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Exploring the Path to Improve the Quality of Student Management Education Based on Knowledge Graph and NB-loT Architecture

Abstract: - To research the effects of the smart classroom environment on college students' motivation to learn and engagement in that learning, as well as the link between those two factors in the smart classroom environment, a multi-scene student posture detection method using meta-learning is proposed. Through a combination of offline and online learning, the method develops a posture detection metamodel and a reasonable adaptation optimizer to quickly domain modify the posture detection model for certain teaching scenarios. A small amount of labelled sample data from a single teaching scene is all that is required for the metamodel to quickly adapt to the data distribution of that scene with the help of the adaptation optimizer in the online learning phase. The method simulates the process of the pose detection model in various types of teaching through two-layer training to train the parameters of the pose detection metamodel adaptation optimizer. The experimental findings demonstrate that college students' independent learning level and learning engagement are significantly higher in the smart classroom environment than they are in the traditional classroom environment. Additionally, there is a strong positive correlation between their independent learning level and learning engagement in the smart classroom environment.

Keywords: learning, environment, optimizer, combination, reasonable

I. INTRODUCTION

In college classrooms, there is a state of "teacher-student separation", which is caused by the single traditional classroom model,the growth of electronic items in the classroom and the loss of engagement and communication between professors and pupils. Smart classrooms are becoming more and more common in colleges and universities as a result of the extensive use of information technology in the fields of education and teaching, which offer college students a positive learning environment and an abundance of resources in the classroom, and the smart learning space can diversify and standardise the classroom while also making it easier for teachers and students to interact and fully engage students' interest in learning.

In teaching, students' posture performance in the classroom (e.g. sitting upright, lying down, etc.) is an important basis for evaluating students' learning status and classroom teaching quality. Schools have been relying mainly on teaching managers to obtain information about students' posture through on-site observation and classroom listening. This method of relying on manual labor has problems such as incomplete information extraction and low efficiency. With the development of intelligent video analysis technology, especially deep learning technology, it has become possible to use deep learning technology to analyze classroom monitoring images and achieve intelligent detection of student posture. The literature [1] first proposed the idea of using target detection to detect students' pose in crowded teaching scenes, and achieved better detection results.

However, deploying pose detection models to real teaching environments often faces many challenges. As shown in Figure 1, on the one hand, there are significant differences in teaching scenarios for different types of schools (universities, secondary schools, and elementary schools), for example, classroom desktops in universities are usually cleaner, while secondary schools tend to have more book detractors; on the other hand, teaching scenarios in the same type of schools also tend to have significant differences, for example, there are often large classrooms, small classrooms, long classrooms, step classrooms, computer labs, etc. inside universities . In addition, the imaging of the monitoring system installed at different times has great differences in resolution, image quality, viewing angle, etc. Therefore, in practical applications, the surveillance image data of the deployment scenes and the training image data of the model usually have large distribution differences, i.e., there

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is a cross-domain offset problem. The cross-domain offset problem makes the model's performance degraded in practical applications.

Figure 1: Example of monitoring images under teaching scenarios

In the field of general-purpose target detection, several approaches have been proposed in academia to address the problem of model performance degradation due to cross-domain offset. In practice, pose detection models need to be deployed in different teaching scenarios, and there are two main problems in applying the above methods directly to this task. On the one hand, a large number of labeled images are required to obtain satisfactory results, which are not necessarily satisfied by some teaching scenarios. On the other hand, when adjusting to a particular teaching scenario, the training process is challenging and it is challenging to train and deploy quickly.

In order to quickly perform domain adaptation for specific application scenarios under short sample conditions and make full use of the empirical knowledge of posture detection model adaption to varied training scenarios, the author suggests employing meta-learning to identify student poses in several scenes. The method starts from the perspective of learning how to perform domain adaptation, proposes the concept of a meta-model for pose detection and designs an adaptation optimizer with reasonable parameters. By modelling the process of posing detection model domain adaptation in multiple instructional contexts, the pose detection metamodel and adaptation optimizer parameters are taught. Only a minimal quantity of labelled sample data is needed when applying the posture detection metamodel to a particular application scenario, and with the help of the adaptation optimizer, the metamodel may be swiftly modified to fit the data distribution of that scenario. Experimental results show that the combined detection accuracy of the author's proposed method on each scene is better than the current mainstream target detection model and the adaptive model of the literature [6] on a multi-scene student pose detection dataset. On new teaching scenarios with fewer labeled images, the adaptation training cost and pose detection effectiveness required by the author's proposed method is also significantly better than the unsupervised and small-sample target detection adaptation methods described above.

II. RELATED WORK

The concept of smart classroom is becoming more and more common in today's era, it was made possible by the "Internet +" mentality and a new wave of information technology, including big data and cloud computing. Zheng Yafeng et al [1] studied the current development status of intelligent educational equipment in China and pointed out that the development of intelligent educational equipment in China starts from VR/AR, creators/STEAM and other educational equipment; Luo Shuirong [2] gave feedback on the online teaching situation and problems during the epidemic prevention and control period and made suggestions to improve the construction of intelligent classroom; based on this, many studies on intelligent classroom have emerged. For example, Zhao Liyan et al [3] researched on the teaching practice of "MOOC+Rain Class" smart classroom; Xue Shushu et al [4] researched on the analysis model of smart classroom learning activities and its application based on EML and xAPI standards, pointing out that the model can realize the hierarchical design and reuse of smart classroom and learning activities. He Xinyu [5] designed an APP for smart classroom, advocating the construction of an intelligent and effective learning space through the intelligent control of hardware facilities. As everyone's research on smart classroom models and practices continues to deepen, this also provides ideas for universities to better build and

control smart classrooms. The flexible and diverse ways of teacher-student interaction and the full call of teaching resources in the smart classroom environment realize a high degree of integration of online and offline teaching, which effectively improves students' interest in learning and classroom participation and is of great significance to improving teaching quality.

