Open-set (re-identification) recognition of pigs

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Declaration of own work

I declare that the work in this MSc dissertation was carried out in accordance with the requirements of the University's Regulations and Code of Practice for Research Degree Programmes and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

Wentao Gao and 06 / 03 / 2022

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1 Introduction

1.1 Motivations

With the rapid development of machine learning technology, machine learning has made great achievements in many fields such as image recognition and natural language processing, especially in the field of image recognition, machine learning technology is widely used in unmanned vehicles, face recognition, agriculture and animal husbandry and other applied research. Meanwhile, with the maturity of deep neural networks, convolutional neural networks and recurrent neural networks are increasingly used to solve practical problems, but both traditional machine learning methods and deep neural network algorithms require a large number of labelled samples during the training process, which poses a great limitation to the research work. Firstly, these labelled samples usually need to be manually labelled, which is costly, and secondly, new classes are constantly added in real scenarios, making it impractical to obtain all classes in the training process. In this paper, we propose an open-set identification method for pig identification in animal husbandry, which can not only classify the classes of pigs that existed in the closed set, but also accurately identify the classes of newly emerged pigs without any auxiliary information. Moreover, the Open-Set Recognition(OSR) method is closer to the reality of real scenarios in which new categories are constantly emerging.

1.2 Aims and Objectives

The research is guided by one goal which is recognize pig in open-set as a good performance . With this in mind, the aims and objectives can be broken down into the following objectives:

1. **Aims:**
   (a) To understand the main idea of recognizing pigs in a closed-set.
   (b) To construct evaluate a model that can recognize real-world pigs which are not in the dataset.
   (c) To increase understanding of open-set recognition
2. **Objectives:**
   (a) To summarise the main current methods of identifying pigs, and to interpret and import theories involving the main identification methods of this study.

(b) To summarise and analyse the methods for processing image samples, to provide an in-depth analysis of the methods for labelling samples and to discuss their limitations.

(c) To address the limitations of current recognition, an open-set approach to identifying pigs is proposed. Using an existing closed dataset of pigs, it is extended to allow the identification of emerging classes. The process of building the model does not require a lot of time and money to collect marker samples or even auxiliary information. Moreover, the Open Set Recognition (OSR) problem is closer to the reality of real scenarios where new classes are constantly emerging.

1.3 Pipeline

The pipeline of the overall pig recognition is shown in Figure 1.1.

