Towards Class-incremental Object Detection with Nearest Mean of Exemplars

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Abstract—Object detection has been widely used in the field of Internet, and deep learning plays a very important role in object detection. However, the existing object detection methods need to be trained in the static setting, which requires obtaining all the data at one time, and it does not support training in the way of class-incremental. In this paper, an object detection framework named class-incremental object detection (CIOD) is proposed. CIOD divides object detection into two stages. Firstly, the traditional OpenCV cascade classifier is improved in the object candidate box generation stage to meet the needs of class increment. Secondly, we use the concept of prototype vector on the basis of deep learning to train a classifier based on class-incremental to identify the generated object candidate box, so as to extract the real object box. A large number of experiments on CIOD have been carried out to verify that CIOD can detect the object in the way of class-incremental and can control the training time and memory capacity.

Index Terms—class-incremental, deep learning, object detection
I. INTRODUCTION

Artificial intelligence has received worldwide attention since it was first proposed in 1956, and the development of deep learning has pushed artificial intelligence to a climax [1]. In the ITS (Intelligent Transportation System), deep learning is widely used in vehicle recognition and perception, license plate recognition, intersection perception and other aspects [2], [3] [4]. In ASR (Automatic Speech Recognition), the combination of DNN (Deep Neural Networks) and GMM (Gaussian Mixture Model) greatly reduces the error rate of words and improves the effect of speech recognition [5]. In addition, news reading software pushes news to users through artificial intelligence technology, and the voice function of mobile phone makes robots more convenient for our lives [6], [7]. With the rapid development and wide application of deep learning, the research of image processing technology based on deep learning is becoming more and more popular [8], and its application has gradually developed from the classification task to the object detection task. Object detection is a popular direction in digital image processing, which is widely used in intelligent video surveillance system, robot navigation, aerospace, industrial detection and many other fields [9], [10], [11], [12], [13], [14]. It has important practical significance to reduce the consumption of human capital through object detection.

In the development of object detection, the traditional object detection method, OpenCV cascade classifier, is applied to the field of face recognition first [15]. Although the traditional object detection algorithm is the first to be applied, with the development of deep learning and the evolution of convolution neural network, the current object detection algorithm based on deep learning has gradually become the mainstream [16]. Object detection based on deep learning can be divided into two categories: two state detection and one state detection. The object detection algorithm of two
state first extracts the candidate box, and then makes the secondary correction based on the candidate box [17]. In 2014, Girsick R team proposed RCNN, RCNN started the application of deep learning to object detection, and it also an important representative of two stage in object detection algorithm [18]. The object detection algorithm of one state directly generates a detection window on the image, and its main representative algorithm is the object detection algorithm of the YOLO series [19]. Compared with the one stage and two stage object detection algorithms, the accuracy of two stage detection algorithm is high but the detection speed is slow, while the accuracy of one state detection algorithms is low but the speed is fast.

However, natural vision systems are inherently incremental, constantly introducing new visual information while preserving existing knowledge [20]. But the above mentioned deep learning based object detection algorithm can only be trained in static settings [21]. In static settings, objects of all classes are known in advance, and training data for all classes can be obtained at the same time [22]. When the training data of all class cannot arrive at the same time, the above object detection algorithm can only fuse the training data of the previous class and the new arriving class to retrain the new model. There are two major drawbacks to this approach. One is that a large amount of memory is needed to store the previous class data, and the other is that as the category continues to increase, the training time is getting longer [23], [24]. For human learning, there is no need to relearn the information of learned classes when performing object detection on newly arrived classes. We call this method class-incremental learning. Class-incremental object detection should satisfy three conditions: (1) It should be possible to train from different classes of data streams at different times. (2) It should provide the object detection model for the currently observed class at any time. (3) Compared to the number of classes currently seen, its computational requirements and memory
footprint should remain limited, or at least grow very slowly [25].

In this paper, we propose class-incremental object detection (CIOD). In CIOD, we divide object detection into two stages. The first stage is the generation of object candidate boxes (CBS) [16]. We improve the traditional OpenCV cascade classifier to meet the needs of class-incremental. Then, the improved OpenCV cascade classifier is used to train the CBS generation model to generate the CBS. In the second stage, we use the concept of prototype vector on the basis of deep learning to train a classifier based on class-incremental to identify the generated CBS, so as to filter out the CBS without the object. In the object detection, the object detection work can be completed by performing the CBS extraction and the CBS identification on the detected image.

The innovations of CIOD are as follows:

1) The traditional object detection algorithm is combined with deep learning to improve the accuracy of object detection.

2) Compared with the existing object detection algorithm, it realizes the object detection based on class-incremental, which makes the training time and memory capacity controllable.

The rest of this paper is organized as follows: related work is discussed in Section II, and the framework and work process of CIOD in Section III. We describe the details of CIOD algorithm in Section IV. Experiments to validate our methods are analyzed in Section V. Finally, we conclude this paper in Section VI.

