research programme of shovel teeth detection, which was designed to monitor the shovel teeth mainly through model comparison. Firstly, a normal three-dimensional model of the shovel teeth was established, and a real-time model of the shovel teeth was established according to the distance between the shovel teeth collected during the working process by using the principle of laser ranging, and finally, a comparative analysis of the two was carried out. In order to improve the speed of model comparison calculation designed by the programme and the speed of processing the collected laser ranging data, so that it can ensure the real-time and effectiveness of the

whole shovel tooth monitoring system, the programme adopts the method of parallel computing. The detection effect of this scheme is suitable for the situation where the environment and light changes are not sensitive due to its use of laser rangefinder.

In 2011, He Lei[7] et al. proposed a shovel tooth detection algorithm that combines the image's morphological features, structural features, and shape features processing techniques, and in order to improve the accuracy of shovel tooth detection, by measuring the interval data of each shovel tooth of the electric shovel, increasing the feature constraints of the shovel tooth during the use of HOG and SVM, and increasing the number of alarms when the shovel tooth passes through the different positions of the detection area.

In 2016, Ser Nam Lim[8] et al. developed a shovel tooth detection system using the optical flow method and the frame difference method. The process of the system is to locate the approximate position of the shovel teeth by collecting a large number of samples of the shovel teeth of large electric shovels in the shoveling work state, and then locate and track the position of the shovel teeth by adopting the optical flow method, and after the positioning is completed, the position of the shovel teeth is corrected by adopting the frame difference method, and then the template matching method and the tooth position are used. After the positioning, the frame difference method is used to correct the positioning position of the shovel teeth, and then the template matching method and the tooth line fitting method are used to accurately locate the targets of the shovel teeth; finally, the grey scale features of the image are used to judge the working status of the shovel teeth.

In 2017, Tang Heng[9] proposed a new bucket tooth shedding detection algorithm, which improves the accuracy of electric shovel shovel tooth shedding detection. Because the electric shovel teeth will generate heat by friction during the shoveling work, the infrared images of the shovel teeth are collected, combined with the traditional target detection method, and the target detection of the shovel teeth is carried out through the Histogram of Oriented Gradient and the Support Vector Machine target detection technology; then, by analysing and comparing the similarity of the images of the electric shovel teeth, and then, by analysing and comparing the shape of the images of the shovel teeth, the target

detection algorithm is carried out. Then, by analysing the similarity of the electric shovel teeth images, the shape features of the electric shovel teeth are sampled through the Shape context algorithm, and the feature constraints on the shovel teeth are added in the detection process. In its experimental verification process, good results are achieved.

In 2018, Wang Ping[10] and colleagues from China University of Mining and Technology further advanced the research by introducing a bucket structure health monitoring system. They used infrared cameras to capture images of the bucket structure, employed convolutional neural networks to classify bucket tooth faults based on preprocessed bucket structure data, and combined SIFT template matching to achieve precise tooth localization and number determination. The actual tooth area size was then used as a basis for assessing tooth faults, improving the bucket tooth fault detection method.

In 2019, Li Dongpeng[11] from Wuhan University of Technology proposed a contact-based bucket tooth detachment monitoring solution. This system consists of a receiving module, a magnetic induction module, and a transmitting module. Signals from the system are wirelessly transmitted to the electric shovel's cabin through 2.4G wireless communication. When there is a significant relative displacement between the bucket and bucket teeth on the electric shovel, indicating detachment or fracture, the magnetic materials attached to the bucket move away from the signal transmitting module on the bucket teeth, triggering an alarm through the signal transmission circuit.

In 2020, Zhou Shilu[12] and colleagues from China University of Mining and Technology employed the Faster R-CNN object detection algorithm. Based on simulated data collected from electric shovel bucket teeth detection, they used the VGG-16 network structure for feature extraction, employed image segmentation techniques to predict the positions of detached bucket teeth, and made preliminary judgments about the degree of wear on the teeth. They successfully implemented bucket tooth object detection, achieving effective bucket tooth fault monitoring.

Also in 2020, Tian Kuan[13] and collaborators from Liaoning Technical University combined convolutional networks with machine

vision theory to design an electric shovel bucket teeth fault detection system. They improved the YOLO-v3 algorithm model, enhancing system stability and synchronization. They also designed a software interface for the bucket tooth fault detection system, allowing functions such as data collection and processing, bucket tooth recognition and localization, fault analysis and viewing, and alarm triggering, among others.

In 2021, Wang Lianjie[14] and others from Liaoning Technical University optimized and improved the system designed by Tian Kuan. They adopted the YOLO-v4 object detection algorithm, applied K-means clustering to recluster candidate regions based on bucket teeth data characteristics, and used logical judgment to determine whether bucket tooth faults had occurred. These improvements significantly enhanced the accuracy and real-time performance of bucket tooth detachment detection.

In summary, researchers have conducted comprehensive studies on electric shovel bucket teeth detachment detection, primarily employing machine vision technology. Machine vision technology, evolving from traditional image processing techniques to modern deep learning-based machine learning methods, has rapidly developed in the fields of target detection, tracking, and understanding in images and videos. Using deep learning-based machine vision for real-time detection of electric shovel bucket tooth detachment has become a prevailing trend in current research.

2.4 Target Detection Algorithm

In machine vision technology, two crucial and fundamental components are object classification and detection, mirroring the basic functionalities of human vision.

Object detection involves determining the location and category of an object within an image while disregarding potential disturbances such as appearance, shape, lighting variations, and partial occlusion. With the rapid development of machine vision technology, object detection methods have found wide applications in technology domains like face recognition, text recognition, industrial security monitoring, intelligent transportation, and more.