Current research on the theory of "self-directed learning" is best known for Zimmerman's 1989 model of self-directed learning, which focuses on the autonomy of students' learning in terms of metacognitive, motivational, and behavioral aspects of learning. However, Clan's survey showed that the majority of students were generally dissatisfied with their self-directed learning ability, indicating that students had a low level of classroom experience and lacked self-control. Some studies have focused on the development of independent learning questionnaires and their corresponding classroom practices, such as Shan Zhiyan's development of an independent learning questionnaire for secondary school students and Zhu Zude's development of an independent learning questionnaire for college students based on the actual situation of college students in China. The research in the field of self-directed learning continues to deepen, providing a direction for China's educational reform.

According to G. Kuh, "engagement in learning" is a positive and active state of mind related to learning, including the extent to which learners are engaged in learning in class and in extracurricular activities, and the degree to which schools encourage their kids to learn both in the classroom and outside of it. Learning engagement is a multidimensional concept, and current mainstream research on learning engagement focuses on three dimensions: students' behavioral engagement, cognitive engagement, and affective engagement. Most of the studies on learning engagement are based on scale questionnaires for in depth exploration. Therefore, it is urgent to pay attention to this aspect, so as to provide reference for improving students' self-directed learning and learning engagement and effectively improving learning quality. As mentioned above, independent learning and learning engagement are important factors affecting students' learning effectiveness, and there are many studies on learning engagement in smart classrooms, but the relationship between independent learning and learning engagement is lacking. Therefore, this study will take this as an entry point to study the relationship between them in-depth.

A multi-scene student posture detection method using meta-learning

By modifying the model parameters in two stages—offline learning and online learning—the pose detection model is adjusted to the data distribution of a specific deployment situation without changing the network structure or adding more network branches. The method achieves fast domain adaptation of the pose detection model under small sample conditions by loading the metamodel as the initialization parameters of the pose detection model and using the adaptation optimizer to direct the pose detection model parameter training process. The method trains the pose detection metamodel and adaptation optimizer parameters based on various classroom data during the offline learning phase. This section will concentrate on the offline learning phase, as depicted in Fig. 2, and introduce the methodology in four aspects: the choice of the pose detection model's fundamental framework, the metamodel's training strategy, the training and use of the domain adaptation optimizer, and the design of the external training optimizer in the two-layer training.
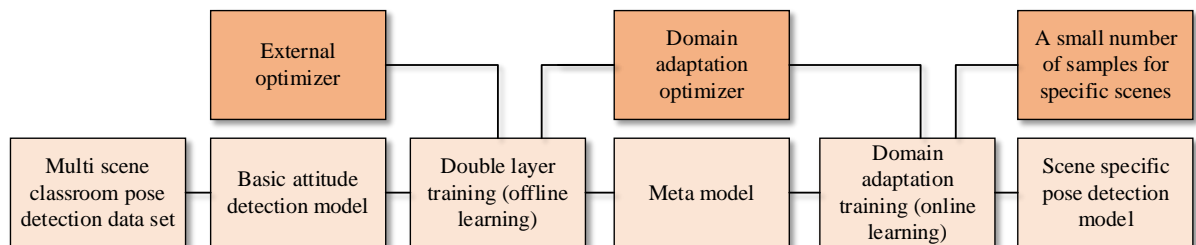

Figure 2: Employing meta-learning, a method for detecting student poses in several scenes.

Elementary Model Framework

Targets having pixel values less than 3232 are referred to as small targets in the COCO dataset, which is considered to be the canonical dataset in computer vision. In the teaching scenario, the back row students are somewhat far from the surveillance camera, which causes the back row human targets on the surveillance images to typically be small and the post categories to be hard to discern. The percentage of image targets classified as

tiny targets in the multi-scene student posture detection dataset utilised in this paper approaches 20%, making accurate Accurate detection is complicated by this. The foundation of the post detection model in this paper is based on the target detection branch of Mask Region-CNN (Mask R-CNN) [8], as seen in Figure 3. In order to address the issue of significant information loss of small targets on high-dimensional feature maps, Residual Network 50 (ResNet-50) [9-10] replaces the Faster Region-CNN's (Faster R-CNN) feature extraction network and the feature pyramid network is introduced. FPN [11] to forecast human stance from several scales of feature maps. The target detection branch of Mask R-CNN has demonstrably outperformed Faster R-CNN in terms of detecting small rear-row targets.
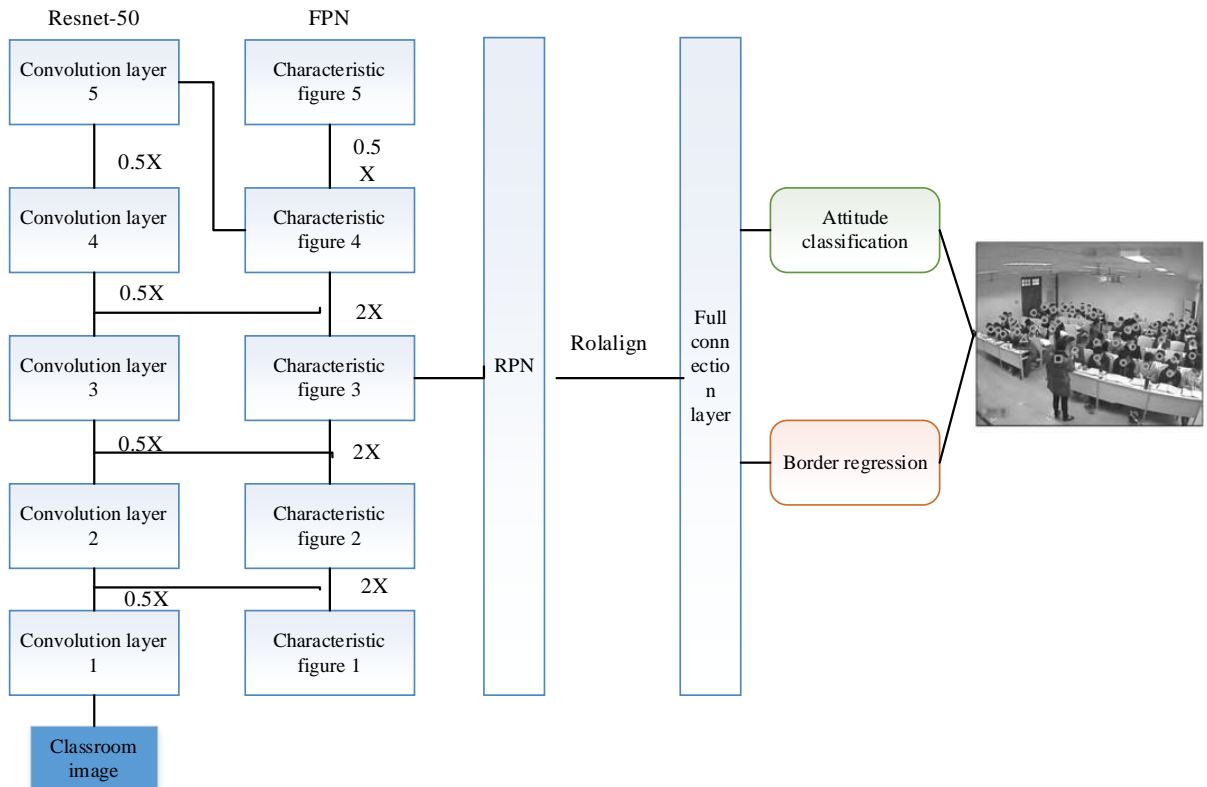
Figure 3: Framework for mask R-CNN target detection.