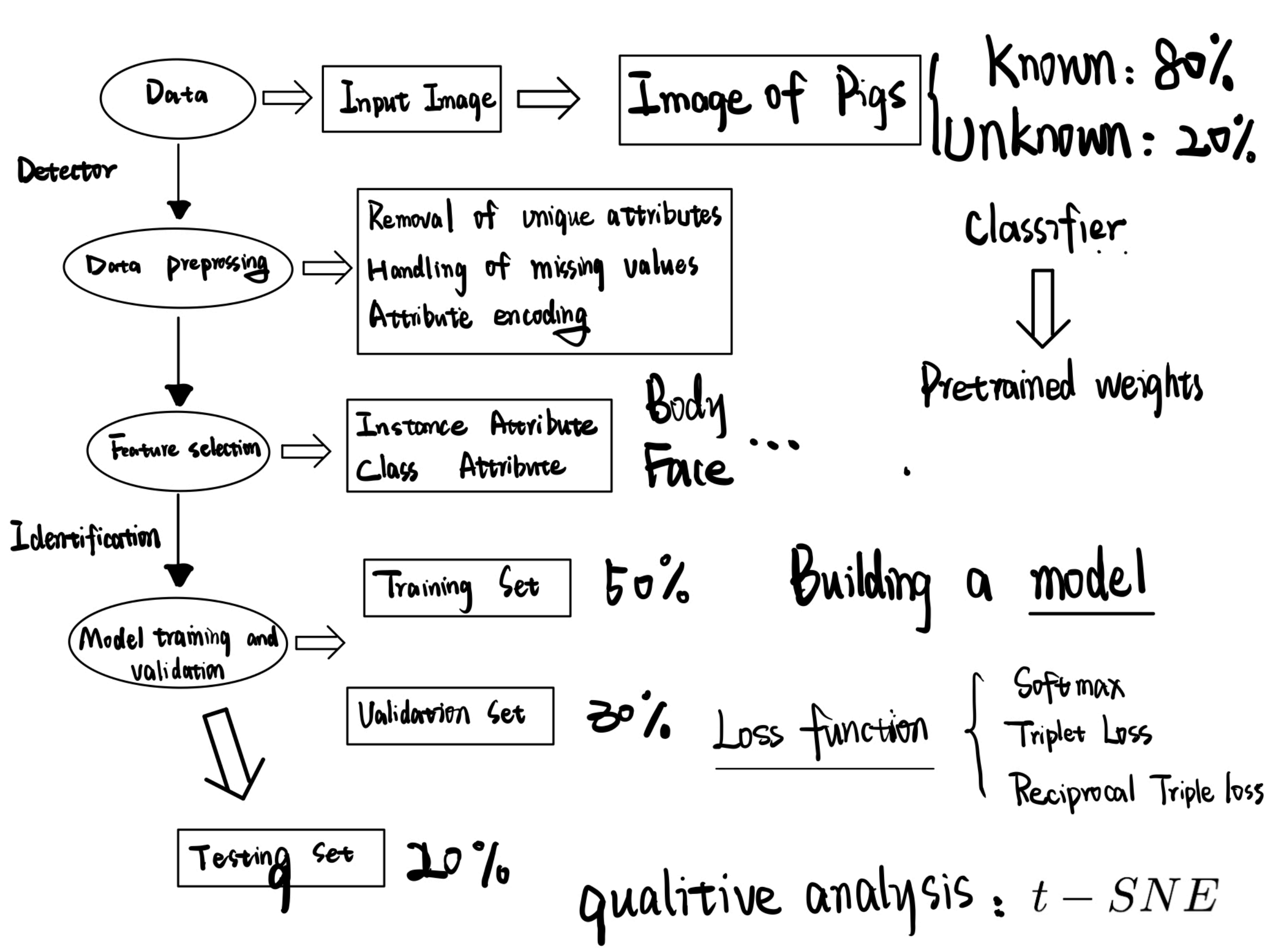

Figure 1.1: Pipeline of pig recognition

2 Literature Review

2.1 Pig recognition

Hansen *et al.* test this in a farm environment, on 10 individual pigs using three techniques adopted from the human face recognition literature: Fisherfaces, the VGG-Face pre-trained face convolutional neural network (CNN) model and the own CNN model that Hansen train using an artificially augmented data set [1]. The feature integration method is applied with the deep neural networks of DPN131, InceptionV3 and Xception networks by Wang *et al.* [2]. An algorithm for associating the head of each pig with its body was designed by Yang *et al.* and he also Proposed use of Faster R-CNN to locate and identify individual pigs in group pens [3]. To further the application of artificial intelligence techniques in agriculture Cang *et al.* propose an approach based on deep neural network to estimate the live weights of pigs in saw stalls [4]. A novel framework composed of computer vision algorithms, machine learning and deep learning techniques is proposed to offer a relatively low-cost and scalable solution of pig recognition by Marsot *et al.* [5]. Therefore, subject of Chen *et al.* was to develop a computer vision based approach that utilised a recurrent neural network-based deep learning algorithm to recognise pig enrichment engagement (EE) behaviours and preliminarily determine the preference to objects [6]. An improved ResNet model was proposed and applied to detect individual pigs based on deep learning knowledge by Song *et al.* [7].

However, local areas of moving animals are difficult to locate and require collaborative animal access to designated areas to obtain local images, which can involve human intervention and lead to complex image acquisition. Therefore, future identification of pigs will move towards holistic and open-set recognition. However, current holistic and open set based identification algorithms need to be greatly improved.

2.2 Object dection

Object detection is a computer technique for detecting a certain class of objects in images and videos. In addition to classification, it localises the object within the image. Kang *et al.*. propose a framework for object detection in videos, which consists of a novel tubelet proposal network to efficiently generate spatiotemporal proposals, and a Long Short-term Memory (LSTM) network that incorporates temporal information from Tubelet proposals for achieving high object detection accuracy in videos [8]. To advance object detection research in Earth Vision, also known as Earth Observation and Remote Sensing , Xia introduce a large-scale Dataset for Object deTection in Aerial images (DOTA) [9]. Due to the gap between the image classification and object detection Li *et al.* propose