Based on the techniques employed, the current object detection methods can be categorized into the following five groups:

1. **Template Matching-Based Approach:** This method necessitates the prior storage of templates for the objects to be detected. During real-time detection, it involves comparing and analyzing the established target templates with the stored reference templates to determine the object's position. However, this approach faces challenges in template selection and efficiency, limiting its widespread use[15].

2. **Image Segmentation-Based Object Detection:** This approach preprocesses images by employing suitable image segmentation methods based on color, shape, and other object properties, which helps extract semantic information concealed within the images[16]. It then separates the object of interest from the image's background and other objects. Finally, classifiers are employed to classify candidate regions. The effectiveness of this method depends on the performance of the image segmentation technique used[17].

3. **Optical Flow-Based Object Detection:** Primarily applied in motion object detection, this method provides velocity vectors for each pixel in the desired detection image, forming a vector velocity field. Pixels on the image correspond to points on a three-dimensional object during specific motion periods. By analyzing the velocity vector characteristics of image pixels, it becomes possible to discern their motion features. In the absence of moving objects, pixel velocity vectors change steadily and continuously. Conversely, when moving objects are present in the captured images, the velocity vectors of these objects significantly differ from those of the background. By exploiting these differences, the method can detect the positions of moving objects effectively[18].

4. **Frame Difference-Based Object Detection:** Similar to optical flow-based detection, frame difference methods are frequently employed in motion object detection. Video images are continuous, and consecutive frames exhibit subtle, uniform changes when no moving objects are present. Conversely, when moving objects appear in the captured images, the differences between consecutive frames become noticeable. The frame difference method detects objects based on this characteristic. It captures consecutive frames in real-time, computes their differences pixel-wise, and identifies moving objects based on the absolute value of the grayscale differences exceeding a predetermined threshold.

This approach is less susceptible to lighting conditions but may not detect objects that suddenly become stationary after motion[19]–[21].

5. Machine Learning-Based Object Detection: Machine learning techniques, capable of learning from a large dataset of positive and negative samples, are applied to develop object classification models[22]. In this method, significant features of the target object are manually extracted, and a large dataset is collected for training. By training the classifier, the system can determine if the object is present in a candidate region during the detection process. A drawback of traditional machine learning-based object detection methods is their reliance on extensive training datasets and the need to select appropriate feature extraction methods and classifiers. While traditional feature extraction methods offer some stability and adaptability, they may lack specificity for particular images and target objects, potentially resulting in information loss during feature extraction. As a result, these methods are not ideal for complex and large-scale detection tasks[23].

Compared to traditional object detection techniques, deep learning-based object detection methods excel in feature extraction from target images without the need for manual operations. They can directly learn, classify, and detect features from the pixel-level data of the target images. With the rapid advancement of technology and deep learning algorithms, the primary approach employed in current object detection applications both domestically and internationally involves the integration of deep learning.

At present, deep learning-based object detection algorithms can be broadly categorized into two groups:

1. Region Proposal + Deep Learning Classification: In this approach, the input image containing the target object undergoes a series of steps. Initially, candidate regions, often generated by methods like Selective Search (SS), are resized to a specific dimension. These regions are then fed into a convolutional neural network (CNN) for feature extraction. The extracted features are used to train a support vector machine (SVM) to obtain weighted scores for each target class. A non-maximum suppression (NMS) algorithm is applied to remove candidate regions with scores above a set threshold. Finally, a regression model is established to adjust the positions of

candidate regions. Well-known algorithms in this category include R-CNN, Fast R-CNN, and Faster R-CNN.

- In 2014, R. Girshick introduced the R-CNN algorithm, which marked a significant shift in the research approach for object detection. R-CNN adjusts the size of candidate regions obtained through Selective Search and uses a CNN to extract target features. These features are then used to train an SVM classifier for each target class, and NMS is employed to filter candidate regions above a certain threshold. A regression model is used to refine the positions and sizes of the candidate regions.

- In 2015, R. Girshick improved the R-CNN algorithm to create Fast R-CNN. This enhancement replaced the last pooling layer with RoI pooling, simplifying the model and improving both detection speed and accuracy.

- In 2016, Ren et al. introduced Faster R-CNN, which integrated the RPN (Region Proposal Network) into the model, enabling simultaneous region proposal, classification, and regression using convolutional features. This approach significantly increased detection speed, with region proposal taking just 10 ms and the entire detection process achieving 5 frames per second (f/s).

2. Deep Learning Regression-Based Methods: Unlike the previous group, these methods do not perform candidate region extraction. Instead, they directly classify detected objects and regress the bounding boxes. This trade-off between detection accuracy and speed has led to the development of efficient models such as the YOLO (You Only Look Once) series and the Single Shot MultiBox Detector (SSD).

- In 2015, Redmon[24] et al. introduced the YOLO model, which unified candidate region extraction and classification into a single step. YOLO achieved remarkable detection speed, but its accuracy for small objects was limited[25].

- YOLOv2, an improvement over the original YOLO, introduced a lighter main network model called DarkNet-19 to reduce computational requirements and increase detection speed. It also expanded the detection categories through joint training techniques, achieving an accuracy of 76.8% at 67 f/s.

- YOLOv3 further enhanced the YOLO series by deepening the network structure with a residual model, resulting in 53 convolutional

layers. It utilized an FPN architecture for multi-scale feature extraction, improving detection speed even further[26].

- Subsequently, YOLOv4 was released, incorporating SPP and PANet within the CSPNet framework to achieve both higher detection speed and accuracy.

- YOLOv5 followed soon after, maintaining high accuracy while optimizing for deployment on mobile devices, making it an excellent choice for various applications.

In summary, different deep learning-based object detection methods have unique advantages and drawbacks. The choice of method depends on the specific application domain and requirements. Object detection technology is mature, and for real-world scenarios, selecting the most suitable algorithm based on specific needs is essential. Currently, the YOLOv5 object detection model appears to hold significant engineering value when applied to the monitoring of shovel tooth detachment, given its balance of speed and accuracy.