II. RELATED WORK

With the wide application of computer vision and the rapid development of deep learning, the research of object detection based on image processing technology of deep learning is becoming
more and more popular. Researchers have done a lot of relevant research on it, and have made important achievements in military object detection, intelligent transportation system and other fields [26], [27], [28]. At present, object detection algorithms are roughly divided into two categories. One is the traditional object detection algorithm. The other is object detection algorithm based on deep learning. In the traditional object detection algorithm, the cascade classifier is more representative. Firstly, it uses different size, different aspect ratio of sliding window to traverse the image for region selection, and then uses Haar, HOG + SVM for feature extraction, and finally uses classifier to classify the region [15], [29]. There are two main problems in this kind of algorithm: (1) the region selection strategy based on sliding window is not targeted, which is easy to cause window redundancy. (2) the features of manual design are not very robust to the change of diversity, which is easy to cause misunderstanding [30]. With the development of deep learning, the current object detection algorithm based on deep learning has gradually become the mainstream.

The object detection algorithm based on deep learning can also be divided into two categories: two state object detection and one state object detection. In 2014, the Girshick R team proposed RCNN, which started the application of deep learning to object detection, and it is also the representative work of two state object detection algorithm [18]. The RCNN object detection algorithm in Pascal VOC dataset is 18.6% higher than the traditional object detection algorithm. Subsequently, the Girshick R team optimized the RCNN and proposed Fast RCNN [31] and Faster RCNN [32]. Compared with RCNN, Faster RCNN adopts the concept of region proposal networks, uses neural network learning to generate candidate regions, and merges two blades of two state into the same network, which greatly reduces the parameter amount and prediction time, and improves the speed and accuracy of prediction. In 2017, Mask RCNN was proposed, which can complete two
state of object detection and semantic segmentation at the same time, and its performance has also improved significantly [33]. The two state object detection pursues the accuracy of object detection, which is more tolerant in time, and it is difficult to achieve the expected results for some processing results with high real-time requirements. In order to solve the problem of two state object detection algorithm, a new type of object detection algorithm named one state object detection algorithm is proposed. Compared with the accuracy of object detection, one state algorithm pays more attention to the time of object detection. They mainly include YOLO series and SDD. In 2015, Joseph and Girshick proposed the YOLO V1 object detection algorithm, which is the first integrated convolution network detection algorithm, effectively improving the speed based on convolution neural network [19]. In the same year, Weiliu put forward SSD object detection algorithm. Compared with YOLO V1, SSD adopts the multi reference window technology in RPN (Region Proposal Network) and proposes to detect on multi-resolution feature map, which not only improves the speed of object detection but also improves the accuracy [34]. However, the follow-up YOLO team put forward YOLO V2 [35] and YOLO V3 [36] on the basis of YOLO V1 surpassed SSD in speed and accuracy of object detection.

Although the object detection algorithm is developing well, the existing object detection algorithm still does not solve the class-incremental problem. On the class-incremental problem, we mainly study the classification problem instead of the object detection problem [37]. There are three common algorithms for classification: (1) the SOINN (Self-Organizing Incremental Neural Network) is a two-layer neural network based on competitive learning. The first layer of the network receives the original data input and generates the prototype neurons adaptively in an online way to represent the input data. These nodes and their connections reflect the distribution of the original data [38].
The second layer calculates the distance between classes and within classes of the original data according to the output of the first layer, and then runs the SOINN algorithm again to stabilize the learning results. Its increment is mainly reflected in its ability to find new patterns in data flow and learn, which will not affect the previous learning results while learning, and is suitable for all kinds of unsupervised learning algorithms. However, the stability of separating overlapping clusters and facing different input sequences needs to be improved [39]. (2) The EM-MDP (Episodic Memory Markov Decision Process) based on the idea of SDM (Sparse Distributed Memory) and ART (Adaptive Resonance Theory) for incremental learning of episodic memory sequences. During the learning process, multiple neurons can be activated at the same time, and each neuron can be regarded as a representative of a similar kind of perception. Compared with SOINN, this method has good environmental adaptability [40]. (3) For incremental learning combined with deep learning, people try to train classifiers by using random gradient descent optimization from the incremental data stream of class, which leads to a sharp decline in classification accuracy, which is called catastrophic forgetting or catastrophic interference [41]. In general, the existing incremental learning algorithms have the following two disadvantages to varying degrees: on the one hand, due to the lack of control over the expected risk of the entire exemplar sets, the algorithm is easy to over-match the training data; on the other hand, due to lack of The forgetting elimination mechanism that has a choice of training data greatly affects the classification accuracy [42].

In this paper, we propose an object detection method based on class-incremental. In this approach, we divide the object detection into two stages. First, the traditional OpenCV cascade classifier is improved for the generation of CBS. Then, on the basis of deep learning, the prototype vectors of each class are extracted, and the candidate boxes are filtered by the matching degree
between the prototype vectors and the feature vectors of the candidate boxes to complete the object detection work.