Posture detection metamodel

A preliminary domain adaptation model created for domain adaptation training for various instructional scenarios in the online learning phase is the pose detection metamodel. This study uses the Model-Agnostic Meta-Learning (MAML) algorithm as the foundation for its offline pose detection metamodel training technique [12]. By combining the test losses of the model after training on diverse teaching scenarios, this research guides the model parameter gradient in MAML's traditional two-layer training mode down to the most suited position for ensuing domain adaption. As seen in Figure 4, the pose detection metamodel strives to have good domain adaptability on all different kinds of teaching scenarios rather than focusing on a single teaching scenario.
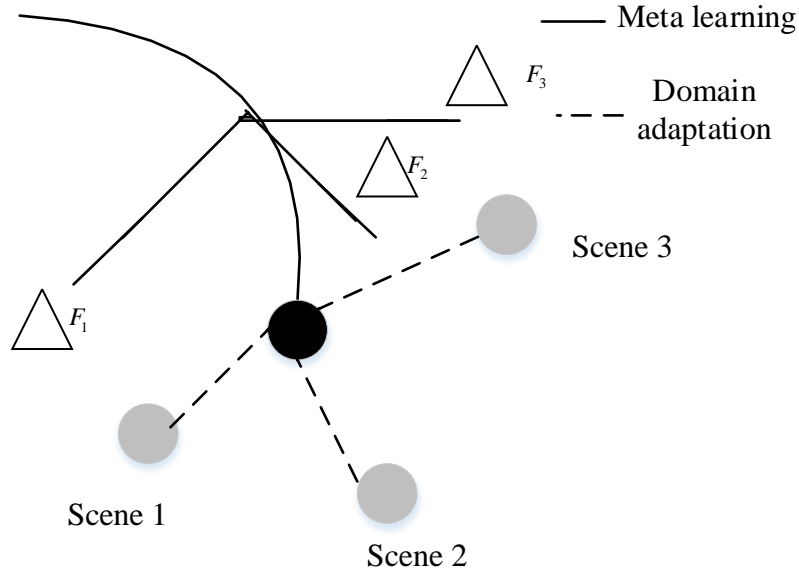
Figure 4: Diagrammatic representation of the metamodel idea.

Based on the training data of the multi-scene posture detection dataset $\{D_i | 1 \le i \le N\}$, N single-scene pose detection datasets are created. A support set $D_i^{\sup}$ and a query set D_i^{que} that are mutually exclusive with the distribution make up each single-scene dataset D_i.

The optimisation goal of the pose detection metamodel parameter $\hat{\phi}$ on the N single-scene pose detection datasets is as follows, assuming that the pose detection metamodel parameter is ϕ.

$$\hat{\phi} = \arg\min_\phi \frac{1}{n} N \sum_i^N F\phi(D_i) \quad (1)$$

The single scenario test loss function $F(\phi, D_i)$ in this instance is defined as follows.

$$F(\phi, D_i) = L\phi - \nabla_\phi L\phi\left(D_i^{\sup} D_1^{q\| e}\right)(2)$$

On the support set D_i^{que} with ϕ pose detection model parameters, $L\left(\phi, D_i^{\sup}\right)$ is the test loss for the pose detection model. The Region Proposal Network (RPN) [9] in Figure 3's positive and negative sample classification and border regression losses, as well as the pose classification and candidate frame regression losses of the final model output, make up the four parts of the pose detection model Mask R-CNN's test loss.

Before being tested on query set D_i^{que}, the single-scene test loss in the study mandates that metamodel parameter ϕ be trained once on that scenario support set $D_i^{\sup}$. The metamodel will pay greater attention to the performance of the post detection model after it has been trained for domain adaptation to a particular scene when testing the loss after training rather than testing directly on dataset D_i^{que}. Following domain adaptation for a particular teaching scenario, this procedure simply uses the model's approximative second-order derivative to optimise the future gradient descent of the model parameters [13].