Chapter3 Research methodology

Research methodology is a critical component of any research project, as it provides a framework for collecting and analysing data, and for drawing Properly conducted research methodology is essential for producing valid, reliable, and generalizable findings that can contribute to the body of knowledge in a given field. This project references the use of research onion[27] to sort out the various elements of the project. Firstly, it is clear that the purpose of this project is to make a software that can identify the safety accidents of shovel teeth dislodging and improve the safety of electric shovels. The project is to develop a programme to detect and identify the teeth of an electric shovel in real time.

3.1 Research philosophy

Research philosophy[28] is the starting point of any project as it defines the way in which the research question is approached and the methods of data collection and analysis. There are four approaches to research philosophy which are pragmatism, positivism, realism and interpretivism. The commonly used two are empirical attention and interpretivism. Positivists believe that

knowledge can only be gained through observation and measurement and that the scientific method is the most reliable method of generating knowledge, so its more focused on objective analysis and processing of data; Interpretivists believe that facts and knowledge are generated based on subjective analysis, so Interpretivism is ideally suited to research that focuses on human behaviour, attitudes and perceptions. Considering the differences between these two doctrines and their focus, the RESEARCH PHILOSOPHY for this project is Positivism. Positivism is a philosophy of science that emphasises the use of the scientific method to gather empirical evidence and draw objective conclusions. This philosophy is well suited to the subject matter of this project in that the final test of the effectiveness of the tooth shovel system is assessed by means of statistics and analysis of objective data during operation, and is not influenced by the experience and personal feelings of the operator, so there is no need to consider the human subjective factor.

3.2 Research Approach

A research method is a general strategy employed by a researcher to answer a research question[29]. The three commonly used methods are deductive, inductive and retrospective. Deductive method can be used to make further research on top of the theoretical basis of other people's research and then test their own results; inductive method is more suitable for building a new theory from scratch without theoretical basis; and retrospective method is a synthesis of deductive and inductive methods, i.e., it makes use of the theoretical basis of the predecessors and makes new discoveries. Under the comprehensive consideration of the actual situation of this project, it was decided to use the deductive method to conduct the research. There is already a certain theoretical and methodological basis in the field of spade tooth shedding detection, so this paper is completed on the basis of previous research.

3.3 Research Strategy

According to the representation of research onion, strategies need to be selected based on the purpose of the research and the data

needed. Strategies can include action research, experimental research, interviews, surveys, case study research or systematic literature review. The purpose of the project as well as the chosen Research philosophy and Research Approach are considered, so the strategy uses a systematic literature analysis as well as experiments. The previous literature in the field of spade tooth detection and the existing literature on algorithms for target recognition were analysed to determine the algorithm to be used in this project, after which experiments were carried out through a combination of software and hardware. The hardware includes a laptop, camera, and capture card; the software includes the corresponding capture card for the camera and debugging tools for the capture card, as well as a test programme that needs to be developed in-house.

3.4 Choices of Methods:

The research choices are mono method, multi-method and mixed method. The research methods are mainly quantitative and qualitative analyses. Qualitative analysis is usually an in-depth analysis based on observation and interpretation, usually used in conjunction with interpretivism and induction, and the type of data collected is usually text and images, which is used to understand the relevant concepts and theoretical experience, etc. It focuses on helping to gain in-depth understanding by collecting more information such as text and images, and this method is biased towards exploring and forming new theoretical hypotheses; quantitative analysis refers to scientific research that determines the quantity of a certain aspect of a thing. prescriptive scientific research, that is, the research method of representing problems and phenomena in quantitative terms and then going on to analyse, test and interpret them in order to gain meaning, the information gathered is usually in the form of charts and figures, which can be used to accurately test hypotheses or confirm theories, and is often used in a pragmatic and deductive way, focusing on establishing specific facts related to the topic. In this section, the author will choose to use the quantitative analysis in the mono method because the author believes in improving the safety of the electric shovel equipment by developing a detection system for shovel teeth falling off instead of a human to achieve 24/7 detection, in order to validate

this, it is necessary to go ahead and create an application to conduct an actual test to validate the hypothesis.

3.5 Time Horizons

This framework helps in determining the time of completion of the project. There are two types of time horizons, the cross-sectional and longitudinal time horizons, and the cross-sectional time horizon is used for this project. The purpose of this project is to improve the safety of electric shovels through the development of a software that detects the falling off of the teeth of the shovels, and detects the falling off of the teeth of the shovels in time. In order to shorten this process, this experiment simulates the occurrence of a tooth falling accident by wrapping black tape around the teeth of the shovel, so as to verify whether the software is able to detect the accident in time and issue a warning.

3.6 Data Collection

Data collection is an important part of any research project because it allows researchers to gather evidence to support the research question. In this project, two types of data will be collected: the set of pictures that make up the image recognition model and the number of times a simulated accident is detected by the detection system.

The set of pictures that make up the image recognition model will be collected by installing cameras in the field to take pictures of the electric shovel bucket. Electric shovel safety accidents will be simulated by wrapping black tape around the teeth of the shovel and recording the number of safety accidents detected by the system. This will allow the researchers to determine the necessity of a tooth removal detection system for shovel safety and whether it will improve the safety of the shovel.

In addition to this, the project will compare different target detection algorithms and determine the algorithm to be used by consulting academic literature on the subject of electric shovel tooth loss. The literature review will provide background information on the topic and enable the researcher to gather theories and experiences from existing research. The literature review will also provide information

on the factors that affect the effectiveness of detection systems which will inform the data analysis.

The data collected through will be analysed using statistical techniques (e.g. descriptive and inferential statistics). Descriptive statistics will be used to summarise the data and inferential statistics will be used to test hypotheses and determine if there is a significant difference in the safety of electric shovels with and without detection systems.