III. THE DESIGN OF CIOD

In this section, we first explain the overall framework of CIOD. Then it describes the CIOD workflow, including how to generate object candidate boxes in a class-incremental manner, and how to filter candidate boxes by class-incremental to preserve the true object position.

We provide a method of object detection for class-incremental (CIOD), which divides the positioning into training and testing. The training phase includes the training of the candidate box generation model (CBGM) and the training of the candidate box identification model (CBIM).

As shown in FIG. 1, in the CIOD framework, the candidate box generation model (CBGM) and the candidate box identification model (CBIM) are trained first. We use OpenCV cascade classifier as CBGM to extract CBS. OpenCV cascade classifier is a traditional object detection algorithm, which has achieved good results in face localization. However, because of its high misunderstanding
rate in the face of complex object detection, a large number of areas without objects will be found at the same time of finding out the real objects. As a result, there are not only real object areas but also non object areas in CBS. Therefore, it is necessary to use CBIM to filter the CBS.

We refer to the concept of the exemplar sets and the prototype vector to generate the CBIM, and the CBS are identified one by one. When training the CBIM, the core is to optimize the exemplar sets selection by continuously adjusting the feature extraction model parameters, and then select a certain amount of exemplar sets for each class. In this paper, each exemplar sets represents the core data set that best represents the data of this class, and the mean value of the feature vector of the exemplar sets is closest to the mean value of the feature vector of all the data of this class. We call the mean of the feature vector of each class of exemplar sets the prototype vectors of this class.

During test, the CBS is first extracted from the test image by using the CBGM, and then the feature vector is extracted from the CBS. By comparing the distance between the feature vector and the prototype vector of each type of CBS, we can determine whether the CBS contains objects and the types of objects, so as to filter the CBS.

Two models are used in CIOD, respectively, the candidate box generation model (CBGM) and the candidate box identification model (CBIM). Unlike the traditional generation model and the identification model, both models are based on class-incremental, which is the core of this paper. Section IV will introduce the details of this CBGM and model CBIM.

IV. DETAILS OF CIOD

In CIOD, CBGM and CBIM are used respectively for the extraction of CBS and the screening of CBS. Unlike traditional generation models and authentication models, both models are based on class-incremental. This section mainly introduces the implementation of CBGM and CBIM based on
A. The Implementation of CBGM based on Class-Incremental

We use OpenCV cascade classifier as CBGM. OpenCV cascade classifier is a relatively traditional object detection algorithm, and its core is AdaBoost algorithm. The reason for choosing the OpenCV cascade classifier to train the CBGM is that it is faster than the current deep learning based object detection algorithm, such as the Fast-RCNN series and the YOLO series. More importantly, when expanding the positioning of new classes, the deep learning based object detection algorithm needs to retrain the new class data with the previous class data. This method needs to save the training data of the previous class, and the memory consumption is large, and the training time will also increase. The OpenCV cascading classifier generates an XML feature document after training, so it is very convenient to extend the positioning of the new class. It only needs to merge the XML feature document generated by the new class with the previous XML feature document, without saving the data of the previous class. It saves a lot of memory, and the previous class does not need repeated training, which shortens the training time.

The OpenCV cascade classifier consists of several strong classifiers connected in series, each strong classifier consisting of several weak classifiers connected in parallel. In this structure, the Haar feature of the detection window is first extracted. The Haar feature, also known as the Haar-like feature, is a simple and efficient image feature based on the similar intensity difference Haar wavelet of the rectangular region. Haar features are characterized by high class variability, low class variability, multi-scale invariance, and high computational efficiency. They are very suitable for extracting detection window features in object detection. After the Haar eigenvalues are calculated, each weak classifier independently determines whether the detection window is a target according to
the calculated Haar feature. Each strong classifier synthesizes the judgment of the weak classifier to make the final judgment on the detection window. Only when all the strong classifiers consider the detection window as the object, can the detection window be regarded as a CBS. Otherwise, the detection window is rejected.

Fig. 2: OpenCV Cascading Classifier Structure

OpenCV cascade classifier has higher recall rate and lower precise rate. A higher recall rate means that the object is more likely to be detected, while a lower precise rate means that non-object can also be detected as an object. So in order to make up for the shortcomings of the OpenCV cascade classifier in this respect, we introduce a template matching method. The principle of template matching is to find the best matching part of another template image in one image. Here, we perform template matching on the CBS generated by the OpenCV cascade classifier, which can alleviate the problem of lower precise rate caused by the OpenCV cascade classifier. There are 6 matching methods for template matching, which are squared difference matching, normalized
squared difference matching, correlation matching, normalized correlation matching, correlation coefficient matching, and normalized correlation coefficient matching. In general, with simple matching (squared difference matching) to more complex matching (normalized correlation coefficient matching), the matching becomes more and more accurate, and the computing resources required are also larger and larger [43].