Domain-specific optimisation tool

When the model parameters are directly optimised using gradient descent under small sample conditions, the parameters are typically challenging to converge to the optimal position. As a result, a parameter-learning domain adaptation optimizer is created. By embedding the domain adaptation optimizer's training in the two-layer MAML training mode during the offline learning phase, the domain adaptation optimizer can give instructions on the direction and size of each parameter's optimisation during the domain adaptation process that follows [14].
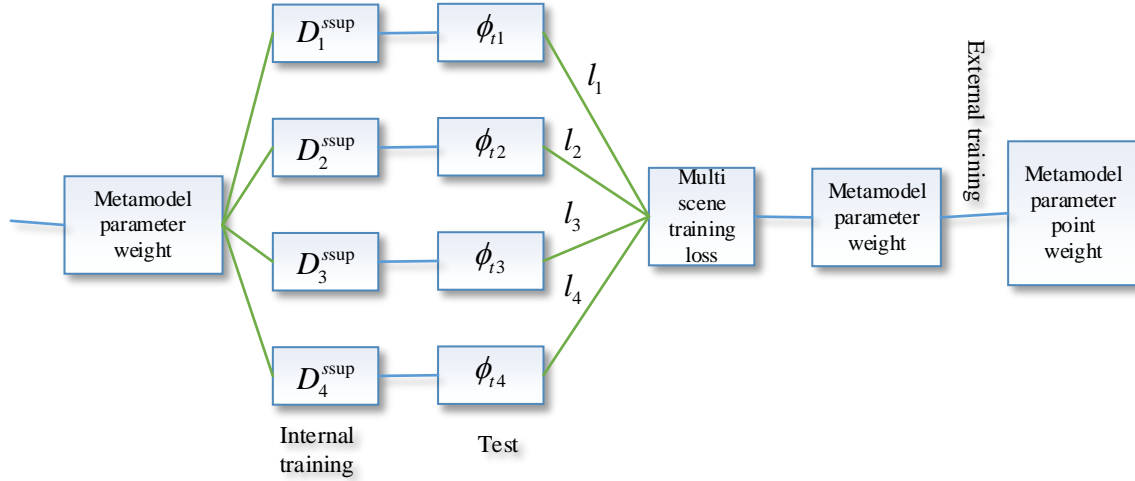
Figure 5 : Double layer training process.

Following the addition of the domain adaption optimizer, Figure 5 shows the two-layer training procedure. The single training step begins with the selection of n single-scene datasets at random, followed by internal training of the detection model using the support set D_i^{sup} the metamodel parameter of the ith dataset ϕ_t the updated model parameter is the same as the starting value ϕ_{ti}; The internal training loss of the scene is then determined by testing the model parameter ϕ_{ti} on the query set D_i^{que}, and the internal training loss of the n scenes is then averaged to determine the multi-scene training loss l_i. The metamodel parameter and the domain adaptation optimizer weight parameter are averaged to create the multi-scene training loss, which is then based on this multi-scene training loss. Finally, the domain adaptation optimizer's weight parameters α_t and β_t metamodel parameters ϕ_t can be externally trained based on this multi-scene training loss.

During internal training, the model parameters ϕ_{ti} are updated in the following way:

$$\phi_{ti}^{'} = \phi_t - \alpha_t \circ \nabla_{\phi_1} L\left(\phi_t, D_i^{\text{ssup}}\right) - \beta_t \circ \phi_t \quad (3)$$

Among them, the pitch weight parameters α_t and β_t are the same variable parameters as the metamodel parameters ϕ_t. In α_t, while providing guidance on the gradient descent direction and step size for each parameter in the model, $\beta_t \phi_t$ provides a weight decay constraint to mitigate the overfitting problem when the model is trained on small samples.

For the single-scene dataset, the internal training loss l_i is determined as follows.

$$l_i = L\left(\phi_{ti}, D_i^{\text{que}}\right) (4)$$

The metamodel parameter for outside training ϕ_t and the weight parameter for the domain adaption optimizer α_t、β_t are changed in the way described below:

$$\left(\phi_{t+1}, \alpha_{t+1}, \beta_{t+1}\right) = \left(\phi_t, \alpha_t, \beta_t\right) - \eta \nabla_{\left(\phi_t, \alpha_1, \beta_t\right)} \frac{1}{n} \sum_{i=1}^{n} l_i \quad (5)$$

Among them, η is the learning rate of external training, which belongs to the artificially set hypermastigote. Since large differences in internal training losses on different types of single-scene datasets can lead to the problem of unstable external training and difficulty in converging the training parameters to the desired position, way of updating the metamodel parameters φ_t and weight parameters α_t、β_t in Eq. (3) will be improving at the optimizer level in the next subsection.

As part of the online learning process, for scene adaption, let the pose detection model's parameters used in a particular scenario be ϕ, and the model's succeeding parameters are modified in the manner described below:

$$\varphi_{t+1} = \varphi_t - \alpha^\circ \nabla_\varphi L\left(\varphi_t, D_i\right) - \beta^\circ \varphi_t \quad (6$$

Combining Eqs. (3) and (6). It is clear that internal training is essentially the process of simulating the metamodel for small-sample domain adaptation on different teaching scenario datasets. The difference is that internal training does not directly affect the final metamodel parameters obtained from offline learning φ, but indirectly affects the update of the metamodel and domain adaptation optimizer parameters by obtaining the multi-scene training losses used for external training.