3.7 Conclusion

In conclusion, this chapter presents a plan on how to complete the research for this project. This plan is based on research on this. This research plan outlines the research philosophy, methodology, strategy, time and data collection methods, etc. These methods ensure that this project can collect the various data needed. Analysing this data will allow us to determine whether this project is correct or not, and whether or not it will be able to detect the occurrence of safety accidents in electric shovels, and to improve the safety of electric shovels in mines.

Chapter 4 Development Methodology

Before starting the software design, this paper will introduce some of the commonly used software development methodologies. In this project, the development of the software is a very important part of the project[30], through the testing of the software can obtain the required experimental data, and then analyse the collected data to obtain the experimental results. All software will go through a life cycle of definition, development, operation and maintenance until eliminated, in order to make the tasks in the software life cycle can be carried out in an orderly manner in accordance with the procedures, it is necessary to follow a certain method of each task to give the procedure constraints. Commonly used software development methods include the waterfall method, incremental method, spiral method, agile development methods.

4.1 Waterfall Method

Waterfall method is an early traditional development method. The development process is through the design of a series of phases in order to start from the beginning of the system requirements analysis until the product release and maintenance, the project development process from one stage "flow" to the next stage, which is the origin of the name of the waterfall method, as shown in Figure 4-1.

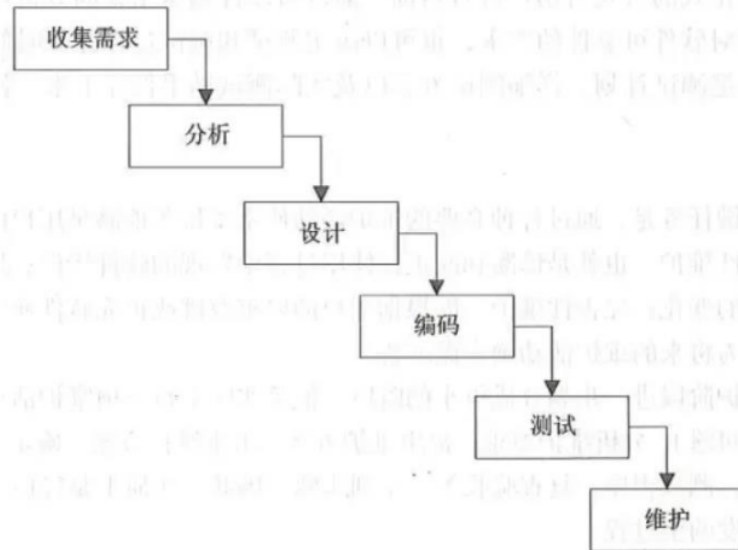


Figure 4-1 Traditional waterfall

The core idea is to simplify the problem according to the process and separate the implementation of functions from the design to facilitate the division of labour, i.e. to separate the logical implementation from the physical implementation by using a structured analysis and design method. The software life cycle is divided into six basic activities, such as planning, requirement analysis, software design, programming, software testing and operation and maintenance, and stipulates a fixed order for them to be connected from top to bottom, just like the waterfall, descending step by step. This approach is like a factory assembly line. This approach is only suitable for software with very clear and fixed requirements, but it requires a lot of wasted time in writing relevant documents during the development process, and it is difficult for users to see the software product before the development is completed.

4.2 Incremental method

When developing software using the incremental approach, the software product is designed, coded, integrated and tested as a series of incremental building blocks. Each building block consists of multiple modules that interact with each other and are capable of performing a specific function. Incremental development completes a high-quality release at each stage, and the latter stage does not make any modifications to the content of the previous stage, but only adds a new implementation of business functionality on the basis of the previous stage, known as incremental, until the last stage, which forms the final software product. Incremental development is just adding new things to the original. Compared to the waterfall approach, incremental development makes it possible to deliver and deploy useful software to the customer faster, although not all features have been included, and users can use the software earlier, while reducing the cost of adapting to changes in user requirements.

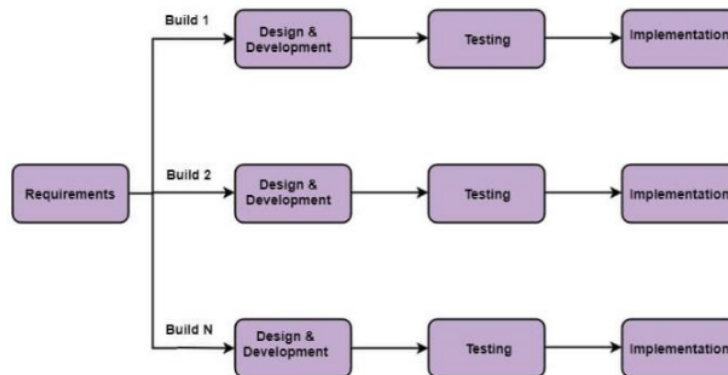


Figure 4-2 Incremental

4.3 Spiral method

The spiral method is often used in the early stages of software development when the requirements are not very clear, and is an incremental development method. Based on a prototype, it rotates along a spiral, with each turn going through the process of planning/risk analysis/implementation/evaluation and obtaining the corresponding new version, and then going through a number of spirals to obtain the final version.