Here, we use template matching to match a class of objects. Over-precision matching improves the precise rate but also filters out many positive samples, reducing the recall rate.

Based on this, we use the normalized flat difference matching in template matching, and the matching formula is:

$$ R_{sq} = \frac{\Sigma_{x',y'}[T(x',y') - I(x + x', y + y')]^2}{\Sigma_{x',y'}T(x',y')^2, \Sigma_{x',y'}I(x + x', y + y')^2} $$

(1)

Where $T$ denotes a template image, $I$ denotes a matched image, $R_{sq}$ denotes a matching result, and $R_{sq} = 0$ is a best match. $x', y'$ represents the coordinates of the pixel value of the template image, and $x, y$ represents the coordinates of the upper left corner of the matched image.

Definition 1: the template set $TS = \{T_1, T_2, ..., T_i\}$, $T_i$ represents the template image of the class $i$.

Template matching is applied to candidate box generation, and the specific algorithm is as follows:

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**Algorithm 1** Object candidate box generation algorithm

**Input:** IMG, TS, TH  // TH is the threshold value of template matching

**Output:** CBS

1: List CBS, Temp_CBS  
2: Temp_CBS ← OCV.cc(IMG)  // IMG generates CBS through the OpenCV cascade classifier
3: For CB in Temp_CBS
4: Standardized CB size to 50 * 50 and turn CB to 64 grayscale
5: For T in TS
6: Standardized T size to 50 * 50 and turn T to 64 grayscale
7:        Match $T$ and $CB$ to get difference value($R$)
8:        If $R < TH$
9:            $CBS += CB$, then break;
10       End if
11       End for
12       End for
13       Return $CBS$

In algorithm 1, firstly, the CBS is generated by OpenCV cascade classifier, then the size of the CBS and template image is reduced to 50 * 50, and the reduced image is simplified to 64 gray level. Finally, the difference value between the CBS and the template image is calculated, and filter out CBS that differs too much from the template. Through this algorithm, the CBS is further screened and improves the precise rate in the CBS. Finally, the remaining CBS are classified accurately through the CBIM.

B. The Implementation of CBIM based on Class-Incremental

The CBGM in this paper is different from the mainstream deep learning based classifier, which does not need to rely on static setting. CBIM is a strategy for learning classifiers and a feature representation simultaneously based on a stream of training data that comes in class-incremental form [26]. The specific framework is shown in Fig. 3:
The CBIM consists of two parts, training and classification. During training, CBIM uses an incremental learning strategy to deal with the problem of various types of data arriving in batches. Whenever new class data arrives, CBIM extracts examples from the new class through feature extraction model, and then adds the examples to the exemplar sets. The feature extraction model also adjusts its network parameters according to the information in the new data. The constant adjustment of the feature extraction model is the key to its ability to learn new types of knowledge (see B.1 for training and updating of the feature extraction model). For classification, the classification of the CBIM depends on the exemplar sets for each class selected in the training. First, the prototype vector of each class is extracted according to the exemplar sets of each class, and then the feature vector is extracted from the classified image. Finally, the distance between the feature vector of the image to be classified and each type of prototype vector is calculated. Sort by distance (see B.2 for details).

1) THE training of CBIM

Whenever CBIM learns data for a new class, the parameters of the feature vector extractor and the exemplar sets are updated. CNN can be used for feature extraction and classification. First extract the feature vector \((\varphi: X \rightarrow R^d, \text{weights } w_1, w_2, ..., w_t \in R^d)\), it is worth noting that we normalize all the extracted feature vectors to enable any operation). Then it uses the sigmoid function to classify. The resulting network outputs are, for any class \(y = 1, \ldots, t\),

\[
g_y(x_i) = \frac{\exp(w_y^T \varphi(x))}{1 + \exp(w_y^T \varphi(x))}
\] (2)

However, in CBIM, the classification of CNN only mentions the update of parameters in CNN, not the real classification. We use CNN as a feature extraction model. We define the parameters in the CNN as \(\theta\), which includes some fixed parameters and variable weights.

The update of the feature extraction model parameters is different from the update of the
parameters in the ordinary CNN network. When we calculate the loss function, we not only consider the classification loss function of the new class, but also introduce the distillation loss function of the previous class. The purpose is to make the CNN learn not to cause catastrophic forgetting of the learned knowledge.