III. EXPERIMENTAL RESULTS AND ANALYSIS

Experimental data set

Currently, 28 smart classrooms offer course mainly for current first-, second-, and third-year undergraduate students. The author selected 10 courses offered in the 2019-2020 academic year as the main research object, and the final grades of undergraduate students who actually took the courses were used as the dependent variables, with students who scored in the top 40% set as 1, defined as high-scoring students, and students who scored in the bottom 60% set as 0, defined as low-scoring students. In terms of the selection of factors influencing student learning effectiveness, the author selected three aspects of smart classrooms to enhance student learning effectiveness, i.e., learning space configuration, information technology application, and teaching design methods of eight In terms of learning space configuration, X1 was selected to represent the recognition of the environmental space of the smart classroom; in terms of information technology application, X2 was selected to represent the recognition of the IoT system of the smart classroom, X3 to represent the recognition of the display equipment of the smart classroom, X4 to represent the recognition of the recording equipment of the smart classroom, and X5 to represent the recognition of the access to learning resources. For teaching design methods, X6 was selected to represent the degree of recognition of classroom teaching design, X7 to represent the degree of recognition of teachers' classroom interaction, and X8 to represent the degree of recognition of smart classroom learning support. The score for the degree of recognition was set from 5 to 1, with 5 being very much recognized, 4 being recognized, 3 being average, 2 being disapproved, and 1 being very disapproved.

In this paper, a binary logistic regression analysis of the survey data was conducted through SPSS statistical software, and the results showed that the significance of the Hosmer-Lemeshow test value reached 76.0%, which is higher than the standard value of 50%, indicating the validity of the study. The results of the R2 fit coefficient of the questionnaire's reliability evaluation reached 0.759, with an alpha coefficient greater than 0.7, indicating a good fit of the questionnaire [4]; through KMO and Bartlett's test, the author conducted a factor analysis of the factors that may affect the effectiveness of student learning in smart classrooms, and the results yielded a KMO value of 0.681, which is close to 1, indicating that these data are suitable for factor analysis . In the meantime, the Tartlett's sphericity test's Sig value is 0.000, which is less than the significance level of 0.05 and shows that the variables are correlated and that a factor analysis can be performed. The following table displays the findings of the empirical analysis.

Table I Analysis results

Variable	B	S E	Wals	df	Sig	Exp	95% C.I. of exp (b)/ lower limit	95% C.I. of exp (b)/ upper limit
Gender (1)	0.077	0.484	0.025	1	0.874	1.08	0.418	2.789
Grade			0.299	1	0.861			
Grade 1	0.28	0.596	0.002	1	0.963	1.028	0.319	4.406
Grade 2	0.028	0.596	0.002	1	0.962	1.023	0.398	3.31
Specialty type (1)	0.022	0.167	5.556	1	0.018	1.324	0.409	2.555
X1	0.627	0.266	5.457	1	0.177	1.837	1.112	3.155
X2	0.288	0.214	1.82	1	0.166	1.41	0.878	2.028
X3	0.344	0.249	1.914	1	0.877	0.967	0.867	2.296
X4	-0.033	0.216	0.024	1	0.001	2.028	0.634	1.476
X5	0.707	0.22	10.311	1	0.01	1.92	1.317	3.122
X6	0.652	0.255	6.357	1	0.524	1.155	1.166	3.162
X7	0.144	0.227	0.496	1	0.931	1.37	0.841	1.801
X8	-0.012	0.239	0.002	1	0.961	0.988	0.618	1.58

Experimental setup

The hardware configuration of the experiment is Intel Xeon E5-2698 v4 processor. Two Tesla V100 graphics cards are used in the experiment, the software environment is Ubuntu 16.04, and the algorithm implementation is based on Python 3.6 and Pytorch 1.1 deep learning framework.

The pre training model of image net dataset [18] is used to initialize the feature extraction network res net-50. In the off-line learning stage, 20000 iterations are conducted for the double-layer training. Four single scene data sets are extracted for each double-layer training, and 10 pictures are extracted for each specific scene data set for internal training. After each internal training, 5 pictures are used for testing. The weight parameters α are initialized as 1e-3 β and 1e-6; The initial learning rate η of the external optimizer is set to 5e-5 and the weight attenuation coefficient κ is 1e-3. In the online learning stage, 10 images of a specific scene training set are also extracted for domain adaptation training.

Analysis of experimental results

Attitude detection results

Table 2 compares the detection results of this paper's method with the current mainstream target detection models [19-21] and the domain adaptive model TUOD [6] on the test set testS. Compared models are all based on the training set t rainS was trained using Stochastic Gradient Descent (SGD) method on the entire data. The results demonstrate that this strategy outperforms the target detection model and the domain adaption model TUOD in the combined detection performance on the multi-scene student postures detection dataset. m AP of this method improves by 4.05 points over the target detection model Mask R-CNN, and the domain adaptation outperforms the TUOD model with adaptive combination of different domain adapters. This indicates that this method can more effectively solve the problem of cross-domain offset in teaching scenes with a large amount of labeled data.

Table 2 Comparison of posture detection results (%)

Method	Feature extraction network	Sit	Stand	Be prostrate	mAP
CCE-FRCNN	VGG16	79.27	81.32	66.03	75.24
EFGRNet	VGG16	87.41	86.51	79.87	84.57
YOLOv4	CSP-Darknet	87.25	88.80	77.87	84.61

| RetinaNet	ResNet-50-FPN	93.73	88.80	77.87	87.21
Mask R-CNN	ResNet-50-FPN	93.28	92.52	76.83	86.86
TUOD	ResNet-50-FPN	93.57	91.40	75.91	87.36
Paper method	ResNet-50-FPN	95.24	96.67	80.82	90.91

In order to compare the fairness of the experiments, a domain adaptation operation is also added to the Mask R-CNN model ψ in Table 2. The same 10 labeled images are used for domain adaptation, and the method is fine-tuned by gradient descent (Fine-Tune) model. Table 3 compares the pose detection results before and after domain adaptation for model ψ and the metamodel. The comparison results show that the detection effect of this method is still better than that of model ψ after the same domain adaptation operation. Although the pose detection of model ψ is better than that of the metamodel, subsequent domain adaptation training improves its detection performance less, which indicates that the secondary training of the model directly with small samples does not improve the performance of the model. The metamodel, although the initial pose detection results are poor, is a better initialization parameter for domain adaptation, and can effectively use the small sample data information for domain adaptation for a specific scene under the guidance of the domain adaptation optimizer.