DetNet which is a novel backbone network specifically designed for object detection [10]. Hu *et al.* propose an object relation module [11]. Zhao *et al.* provide a review on deep learning based object detection frameworks [12]. Given this period of rapid evolution, the aim of Liu *et al.* is to provide a comprehensive survey of the recent achievements in this field brought about by deep learning techniques [13]. To address these issues Cheng *et al.* propose a simple but effective method to train rotation-invariant and Fisher discriminative CNN models to further boost object detection performance [14]. In order to understand the main development status of object detection pipeline thoroughly and deeply Jiao *et al.* describe the benchmark datasets at first [15]. Wu *et al.* cover a variety of factors affecting the detection performance in detail, such as detector architectures, feature learning, proposal generation, sampling strategies, etc[16]. Liang *et al.* propose to exploit multiple related tasks for accurate multi-sensor 3D object detection[17].

The development of object detection and indeed the whole field of artificial intelligence is now largely data-driven. Open source datasets have become very rich thanks to the continuous efforts of academics. Some standard datasets have become benchmarks for competitive evaluation of model performance. However, in an era of expanding application scenarios and big data explosion, relatively few datasets with good labels are available. The importance of open set identification is thus self-evident.

2.3 Open-set recognition

Open set identification is to be able to identify both classes that have appeared in the training set and classes that have not appeared in the training set. In contrast, Yoshihashi *et al.* train networks for joint classification and reconstruction of input data [18]. A model based on Generative Adversarial Network (GAN), called OpenGAN is proposed to address the open-set recognition without manual intervention during the training process by Yang *et al.* [19]. Oza *et al.* propose a novel deep convolutional neural network (CNN) based multi-task learning approach for open-set visual recognition [20]. Schlachter *et al.* propose a method to use deep neural networks as end-to-end open-set classifiers [21]. Oza *et al.* propose an open-set recognition algorithm using class conditioned auto-encoders with novel training and testing methodology [22]. Liu *et al.* develop an integrated e Open Long-Tailed Recognition(OLTR) algorithm that maps an image to a feature space such that visual concepts can easily relate to each other based on a learned metric that respects the closed-world classification while acknowledging the novelty of the open world [23]. Liu *et al.* combines the random selection of a set of novel classes per episode, a loss that maximizes the posterior entropy for examples of those classes, and a new metric learning formulation based on the Mahalanobis distance [24]. Perera *et al.* propose two techniques to force class activations of open-set samples to be low [25]. For application of convolutional prototype network(CPN) in OSR Yang *et al.* propose two rejection rules for detecting different types of unknowns [26].

3 Impact Assessment and Risk Register

3.1 Impact Assessment

In this section, potential social, environmental, economic, political, legal or ethical implications will be considered.

3.1.1 Social

With the development of machine vision, bottlenecks in autonomous driving are being broken and the development of autonomous driving will gradually bring greater convenience to humans. Open set recognition is a way to bring machine vision technology closer to reality, recognising new categories and making decisions accordingly. It will have a long-lasting impact on the progress of society as a whole. But the contradictions will be more pronounced when it comes to labour employment. As machine learning can replace human beings in all kinds of mental work, the efficiency of society as a whole will be greatly improved, but at the same time some people will have to change their job type, even causing unemployment.

3.1.2 Environmental

The development of machine vision can have a better impact on the environment, such as air quality detection, new coronavirus density monitoring, plant growth monitoring, animal detection, etc. The development of open set recognition will allow these inspections to be more accurate and have a greater range of application, allowing for higher accuracy in practice.

However, there are some negative aspects to the environment. Trainning a model will have a high power consumption.Using the training cycle of several common large AI models as an example, the process was found to emit over 626,000 pounds of CO_2, almost five times the lifetime emissions of an average car (which includes the manufacturing process of the car itself).

3.1.3 Economic

Innovation plays a key role in both the creation of value and the improvement of living standards, which is why information technology systems since the birth of machine vision have created the first wave of value for people. But technological advances will lead to significant income inequalities.

The widespread use of Open Set Recognition will require significant capital investment, but the value it generates is more than that. Its application in a variety of fields can have significant economic benefits. For example, in this study, open set identification of pigs, there are many types of pigs and new categories may emerge as well, and each time a new category emerges, the closed set will need to be augmented with a dataset of the new category. Each time a new dataset is added, the closed set will need to be re-trained and the cost will continue to increase. Open set recognition, on the other hand, can be adaptive to new categories and has a high accuracy rate.