Definition 2. For new class classification loss function \( \text{loss}_{\text{classification}} \), the distillation loss function of previous class \( \text{loss}_{\text{distillation}} \) and total loss function \( \text{loss}_{\text{total}} \) satisfies:

\[
\text{loss}_{\text{classify}} = - \sum_{(x_i,y_i)} \sum_{y=t+1}^{s} \delta_{y=y_i} \log(g_y(x_i)) + \delta_{y\neq y_i} \log(1 - g_y(x_i)) 
\]

(3)

\[
\text{loss}_{\text{distillation}} = - \sum_{(x_i,y_i)} \sum_{y=t+1}^{s} q_i^y \log(g_y(x_i)) + (1 - q_i^y) \log(1 - g_y(x_i))
\]

(4)

\[
\text{loss}_{\text{total}} = \text{loss}_{\text{classify}} + \text{loss}_{\text{distillation}}
\]

(5)

Where \( q_i^y \) represents the classification of previous classes before the parameter update. The update of the feature extraction model parameters \( \theta \) is as shown in Algorithm 2:

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**Algorithm 2**

The update of \( \theta \)

**Input:** \( D_{t+1}, \ldots, D_s \) // training examples in previous sets

**Output:** \( \theta \)

**Require:** \( ES=\{E_1, E_2, \ldots, E_t\} \) // current exemplar sets

**Require:** \( \theta \) \hspace{1cm} // current \( \theta \)

1: \( D \leftarrow (D_{t+1}, \ldots, D_s) \cup ES \)

2: \textbf{For} \( y = 1,2, \ldots, t \) \textbf{do}

3: \hspace{1cm} \( q_i^y \leftarrow g_y(x_i) \quad x_i \in D \)

4: \hspace{1cm} \textbf{End for} |

5: Training network with \( \text{loss}_{\text{total}} \) for \( D \)

6: \textbf{Return} \( \theta \)

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In Algorithm 2, first, the data set is extended, and the expanded data set is composed of the data of the new class and the stored exemplar sets of the previous class. Next, evaluate the current network for the stored exemplar sets of previous class and store the results of the network output. Finally, the network parameters are updated by minimizing a loss function that for each new image
encourages the network to output the correct class indicator for new classes (classification loss), and reproduce the scores stored in the previous step (distillation loss) for previous classes.

In training, in addition to constantly adjusting the parameters of the feature extraction model, the update of the exemplar sets is also very important. As new classes are added, the exemplar sets will grow larger and more memory will be required. In order to save memory, it is necessary to update the existing exemplar sets. The updated principle is that when the memory is fixed at $MC$, the old classes are $1, 2, \ldots, t$, and the new classes $t + 1, \ldots, s$ are added. The number of examples sets for the new class is $MC / s$. The number of examples in each class of the previous class is updated from $MC / t$ to $MC / s$. The training process of CBIM is shown in Algorithm 3:

**Algorithm 3** the training of CBIM

Input: $D_{t+1}, \ldots, D_s$  // training examples in previous sets  
Input: $MC$  
Output: $ES, FEM$  // $FEM$: feature extraction model  
Require: $ES=\{E_1, E_2, \ldots, E_t\}$  
Require: $\theta$  
Require current feature function $\varphi: X \rightarrow R^d$  

1: $\theta \leftarrow$ UPDATEPARAMETERS($D_{t+1}, \ldots, D_s, ES, \theta$)  
2: $n \leftarrow MC / s$  
3: For $y = 1, 2, \ldots, t$ do  
4: $E_i \leftarrow (e_1, e_2, \ldots, e_n)$  
5: End for  
6: For $y = t + 1, \ldots, s$ do  
7: $\mu \leftarrow \frac{1}{num_{new, data}} \sum_{x \in X} \varphi(x)$  // mean value of class feature vector  
8: For $k = 1, 2, \ldots, n$ do  
9: $e_v \leftarrow \text{argmin} |\mu - \frac{1}{n} [\varphi(x) + \sum_{i=1}^{t-1} \varphi(e_i)]|$  
10: End for  
11: $E_{t+1} \leftarrow (e_1, e_2, \ldots, e_n)$  
12: End for  
13: $ES = ES \cup E_{t+1} \cup \ldots \cup E_s$  
14: Return $ES, FEM$
In Algorithm 3, first, the parameters in the feature extraction model are updated. For the detailed update process, it can see Algorithm 2. Second, update the exemplar sets. For the previous classes, each class directly retains the first \( n \) exemplar. For new class, add exemplar to the exemplar sets one by one until \( n \) exemplar are added. When adding, we should try to ensure that the mean of the exemplar sets is closest to the mean value of class feature vector, and sort the exemplar according to the order in which the exemplars are added. Finally, the exemplar sets of the new class are fused with the exemplar sets of the previous class to form exemplar sets, and the fused exemplar sets and the updated model are returned.

2) THE classification of CBIM

The classification of CBIM uses the NME (nearest-mean-of-exemplars) algorithm. For a general multi-classifier classifier, the classification prediction rule is equivalent to the use of a linear classifier with non-linear feature map \( \phi \) and weight vectors \( w_1, w_2, \ldots, w_t \). While in class-incremental learning, separating \( \phi \) from weights \( w_1, w_2, \ldots, w_t \) can lead to catastrophic forgetting. Therefore, the general multi-classifier classifier is not suitable for class-incremental learning. The NME algorithm is chosen because it does not have a decoupling weight vector. When the feature representation changes, its weight is automatically updated, which makes the classifier more robust. The specific process of CBIM classification can refer to algorithm 4.