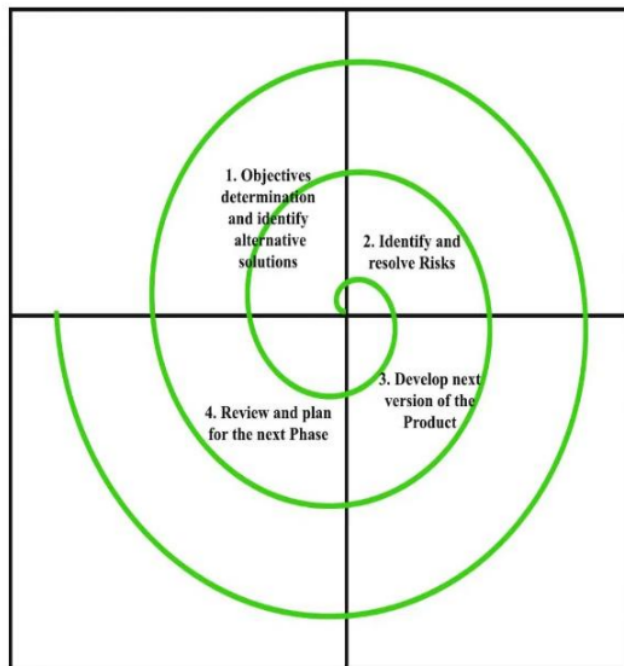


Figure 4-3 Spiral Method

The spiral method follows the spiral for a number of iterations, and the four quadrants in Figure 4-3 represent the following activities:

- (1) Developing a plan: defining software objectives, selecting an implementation plan, and clarifying project development constraints;
- (2) Risk analysis: analysing and evaluating the selected options and considering how to identify and clarify risks;
- (3) Implementation engineering: implement software development and validation;
- (4) Client assessment: evaluating the development work, suggesting corrections, and formulating next steps.

The Spiral Model is largely a risk-driven methodological system, since a risk assessment must first be performed before each phase and before the cycles that often occur. This approach is more demanding for software testing than the first two.

4.4 Agile Development Methods

Agile[31] is more like an idea than just a method, here is an example of the commonly used scrum, which is an iterative and incremental

approach to software development. The essence of agile development is to encourage team communication and value the role of people, the whole team communicates frequently during development to reduce errors caused by lack of communication and fully respect the value of people.

The development team completes the development of one or more iterable modules in sprints. A sprint is usually 2-4 weeks long, and the next sprint starts immediately after the previous one is finished, and the iterative modules are planned, analysed, coded, and tested within a single sprint. In scrum, requirements are documented in the form of user stories, which are composed in this simple form - "As a [persona], I [want to], [so that]." Decomposed into a single canonical behaviour of a system it becomes a user case. in other words, a user is a user action, a user case is a system behaviour, and a user story can correspond to a single user case or a combination of multiple user cases.

Flexibility is the most important advantage of Agile because it can respond quickly to changes. Agile involves face-to-face communication and collaboration between various cross-functional team members. Agile development requires frequent feedback to users and users can provide feedback during the development process. As a result, the final product will be maximally close to the users' needs. However, it is also important to be aware of the negative impact of this characteristic. Agile encourages users to continuously adjust their requirements during the development process, resulting in the deletion of some of the completed modules.

In this project, there is no development team, only one person for development, and the purpose of this project is not to design a powerful commercial software, but just a software that can satisfy the minimum feasibility of the experiment. Considering the actual situation of the project and the previous analysis of the development difficulty of each development method, the most suitable development method is to use the Agile thinking development method, which can develop a software containing the core process of shovel tooth inspection with a small amount of tasks.

Referring to the Scrum process for the development of this project:

- Collect and make user story from user requirements and record

it in product backlog.

- Refine user story and add to sprint backlog.
- Develop user story
- Test the functionality
- Back to step 2

Chapter5 Design

This section documents the software development and design process for a shovel tooth inspection system using YOLO v5. The software requirements are listed in the form of a USER STORY and a flow chart is used to show the functional flow of the test software. In this section, the author shows some of the requirements so that the reader can understand the purpose of testing the software more clearly and also draws a system flowchart with class diagrams to help the reader understand the functionality that the software has.

5.1 Requirement Analysis

The purpose of this test software is to detect the number of shovel teeth by using the target detection algorithm YOLO v5 on the electric shovel teeth, and to determine whether they have been detached or broken by comparing the detection results with the number of normal electric shovel teeth.

To better grasp the core requirements of the software, the following epub is listed:

- As a user, I want to see the camera screen in real time and be alerted in case of an incident.
- As a user, I want to set parameters such as camera brightness, resolution and other related settings such as photo storage path format.
- As a user, I want to set the conditions for the teeth alarm, such as the number of teeth to be removed.

Epics all contain multiple user stories, so the above epics are further split up for clarity:

The first epic, "As a user, I should be able to see the camera screen in real time and be alerted in case of an incident in time." , which can be divided into

- As a user, I want to see the camera feed.
- As a user, I want to receive accident warnings.
- As a user, I want to process the warning message.
- As a user, I want to adjust the camera settings. □
- As a user, I want to adjust the camera settings.
- As a user, I want to adjust the storage path.
- As a user, I want to adjust the alarm settings

These USER STORIES have clearly documented every user requirement point, which can then be recorded on the BACKLOG and implemented. In addition to this there are some epic, for example:

- As a user, I want to remotely view the current status of the operation and modify the current setup choices using my mobile phone or by logging into the website.
- As a user, I want to train my own algorithmic models and apply them to the software.

Epics such as these likewise document many user requirements, but do not affect the effectiveness of the minimal validation procedure, so they are not added in this project. The algorithmic models used in this project were generated directly from code files rather than programs.