Table 3 Comparison of test results before and after domain adaptation (%)

Method	Domain adaptation	Sit	Stand	Be prostrate	mAP
Mask R-CNN	×	93.28	91.40	75.91	86.86
	√	93.26	91.23	76.30	87.13
Paper method	×	92.10	92.60	67.42	84.04
	√	95.24	96.67	80.82	90.91

Note: × represents the detection index measured when the model is not trained for domain adaptation, √ represents the detection index measured after the model is trained for domain adaptation.

In order to visualize the effect of domain adaptation on metamodel detection, three representative scenes, namely, a small classroom, a step classroom and a computer room, are selected and the metamodels obtained by traditional training methods and the pose detection results after metamodel domain adaptation are visualized. Since it is difficult to distinguish the detection results in a dense teaching scene by printing rectangular boxes and adding labels, three small icons are designed to display the pause detection results. Three types of small icons are designed to display the detection results of various types of postures. As shown in Figure 6, the hollow circle represents the detected "sitting" posture, the hollow square represents the "standing" posture, and the hollow triangle represents the "lying" posture.
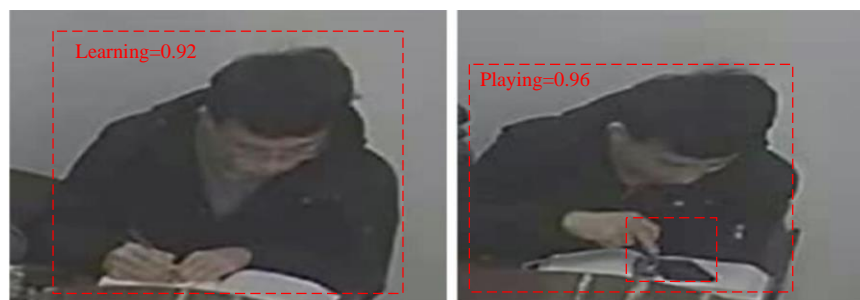
Figure 6:Visualization of attitude detection results.

As shown in Figure 6, although the metamodel can basically recognize human targets, the main problem is that the classification of "sitting", "standing" and "lying down" postures is poor. As shown in the oval circled area in Fig. 6, the domain adaptation process has significantly improved the pose classification effect. This phenomenon indicates that for Mask R-CNN, the two-stage target detection network used in this paper, the influence of domain adaptation training on the classifier is greater under its mechanism of extracting a large number of candidate regions before classification.

Ablation experiments

I compared Meta-SGD, meta-learning based optimizer learning method in the literature [14], and created ablation experiments to test each component of the author's suggested methodology, and the experimental findings are displayed in Table 4. Among them, MAML represents the experimental method of training only the pose metamodel and completing the domain adaptation operation by gradient descent directly; MAML+ETO denotes the use of the author's suggested external training optimizer (ETO) to the two-layer training of MAML; MAML+DAO represents the addition of the domain adaptation optimizer (Dome-Adapted Optimizer (DAO)) designed by the author on top of MAML. The training and application of the author's Domain Adaptation Optimizer (DAO) based on MAML is represented by MAML+DAO.

Table 4 Results of ablation experiments (%)

Method	Sit	Stand	Be prostrate	mAP
Meta-SGD	93.61	94.44	72.82	87.02
MAML	92.01	91.27	73.86	85.45
MAML+ETO	94.23	94.55	74.09	85.49
MAML+DAO	94.45	95.55	76.09	88.64
Paper method	95.34	95.24	80.82	90.91

The ablation experiments show that the domain adaptation optimizer has the largest contribution in the author's proposed method, indicating that the domain adaptation optimizer obtained after two-layer training can provide effective guidance for the process of metamodel migration in various types of teaching scenarios. Its domain adaption impact is superior to that of Meta-SGD, demonstrating that the inclusion of an adaptive weight decay constraint can enhance the model's generalisation effect in some cases with limited sample sizes. The employment of an external training optimizer can help the metamodel and domain adaption optimizer work more effectively in real-world applications by enhancing their ability to generalise in a variety of teaching settings.

Learning Intention Analysis

It was hypothesised that college students were substantially more engaged in their classroom learning in the smart classroom setting than they were in the traditional one. To determine whether college students' engagement in learning changes in the smart environment from that in the traditional classroom, an independent samples t-test was conducted by SPSS on the overall situation of the two data sets of college students' classroom engagement in different environments, and Table 5 displays the outcomes.

Table 5 Analysis of the difference in learning inputs between smart classrooms and regular classrooms (N=88)

Dependent variable	Independent variable	M±SD	t±
Learning input	Wisdom classroom	83.545±9.199	5.989
	Ordinary classroom	68.431±13.984	

As showed in Table 5, there is a significant difference in the level of classroom learning engagement between the smart classroom environment and the regular classroom environment (t=5.989, p<0.001). It can be seen that the rich teaching tools in the smart classroom environment can effectively support teachers to guide students in a variety of teaching methods such as cooperative learning, which can have a significant impact on enhance the behavioral, cognitive, and affective dimensions of college students' engagement significantly.

It was hypothesised that college students' mean levels of enthusiasm, vigour, and focus in the classroom learning engagement were much higher in the smart classroom setting than they were in the traditional classroom environment. To ascertain whether college students' participation in learning in the three subcomponents changes in the smart environment from that in the traditional classroom, an independent samples t-test was conducted by SPSS on the three dimensions of motivation, energy and concentration of college students' classroom engagement, and the results are shown in Table 6.