![Algorithm 4](image-url)
To predict the category ($y$) of the image to be classified ($TI$), the prototype vectors of the known classes are calculated first.

Definition 3: \[ PVS = \{PV_1, PV_2, ..., PV_i\}, PV_i = \frac{1}{|E_i|} \sum_{e \in E_i} \phi(e), \] where $PV_i$ represents the average feature vector of the instance set of class $i$, which is called the prototype vector ($PV$) of class $i$, $E_i$ represents the instance set of class $i$, $\phi(e)$ represent extracting feature vectors from instances $e$.

Then the feature vector of the image to be classified is extracted, and the most similar prototype is used to label the image to be classified.

Definition 4: \[ T_C distance = \{TC_1, TC_2, ..., TC_i\}, TC_i = |\phi(TI) - PV_i|, \] where $TC_i$ represents the distance between the feature vector of the image to be classified and the prototype vector of the class $i$, and $\text{argmin}(T_C distance)$ represents the minimum value in $T_C distance$, and $\text{argmin}_{2\text{th}}(T_C distance)$ represents the second smallest value in $T_C distance$.

To reduce the rate of misunderstanding of the CBS, we set the threshold value of $max\_distance$ manually. If $\text{argmin}_{2\text{th}}(T_C distance) - \text{argmin}(T_C distance)$ is less than $ax\_distance$, the image to be classified is not considered to belong to any known category. Otherwise, the image will be classified as the class corresponding to the minimum distance in $T_C distance$. The inspiration for this setting comes from our belief that the distance between an object with high classification accuracy and its corresponding category should be significantly different from the distance between the object and its non-corresponding category. When this gap is not
obvious, we think that the object may not belong to any one of all the trained categories.

The selection of the average vector as the prototype vector is inspired by the nearest mean classifier [44], which uses a fixed feature representation in incremental learning. In the setting of class-incremental, we can't get the real mean value of a class of data, because we can't store all the training data, otherwise it violates the original intention of class-incremental learning, so we use a certain number of sample set average value, which is closest to the real mean value.

C. The Industrial Applications based on CIOD

Target detection technology based on artificial intelligence is widely used in industrial detection, medical assistance diagnosis, intelligent video surveillance, robot navigation, aerospace and many other fields. Target detection can reduce the consumption of human capital, which has important practical significance. In addition, target detection is an important basic algorithm in the field of pan-identity recognition, and it plays an important role in subsequent crowd counting, instance segmentation, and face recognition.

In the field of industrial inspection, unmanned quality inspection technology based on target detection can effectively solve the problems of high professionalism, difficulty in recruiting, and lack of manpower in the quality inspection process for a long time. EL quality inspection products for polycrystalline cells and components based on target detection have a single cell recognition accuracy of more than 99%, and a component recognition accuracy of more than 95%. This effectively solves the decline in accuracy of manual recognition due to visual fatigue, and improves recognition The precision reduces labor costs at the same time. The assisted diagnosis method for skin diseases based on target detection can automatically mark the diseased parts in the skin disease image to assist the doctor in diagnosis, it can automatically mark the range of malignant skin tumors
and assist the doctor in determining the range of surgical resection of the tumor, making the scope of surgery more accurate and the wound smaller. Industrial parts statistics based on target detection can detect the total number of parts in the field of view, obtain information such as the number and category of the target, and send out an alarm when the number and category are different from the setting. The application of target detection in the industrial field as shown in Fig. 4.

![Fig. 4: Application of target detection in the industrial field](image)

In practical industrial applications, it is often difficult to obtain all categories of data at once. CIOD can achieve target detection of known categories without repeating training on the trained data when the data arrives in batches by category. In medical assisted diagnosis, we cooperated with hospital dermatologists and based on real data (dermoscopic images of demodicosis and flat warts), we proposed the LLTO detection method for lesions. LLTO can not only detect a single lesion, but also achieved good results in the detection of multiple lesions. In clinical diagnosis, the accuracy of lesion detection can be more than 80% accurate, which can assist doctors in diagnosing diseases.
CIOD can maintain the recognition accuracy of various skin diseases when the types of skin diseases increase (such as: increasing seborrheic keratosis dermoscopy data).

V. EXPERIMENTS

In this paper, the CIOD method is proposed, which transforms the traditional OpenCV cascade classifier into a CBGM based on class-incremental, and combines with the CBIM based on class-incremental to achieve class-incremental based object detection. In order to verify the effectiveness of CIOD, we have carried out a series of experiments. This section mainly tests the validity of class-incremental object detection, the time and space consumption of class-incremental object detection, and discusses the influence factors of class-incremental object detection.