3.1.4 Legal and Ethical

Technology that relies on machines rather than humans is prone to problems at the legal and ethical level. It is inconclusive whether machines that rely on machine vision to make decisions will sacrifice the few to protect the many or the many to protect the few when faced with ethical issues; there is no nobility in life, nor is there a distinction based on numbers. And legally speaking, the laws vary greatly from region to region.

3.2 Risk Register

The table of risk register is shown below:

Category	Risk	Probability (1 = unlikely, 3 = likely)	Impact (1 = low, 3 = great)	Product (1-9)	Risk Assessment
Commercial	Lose Funding	1	3	3	Low
Computer	Computer get problems	1	3	3	Low
Software	Software licensing changes.(Pycharm et. al.)	1	2	2	Low
Software	Failure of applications software	2	1	2	Low
Equipment	Mains power failure to vital equipment.	1	3	3	Low
Equipment	Failure of telephone exchange system.	1	2	2	Low
Equipment	Serious damage or loss of use of a Data Centre	1	3	3	Low
Equipment	The training equipment out of work. Or the training time longer than setting time.	1	3	3	Low
Electric connetivity	Damage or failure to network infrastructure.	2	2	4	Medium
External constrains	Outsourced services(including Google Apps for Education, BlackboardLearn, Talis, Planon, andStarRez)	2	2	4	Medium
Resource	The poor dataset will lead to underfitting.	3	3	9	Great
Model	Final model have a poor result on the test.	3	3	9	Great

Figure 3.1: Table of risk register

4 Timeline

To increase the efficient of the dissertation achievement. A gantt timeline have been designed and shown below:

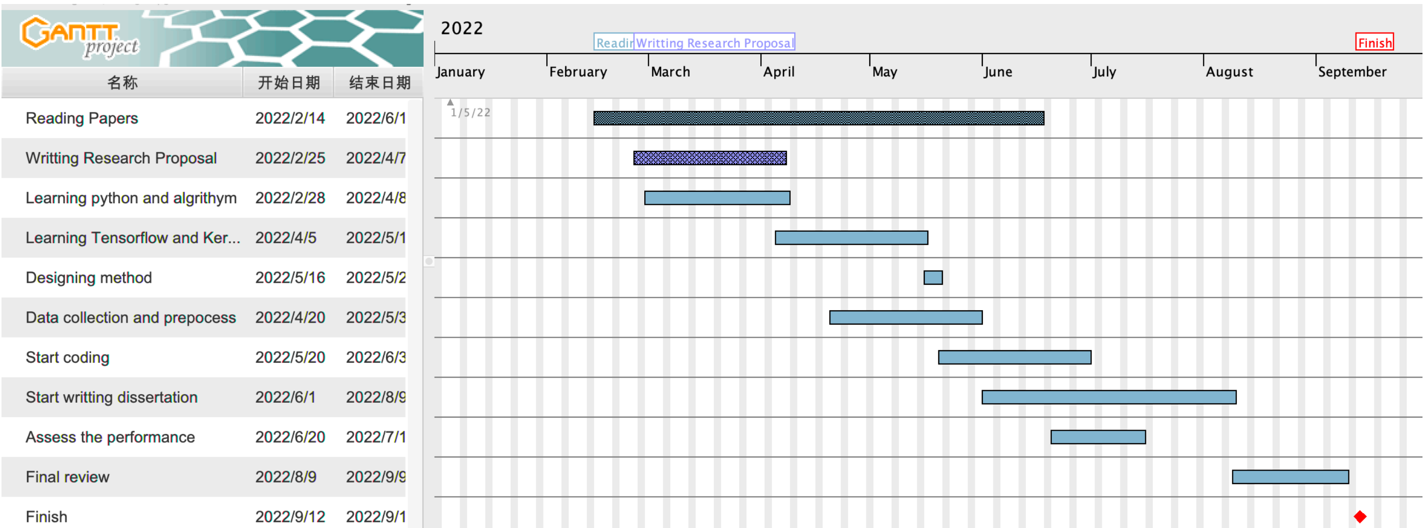

Figure 4.1: Timeline of dissertation plan

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