Table 6 Analysis of the differences in motivation, energy and concentration of learning engagement in smart classrooms versus regular classrooms (N=88)

Dependent variable	Independent variable	M±SD	t±
Motivation	Wisdom classroom	31.045±3.912	6.557
	Ordinary classroom	25.750±3.661	
Absorbed	Wisdom classroom	23.863±2.966	4.063
	Ordinary classroom	19.396±6.689	
Energy	Wisdom classroom	28.636±3.871	4.421
	Ordinary classroom	23.296±7.107	

Table 6 shows that there is a significant difference in the levels of the three dimensions of classroom learning engagement between the smart classroom and the regular classroom. In terms of motivation, the smart classroom scores were significantly higher than the scores in the regular classroom (t=6.557,p<0.001); in terms of concentration, the smart classroom scores were also significantly higher than the scores in the regular classroom (t=4.063,p<0.001); in terms of energy, the smart classroom scores were still significantly higher than the scores in the regular classroom (t=4.421,p< 0.001). It can be seen that the many emerging interactive tools in the smart classroom environment can effectively guide students to learn in a variety of ways, such as self-study, discussion and questioning, and have a significant effect on improving college students' motivation, concentration and engagement levels.

It was predicted that college students will learn independently in the classroom much more in the smart classroom than in the traditional classroom. In order to investigate whether the independent learning of college students in the smart environment differs from that in the regular classroom environment, an independent samples t-test was conducted by SPSS on the overall situation of the two sets of data for different environments of college students' classroom engagement, and the results are shown in Table 7.

Table 7 Analysis of the difference between smart classrooms and regular classrooms for independent learning (N=88)

Dependent variable	Independent variable level	M±SD	t
Autonomous Learning	Wisdom classroom	292.977±25.791	3.306
	Ordinary classroom	273.777±28.466	

As shown in Table 7, there is a significant difference in the level of independent learning between the smart classroom environment and the regular classroom environment (t=3.306, p<0.01).

can be seen that the better the perceptibility of students to technology in the smart classroom environment, the easier it is for students to actively participate in classroom learning, the easier it is to motivate students to learn, and to some extent in the promotion of independent learning behavior input.

Table 8 Self-directed learning and learning engagement among college students: a correlation analysis (N=88)

	M	SD	r
Autonomous Learning	283.4328	28.61975	0.392
Learning input	75.7303	14.14034	0.392

The correlation between the data collected on learning input and self-directed learning was analyzed by SPSS, and the results showed that the correlation was r=0.392 and were significant at the 0.01 level.

IV.   CONCLUSIONS

Student learning engagement and independent learning in classrooms are significantly higher than those in regular classrooms, and a multi-scene student poses detection method using meta-learning is proposed to mitigate the degradation of pose detection model s-type performance caused by the cross-domain offset problem. The technique produces quick domain adaptation of the pose detection model under small sample conditions by training a meta-model and a domain adaptation optimizer based on a multi-scene student pose detection dataset. Under the smart classroom, the traditional teaching model is broken, which not only highlights the students' independent inquiry ability and participation and communication ability, but also reflects the new teaching concept of student-led teacher-led and the students' information sources are actively selected rather than passively accepted, which stimulates the students' independent learning enthusiasm and cultivates the students' independent thinking and problem-solving ability.

In the future, this paper will further expand the multi-scene student posture detection dataset and study how to make fuller use of the existing classroom scenes with similar distribution to the new scene dataset to improve the domain adaptation capability of the posture detection model on the new scene with fewer samples.

Data Availability
The dataset used in this paper are available from the corresponding author upon request.
Conflicts of Interest
The authors declared that they have no conflicts of interest regarding this work.

Author Contributions:

The authors confirm contribution to the paper as follows: study conception and design:Lin Liu ; data collection: Jing Yang; analysis and interpretation of results: Lin Liu; draft manuscript preparation: Jing Yang. All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

[1] Kim H J , Seo M S , Park D . Factors influencing intention to intervene in elder abuse among nursing students[J]. PeerJ, 2021, 9(4):e12079.

[2] Park S Y , Cha S B , Lim K , et al. The relationship between university student learning outcomes and participation in social network services, social acceptance and attitude towards school life[J]. British Journal of Educational Technology, 2014, 45(1):97-111.

[3] Titus M A . An Examination of the Influence of Institutional Context on Student Persistence at 4-Year Colleges and Universities: A Multilevel Approach[J]. Research in Higher Education, 2004, 45(7):673-699.

[4] Tang S , Hanneghen M . State-of-the-Art Model Driven Game Development: A Survey of Technological Solutions for Game-Based Learning[J]. Journal of Interactive Learning Research, 2011, 22(4):551-605.

[5] Nicaud J F , D Bouhineau, Chaachoua H . Mixing Microworld and Cas Features in Building Computer Systems that Help Students Learn Algebra[J]. International Journal of Computers for Mathematical Learning, 2004, 9(2):169-211.

[1]   Maltezos E , Doulamis A , Doulamis N , et al. Building Extraction From LiDAR Data Applying Deep Convolutional Neural Networks[J]. IEEE Geoscience and Remote Sensing Letters, 2018, 16(1):155-159.

[2]   D Buraczewski, Damek E , Y Guivarc'H, et al. Tail-homogeneity of stationary measures for some multidimensional stochastic recursions[J]. Probability Theory & Related Fields, 2009, 145(3-4):385-420.

[3]   Yang H L , Yuan J , Lunga D , et al. Building Extraction at Scale Using Convolutional Neural Network: Mapping of the United States[J]. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2018, 11(8):2600-2614.

[4]   Zhang Y , Zeng J , Li Y , et al. Convolutional Neural Network-Gated Recurrent Unit Neural Network with Feature Fusion for Environmental Sound Classification[J]. Automatic Control and Computer Sciences, 2021, 55(4):311-318.