A. Experimental Data and Evaluation Indexes

We are the experimental data from the daily collection of life photos and online images. We mainly detect the face, cat face, eyes and other objects. We collect 800 pieces of data for each category, 500 of which are used for training and 300 for testing. Our evaluation indexes for the experiment mainly include the following aspects:

1) Intersection over Union (\textit{IOU}): we define the area of the predicted border as $CB_{predict}$, and the area of the real border as $CB_{trust}$. As shown in Formula 6, \textit{IOU} calculates the ratio of the intersection and union of the predicted border and the real border.

$$IOU = \frac{CB_{trust} \cap CB_{predict}}{CB_{trust} \cup CB_{predict}}$$ (6)

2) The precise rate (\textit{PR}) is for our prediction results. It shows how many of the predicted object boxes are real object boxes. Recall rate (\textit{RC}). \textit{RC} is for our original object, it means how many objects in the sample are correctly detected.

3) Accuracy (\textit{AC}). We define this test image which \textit{PR} is 100% and \textit{RC} is 100% as \textit{FC}, \textit{AC}
is defined as follows:

\[
AC = \frac{Num_{FC}}{Num_{total}}
\]

(7)

Where \(Num_{FC}\) represent the number of \(FC\), and \(Num_{total}\) represent the total number of test images.

**B. Object Detection Effect Display**

In this experiment, we first use 500 face data and 1500 background images (daily pictures without objects) to train a class of object detection model that can be used for face detection, and then based on a class of object detection model, we add data from 500 eyes to train for detection two class of object detection models for faces and eyes. Finally, on the basis of the two class of object detection models, 500 cat face data are added to train three class of object detection models for detecting human faces, eyes, and cat faces. Figures 5, 6, and 7 show the detection effects of three class of object detection models on human faces, eyes, and cat faces, respectively.
As shown in Fig. 5, Fig. 6 and Fig 7, the upper row of the figure shows the effect of CIOD based on class-incremental object detection. The red box represents the true position of the object, and the green box represents the position of the object predicted by CIOD. The figure shows the Intersection over Union (\( IOU \)) of the real location of the object and the location predicted by CIOD. The bottom row shows the effect of OpenCV cascade classifier detection for generating CBS. From the above image, we can see that the three class of object detection models have achieved good detection results on human faces, eyes, and cat faces, and the IOU of object detection has basically reached above 0.8, which fully proves the achievability of CIOD for class-incremental object detection. In addition, CIOD is compared with OpenCV cascade classifier (OCC) and Yolo V3 in the case of class-incremental oriented. The comparison results are shown in table I:
As shown in Table I, the OCC detection accuracy rate is much lower than that of COID in the basic class or in the new class. YOLO V3 performs well in the statically set basic class, but it is not applicable to class increase. The amount of object detection, when the class is added, YOLO V3 has catastrophic forgetting, resulting in a sharp decline in accuracy. Compared with the above two methods, COID shows good detection accuracy in both the basic class and the new class. Through the analysis of the COID object detection effect and the comparison with other methods of object detection accuracy, this experiment fully demonstrates the superiority of COID for class-incremental object detection.

### C. The Experiment of Various Index Change Based on Class- Incremental

This experiment is to further verify the feasibility of CIOD in class-incremental based object detection. In this experiment, we used 500 training sets and 185 test sets for each class. We first use 500 face data to train a class of object detection model for face detection, and then 500 eyes data are added to train two classes of object detection model based on the class of object detection model for face and eye detection. Finally, we add the data of cat face to two classes of object detection models to train three classes of object detection models for face, eye and cat face detection. We mainly test the change of accuracy rate, recall rate and accuracy rate of one class of object detection model, two classes of object detection model and three classes of object detection model. The specific experimental results are as follows.
As shown in Table II, the recall rate ($RC$) and precise rate($PR$) in CIOD object detection are relatively high, and the accuracy rate($AC$) is basically above 70%. In addition, compared with the recall rate, CIOD shows a higher PR in object detection. However, with the increase of class, the $PR$, $RC$ and $AC$ all slightly decreased, which is acceptable for the object detection of class-incremental. Because our calculation method of accuracy rate is relatively strict, the accuracy rate of about 70% is almost the same as that of YOLO and RCNN, which shows that CIOD is feasible in object detection based on class-incremental.