5.2 system design

An overview of the design of the entire system, based on the requirements of the minimum viable product, can be illustrated using Flowchart 5-1:

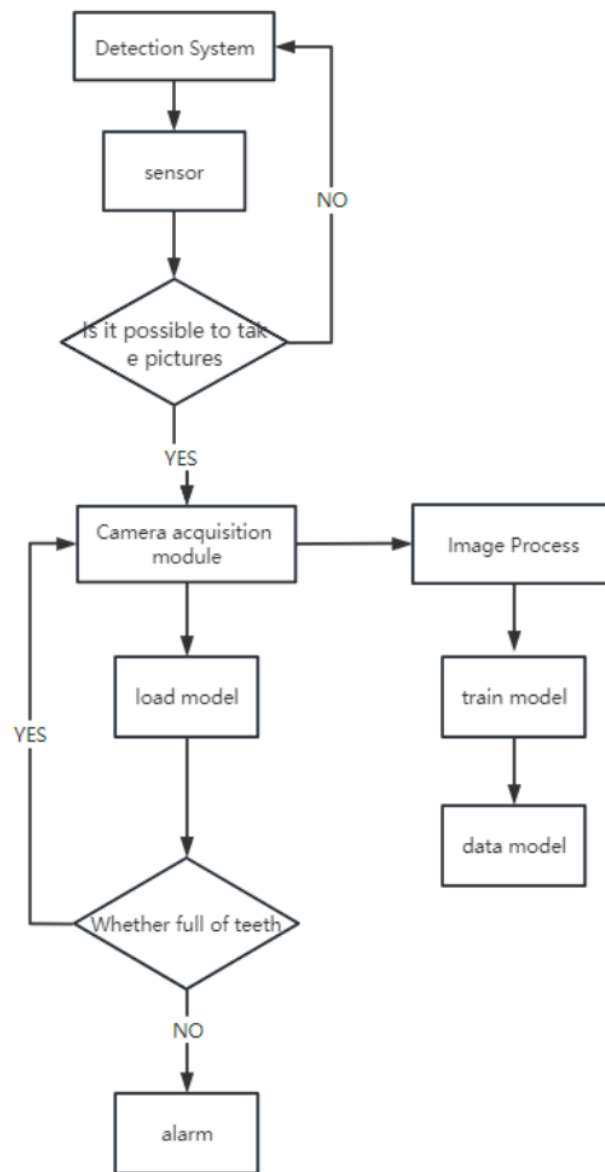


Figure 5-1 Flowchart

When running the Shovel Tooth Monitoring System, the first step needs to be the initialisation setup of the system, configure the industrial camera according to the site conditions, set up the parameters of the control port as well as the image file and the saving path of the image file, collect a large number of valid images for pre-processing and training the model, and then start to monitor

the bucket. When the computer receives the open bucket signal collected from the control terminal, it controls the industrial camera to automatically collect and store the current image to the specified path. Then the teeth detection module starts to read the image from the storage path, and the target detection algorithm detects the number of teeth, determines whether the number of teeth of the bucket to be detected is in accordance with the normal number, and displays the result on the main page of the system after the logical judgement is finished, and saves the detected result as a backup data. During the detection process, if the number of detected teeth is the same as the number of teeth of the actual electric shovel, it will judge that the teeth have not fallen off and wait for triggering the next opening signal to control the camera to collect pictures; if the number of detected buckets is less than the actual number, it will judge that the teeth are in trouble, and the system will control the alarm device in the cab to send out an alarm. Finally, the operator can choose the corresponding processing measures according to the output of the intelligent monitoring system of the shovel teeth, and the operator can choose the corresponding processing measures according to the output of the intelligent monitoring system of the shovel teeth.

Each step in the flowchart can be one or more classes, and a class diagram is used to summarise all the functions and requirements of the system, as shown in Figure 5-2:

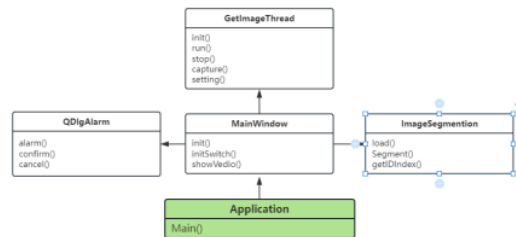


Figure 5-2 Class diagram

Chapter6 Implementation

This chapter deploys the software based on the previous requirements analysis, briefly describing the software, technology,

and hardware products used. Afterwards, the authors provide a brief discussion of some of the issues encountered during the design and implementation process so that the reader can have a clear understanding.

6.1 Resources

In order to realise the functionality required by the test software, a combination of software and hardware is required to complete the project. On the hardware side, magnetic switches, capture cards, cameras, transformers, desktop computers, laptops, wires, and network cables were needed; on the software side, sensor drivers, capture card drivers, camera SDK, camera demo programs, QT, YOLOv5, and related documentation manuals were needed. This was all used to help the project to be completed.

Hardware:

- Magnetic switches
- Capture card
- Cameras
- Transformers
- Desktop computers
- Laptops
- Cables
- network cables

Software:

- Sensor Driver
- Capture card driver
- Camera SDK and secondary development manuals
- Imager demo application
- QT and help files
- Official YOLOv5 package

In addition, the use of Microsoft excel was required to record the statistical results of the data for the final test. Further details of the use of the above resources are provided in the next subsections.

6.2 Hardware implementation

Camera is the most important hardware device in this software, this programme needs all the image data, all need to be collected

through the camera. The normal operation of the camera requires two wires, one is the data line, the camera through the network cable for data transmission, and the other is the power line, the camera needs 24V power supply, due to the internal circuitry of the electric shovel can not be accessed arbitrarily, and the electric shovel indoor only 220V power supply, so it is necessary to use a transformer, the power will be converted to access the camera.



Figure 6-1 Camera

Considering the project time and development difficulty, we directly use the camera demo programme to assist the development, and call the setup interface in the camera demo programme according to the camera's development manual to complete the camera's parameter adjustments, while the camera screen is directly passed into the main interface of the test programme using the camera SDK to render the image in the display space of QT.

The magnetic switch and the acquisition card are responsible for transmitting the trigger signal. When the electric shovel is working, it is not possible to keep the shovel teeth in a clearly visible state all the time, so the way to shoot at a special time ensures that the shovel teeth are clearly visible. By observing the shovel, we finally chose to shoot when the shovel is unloading the ore. This can be achieved by capturing the special movements of the operating lever inside the shovel.