[5]   Murphy, J. Unpacking the Foundations of ISLLC Standards and Addressing Concerns in the Academic Community[J]. Educational Administration Quarterly, 2005, 41(1):154-191.

[6]   Machado C . Gender differences in student discourse on discussion board and blogs: An instructor's quest to create a level playing field in a hybrid classroom[J]. Journal of Interactive Online Learning, 2011, 10(1):36-48.

[7]   Park, Kang-Hee. A Case Study of Using Smart Phone Applications for Improvement of Ability of Expression in English for Novice Students[J]. International language and literature, 2016(34):103-123.

[8]   Philip T M . Moving beyond Our Progressive Lenses: Recognizing and Building on the Strengths of Teachers of Color[J]. Journal of Teacher Education, 2011, 62(4):356-366.

[9]   Taylor, Roberta. The multimodal texture of engagement: Prosodic language, gaze and posture in engaged, creative classroom interaction[J]. Thinking Skills and Creativity, 2016, 20:83-96.

[10]   Park S Y , Cha S B , Lim K , et al. The relationship between university student learning outcomes and participation in social network services, social acceptance and attitude towards school life[J]. British Journal of Educational Technology, 2014, 45(1):97-111.

[11]   Zeng, Y., & Chu, B. The Appropriate Scale of Competition Between Online Taxis and Taxis Based on the Lotka-Volterra Evolutionary Model. Journal of Combinatorial Mathematics and Combinatorial Computing, 117, 25-36.

[12]   Aminta Stella Casas Sánchez, María Patiño, Camargo D . Association between the sitting posture and back pain in college students[J]. Revista Salud Uis, 2016, 48:págs. 446-454.

[13]   Hajar, Al, Sultan. Translanguaging with Multilingual Students: Learning from Classroom Moments by Ofelia García and Tatyana Kleyn (review)[J]. Chiricú Journal: Latina/o Literatures, Arts, and Cultures, 2017, 1(2):233-237.

[14]   Kulikajevas A , Maskeliunas R , Damaeviius R . Detection of sitting posture using hierarchical image composition and deep learning[J]. PeerJ Computer Science, 2021, 7(e442).

[15]   Zhang Z, Zhang C, Li M, et al. Target positioning based on particle centroid drift in large-scale WSNs[J]. IEEE Access, 2020, 8: 127709-127719.

[16]   Lin Y T . Impacts of a flipped classroom with a smart learning diagnosis system on students' learning performance, perception, and problem solving ability in a software engineering course[J]. Computers in Human Behavior, 2019, 95(JUN.):187-196.

[17]   Noordin Y , Azizi Y , Jamaludin R , et al. The Effects of Motivational Factors in Learning among Students in Secondary School in Negeri Sembilan[J]. International Journal of Psychological Studies, 2010, 2(1):128-136.

[18]   O'Loughlin, Dean V . Does the Use of Interactive Exercises in Anatomy Lecture Increase Student Performance?: A Multi-Year Study Presented[J]. The FASEB Journal, 2006, 20(4):A419.

[19]   Shen C W , Wu Y , Lee T C . Developing a NFC-equipped smart classroom: Effects on attitudes toward computer science[J]. Computers in Human Behavior, 2014, 30(jan.):731-738.

[20]   Brok P D , Brekelmans M , Wubbels T . Multilevel issues in research using students' perceptions of learning environments: The case of the Questionnaire on Teacher Interaction[J]. Learning Environments Research, 2006, 9(3):199-213.

[21]   Zhang C, Xie T, Yang K, et al. Positioning optimisation based on particle quality prediction in wireless sensor networks[J]. IET Networks, 2019, 8(2): 107-113.

[22]   Parvez M S , Rahman A , Tasnim N . Ergonomic mismatch between students anthropometry and university classroom furniture[J]. Theoretical Issues in Ergonomics Science, 2019, 20(5):603-631.

[23]   Karns, G. L . Marketing Student Perceptions of Learning Activities: Structure, Preferences and Effectiveness[J]. Journal of Marketing Education, 2005, 15(2):3-10.

[24]   Hora M T , Ferrare J J . Instructional Systems of Practice: A Multidimensional Analysis of Math and Science Undergraduate Course Planning and Classroom Teaching[J]. Journal of the Learning Sciences, 2013, 22(2):212-257.

[25]   Ali S , Rohindra D , Coll R K . Student perceptions of a culturally diverse classroom environment[J]. Research in Science & Technological Education, 2008, 26(2):149-164.

[26]   González García, Cristian, Núez-Valdez, Edward Rolando, Moreno-Ger P , et al. Agile development of multiplatform educational video games using a Domain-Specific Language[J]. Universal Access in the Information Society, 2019, 18(3):599-614.

[27]   Wu D, Zhang C, Ji L, et al. Forest Fire Recognition Based on Feature Extraction from Multi-View Images[J]. Traitement du Signal, 2021, 38(3): 775-783.

[28] Li H, Zeng D, Chen L, et al. Immune Multipath Reliable Transmission with Fault Tolerance in Wireless Sensor Networks[C]//International Conference on Bio-Inspired Computing: Theories and Applications. Springer, Singapore, 2016: 513-517.

[29] Zylstra M J , Knight A T , Esler K J , et al. Connectedness as a Core Conservation Concern: An Interdisciplinary Review of Theory and a Call for Practice[J]. Springer Science Reviews, 2014, 2(1-2):119-143.

[30] Sitti S , Sopeerak S , Sompong N . Development of Instructional Model based on Connectivism Learning Theory to Enhance Problem-solving Skill in ICT for Daily Life of Higher Education Students[J]. Procedia - Social and Behavioral Sciences, 2013, 103(1):315-322.