D. The Time and Memory Capacity Trends Experiment

In this experiment, we mainly study the change trend of the time needed in the training stage and the memory capacity needed in the training data storage with the increase of the number of class in the object detection. We train eight kinds of objects in the way of class-incremental. Each object contains 500 pieces of training data, and set the memory capacity to 1000. With the increase of class, the trend of training time and required memory capacity is shown in Fig. 8. Considering the differences in the computing power of different machines, we use a $Time_{Unit}$ to describe the change in time. Define the time required for the first class of training as $Train_{Time}_{1-th}$, and the

| Class        | TP   | FP  | FN  | PR  | RC  | AC  |
|--------------|------|-----|-----|-----|-----|-----|
| human face   | 330  | 32  | 79  | 0.916| 0.807| 0.741|

| Class        | TP   | FP  | FN  | PR  | RC  | AC  |
|--------------|------|-----|-----|-----|-----|-----|
| human face   | 325  | 37  | 81  | 0.898| 0.801| 0.730|
| eyes         | 594  | 72  | 82  | 0.892| 0.879| 0.719|

| Class        | TP   | FP  | FN  | PR  | RC  | AC  |
|--------------|------|-----|-----|-----|-----|-----|
| human face   | 322  | 40  | 84  | 0.885| 0.793| 0.703|
| eyes         | 580  | 86  | 90  | 0.871| 0.866| 0.708|
| cat face     | 210  | 35  | 63  | 0.857| 0.769| 0.697|
time required for the i class of training as $Train\_Time_{i-th}$, then the time required for the first type of training is 1 $Time\_Unit$, the time required for type i training is $Time\_Unit_i$.

$$Time\_Unit_i = \frac{Train\_Time_{i-th}}{Train\_Time_{1-th}} \quad (8)$$

In addition, considering that the memory capacity occupied by images of different sizes is different, we use the concept of $Memory\_Unit$ to describe the change in memory capacity. One image represents 1 $Memory\_Unit$.

In Fig. 8, the (a) and (b) respectively show the trend of memory unit and time unit with memory capacity of 1000, number of training rounds of 50 and 100. (c) and (d) respectively show the trend of memory capacity and time with memory capacity of 2000, number of training rounds of 50 and 100. From the blue line in Fig. 8, we can see that as the class increase, the required memory capacity also increases. However, after reaching our set threshold, the memory capacity remains stable and will
not continue to increase, which is independent of the threshold. This verifies the superiority of CIOD in class-incremental based object detection over other object detection algorithms in terms of memory capacity consumption. In addition, as shown by the red line in Fig. 8, our training time is relatively short on the first class, and the training time of other class fluctuates within the range of 1 to 1.45 times of the first class of training, and the fluctuation range is independent of the number of training rounds. It is because the first class does not need to calculate the distillation loss of the existing class. However, in general, the training time does not increase with the increase of class, but tends to be stable. This also reflects from the side that CIOD does not need to repeat training on all the data that has been trained during the training. So the training time of CIOD in class-incremental based object detection is controllable.

E. Indicator Impact Factor Experiment

In this experiment, we mainly discuss the factors that affect the changes of various indicators. The number of rounds generated by the CBS (ROCB) and the threshold value in the CBS selection (TOCB) are two important factors that affect various indicators. When the ROCB is $x$, which means that there are at least $x$ rounds. The object box is considered to contain the object, and the object box is regarded as a CBS. TOCB is the $\text{max\_distance}$ in algorithm 4, when the TOCB is $q$, and the object classification is $y$, that is, when the distance between the object box and other classes minus the distance between the object box and $y$ is greater than $q$, the CBS is considered to contain the object $y$, otherwise the CBS is filtered. In this experiment, we train a total of four types of objects in the class-incremental manner. After training, we used one of the object face for testing. The test data is 172, including a total of 361 face objects. Fig. 9 shows the impact of the ROCB on various indicators, and Fig. 10 shows the impact of the TOCB on the various indicators.
From Fig. 9, we can see that compared with the small number of ROCB, $TP$ decreases relatively slowly, $FP$ decreases significantly, and $FN$ increases slowly when the ROCB increases. Therefore, the $RC$ decreases as the ROCB increases, and the $PR$ increases as the ROCB increases. The $AC$ initially increases with the ROCB. When the ROCB is 4, the $AC$ peaks at 70.35%. At this time, the $AC$ decreases as the ROCB increases. From Fig. 10, we can see that when the TOCB is small, there are more $TP$ and $FP$ and less $FN$. The $RC$ decreases significantly as the TOCB increases, and the $PR$ increases as the TOCB increases. The $AC$ fluctuates with the increase of the TOCB. In general, the $AC$ reaches the maximum between the TOCB of 0.15 and 0.2, and an
excessively high TOCB causes the $AC$ to decrease rapidly.

VI. CONCLUSION

In this paper, an object detection method named CIOD based on class-incremental is proposed. The first stage is the generation of object candidate box. We improve the traditional OpenCV cascade classifier to meet the needs of class-incremental. Then, the improved OpenCV cascade classifier is used to train the object candidate box generation model to generate the object candidate box. In the second stage, we use the concept of prototype vector on the basis of deep learning to train a classifier based on class-incremental to identify the generated object candidate box, so as to extract the real object box. In object detection, object detection can be completed by extracting object candidate box and identifying object candidate box. CIOD breaks the barrier that object detection needs to be trained in static settings, and can solve the problem that multiple types of data cannot arrive at the same time in multi-object detection. In the future work, we will expand the application scenario of CIOD method to further improve the precision and speed of CIOD in object detection.

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