Because the electric shovel used in the test is an older model, the internal information technology is not high, and can only use the combination of magnetic switch and capture card to capture the

signal. The principle of the magnetron switch is to detect the size of the magnetism to switch switch, so it is necessary to set some strong magnets on the driver's operating rod, but this largely interferes with the driver's operation, and then after the mine agreed to the capture card directly into the electric shovel internal circuit switch. This solves the problem of trigger time.

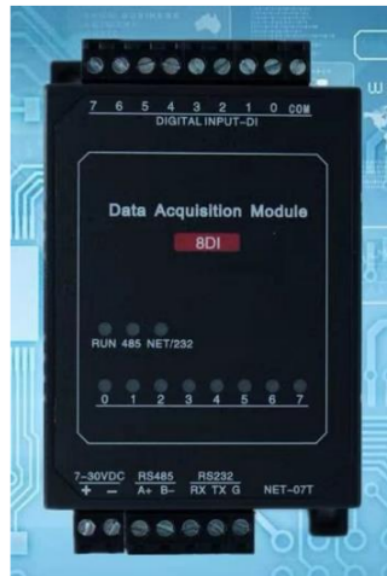


Figure 6-2 Capture Card

The capture card also uses a network interface to transmit data, and the capture card requires a computer port IP address and port number, which can be modified to achieve the communication function.

The hardware of the test programme consists of these two parts, i.e. the capture card and the camera, as well as the matching transformer, wires and other cables.

6.3 Software implementation

The YOLOv5 algorithm is one of the most important parts of the software's effectiveness, but the training process of the model requires a large amount of arithmetic, which cannot be met by a typical computer CPU, so the authors found another desktop computer with a GPU of 3090 and used the GPU instead of the CPU for training. In this process, the algorithm version of the GPU was

extremely demanding in terms of environment configuration, so the authors kept trying multiple python versions and combinations of cudn, cudnn and pytorch.

Of course the biggest problem during this project was not the algorithms, but the development of the camera part. Since the camera used a commercial camera with an extremely extensive SDK and development manual, it was difficult to read them and find out how to call the camera to transfer images. What the author didn't expect is that the camera's image acquisition time is not fixed, but dynamically calculated by the camera's exposure time, camera brightness and other camera information, so he had no choice but to find this part of the relevant content in the camera's development manual. When the camera calling and taking pictures are completed, and the picture is accessed to the software, a new problem is encountered. After the programme receives the signal and takes a picture for recognition, the front-end interface of the software will be stuck and display abnormally because there is only one process, the author puts the camera picture acquisition and the recognition processing of the image in two different processes to ensure the normal operation of the whole software. And when receiving the trigger signal, the camera acquisition of the image is not every time just right, which leads to if the test software only once recognition results as the basis for the algorithm recognition of the accuracy of the requirements of the high, so in order to reduce the occurrence of such false alarms, in the software's alarm logic is modified to a group as a unit of statistics, when a group of photographs of a ratio of less than a certain degree of warning, and increase the setting delay time of the trigger. And increase the delay time for setting the trigger.

In addition, the use of QT as the interface development for the project to reduce a lot of pressure, its good documentation support really helped a lot.

All in all, the implementation of this validation programme provides a wide range of knowledge for this kind of, which is a real development project, including the use of the QT framework, the use of commercial software SDKs and secondary development manuals, the application of algorithms and so on. In addition, there is still a lot of room for improvement in this software by not using a database to

store the data and applying it to such older models of electric shovels, etc., which could be continued to be explored on if there is time and money available in the future.

Chapter7 Results & Conclusion

In this section, the author will briefly describe the statistics of the validation software and the meaning of these data. The aim of the project was to develop a software program to replace a human being by using a camera as the "eye" of the program, in order to detect safety accidents involving the removal of shovel teeth in a timely manner, and so to simulate this process by building a minimum feasibility verification software and recording the number of detections to verify that the effect was achieved.

The electric shovel used for the test had a total of 5 shovel teeth. First of all, verify whether the software can meet the basic recognition requirements. The normal state of the electric shovel loading process recognition, a total of 20 photos, test results as shown in Table 7-1:

Number	0	1	2	3	4	5	SUM
times	0	0	0	0	0	20	20
percentages	0%	0%	0%	0%	0%	100%	100%

Table 7-1 Normal state electric shovel test results

From the data in the table, it can be seen that in 20 tests, the number of shovel teeth is detected as 5, which is consistent with the actual number of shovel teeth, proving that the software can identify the electric shovel in normal condition.

Secondly, it is verified whether the software can detect the occurrence of accidents of shovel teeth falling off. Because of the uncertainty of the safety production accident of shovel teeth falling off in the mines, we simulate the falling off of shovel teeth by using the tape winding method. Since the probability of two or more teeth falling off at the same time is extremely low according to the past records of mines, only the case of wrapping one shovel tooth was tested. The identification test of the loading process of the electric shovel with only one wrapped shovel tooth was conducted, and the results are shown in Table 7-2:

Number	0	1	2	3	4	5	SUM
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times	0	0	0	0	17	3	20
percentages	0%	0%	0%	0%	85%	15%	100%

Table 7-2 Electric Shovel Test Results for Wrapped Tapes

As can be seen from this data, the detection rate was 85% correct and the detection error rate was 15% in that test, and the error case was the successful identification of the entangled shovel teeth. As YOLOv5 uses colour photographs during training, there is some possibility of this simulation being recognised in itself. In the overall picture, the software also enables the detection of accidents.

Afterwards, the validation software was run on the electric shovel following the actual production for 3 hours, and a total of 311 image data were collected, and the test results are shown in Table 7-3:

Number	0	1	2	3	4	5	6	SUM
times	19	7	0	13	37	212	23	311
percentages	6.10%	2.25%	0%	4.18%	11.90%	68.16%	7.40%	100%

Table 7-3 Actual test 3 hours results

The accuracy of software recognition in this test was only 68.16%, which could not meet the demand of actual production. In order to improve the effect of the software, we analyse the image data collected on site and find that most of the images with the detection number of 0-3 are due to the influence of the camera and the operation of the shovel driver, which leads to the blurring of the collected pictures or the bucket is not included, and most of the images with the detection number of 4 and 6 are due to the ore residues or soil in the gap between the shovel teeth, which leads to the error in the detection of the teeth of the shovel.

Of course, when an accident really occurs, the number of teeth identified by the software must always be smaller than the normal value, so the judgement logic is adjusted not on the basis of a single occurrence of the effect, but on the basis of a combination of several consecutive photos, when there are three consecutive images of abnormal number of teeth, then trigger an alarm; and taking into account the previous fall situation in the mine and the effect of the test, the photos that are lower than the number of teeth of more than two are regarded as ineffective photos The photos with more than 2 teeth lower than the number of shovel teeth are regarded as invalid

photos, which are not counted in the statistics.

The field test is conducted again, still following the actual production run for 3 hours, a total of 289 pictures were collected, and the test results are shown in Table 7-4:

Number	0	1	2	3	4	5	6	SUM
times	29	0	0	6	10	209	35	289
percentages	10.03%	0%	0%	2.08%	3.46%	72.32%	12.11%	100%

Table 7-4 3-hour results of modified test

It is worth noting that although the accuracy of the data collected this time was still low, no alarms were raised during this run. Considering the above, the software is able to achieve the effect of detecting the safety accident of shovel teeth dislodging. However, this process does not only rely on the design of the software itself, but also adds part of the logic processing.

This proves that this method is feasible, but there are still many problems that can be improved. The hardware of this project mainly uses ordinary industrial cameras, so the tests are all conducted during the day. But in reality, the mine is working 24 hours a day, even at night it will work, but there is no light around the electric shovel at night in open pit mines, only the lamps of the electric shovel work lighting, which does not satisfy the conditions of taking pictures, so the image quality of the image captured by the ordinary camera is poor, but this situation is also easy to improve, it can be improved by using infrared cameras. But the infrared camera in the summer and other hot weather and may be interfered with, so the specific effect needs to be tested to know.

In addition, this test is only on one type of electric shovel, and the number of teeth of this electric shovel is small, for large-scale mines, this test is not accurate, for example, it is known that most of the large-scale coal mines in China use equipment with a number of teeth of more than 10 shovels, and ordinary industrial equipment can not even be captured in one camera to capture all of the teeth of this giant equipment, so it is necessary to use a wide-angle or similar technology to zoom the image. Therefore, it is necessary to use a wide-angle or similar technology to zoom in and out of the picture.

Also, the shovels used in this study are older, with more than 20 years of experience, and although there are many of them in use, they are not the same as the newest shovels being produced today,

so the researchers can look for new types of shovels to conduct experiments with, which may be easier to collect the data needed for the tests, and can be better applied to actual production.

Secondly, the algorithm used this time is not the latest algorithm, the focus of this project is on the development of the whole system, the algorithm is only a part of it, so later researchers can also use different algorithms for experiments and comparisons, but also the internal structure of the algorithm can be adjusted and optimised processing, so as to make it more in line with the environment in which it is used. This test focuses on verifying the feasibility of this approach, so the use of a laptop computer for the test, but for this large mechanical equipment in the engineering field, laptop and window system is not a good choice, you can use the smaller size of the device to deploy.

Chapter8 Reflection

This chapter will present some personal reflections on what I have learnt from carrying out the project, the problems I have actually encountered, the accidents that have occurred in the field, and so on.

The theme of this project is actually from a scientific research project that my teacher used to work on, although this accident seems to happen very few times, according to the past information of the mine where I tested it, on average, such an accident will only happen once a year, but the economic loss it causes is huge, the value of the machine that crushes the ore is over ten million dollars, and when there is a shovel tooth mixed with it, it will surely cause damage to it, even a simple repair will cost hundreds of thousands of dollars, and every time such an accident occurs, the whole mine has to stop production for repairs, and this indirect loss is up to millions, and with the increase in the size of the mine, this loss will be more and more, so I want to try to solve this problem through my knowledge of learning computers, so there is a theme for this project.

The first problem I faced in this project was that even decades old electric shovels have a complex internal structure and are mostly a combination of electrical systems and mechanical devices with little to no digitised data, so in the beginning it was a problem to capture

the right pictures, as mentioned in section 6.2 I tried to do this by observing the drivers operating habits and using magnetic switches and magnets for the operating levers. As mentioned in section 6.2, after observing the driver's operating habits, I tried to detect the position of the lever by means of a magnetic switch and a magnet for the lever, but the driver feedbacks that this will seriously affect the driver's operation, so in order to solve the problem, I can only communicate with the maintenance personnel of the electric shovel, and then I was told that there is a switch with a similar function inside the lever, and I can connect the device to this switch, which will solve the problem for us, and connecting the device to the internal switch can be more ready for the collection of signals, so I also communicated with the mining company. So again, we communicated with the mining company to allow us to do this.

During the software development of this project, I quickly learnt a lot of new technologies and experiences, such as the QT framework, calling the software SDK according to the secondary development manual of the commercial camera, and the acquisition of sensor parameters. I found that QT is very powerful, I can write the operation interface very quickly, and it can also support two languages python and C++. But there is a problem is that both the QT help file and the camera's secondary development manual are very complex, a lot of content, for the beginning of me, some can't start, but as time goes by, the content of the understanding of the gradual increase, I can gradually understand the logic of it, increased my own confidence. This is the first complete project I have ever worked on, and the experience and knowledge it has brought me makes me believe that I can persevere on this path of software development.

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GENERAL COMMENTS

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