Machine learning system to guide teacher reflection on behavior management skills

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Abstract: This paper presents a classroom behavior management skills classification system based on machine learning to assist teachers to develop their classroom behavior management skills through guided reflection. Such a system would enable more cost-effective application of demonstrably successful approaches to having expert observers identify suggestible moments for reflection. The proposed system accepts input videos from teachers and provides classification results of specific behavior management skills that occurred on those videos. The classification results, together with relevant additional information will be provided to teachers as suggestions for reflection. The proposed approach relies on deep learning and computer vision techniques to provide the classification results. Additionally, the proposed approach has been evaluated on videos containing four of the essential teaching skills and has achieved an average F1-score of 84.75%.

Introduction

There is no doubt that a successful teacher-student interaction in the classroom is essential for the educational and social development of students. High-quality teachers typically demonstrate effective behavior management, including by ensuring emotionally supportive environments that contribute to the student's overall development. Teaching is a relational process and the behaviors of the teacher transmit signals that are interpreted by students who generate their own behaviors in response. It is therefore critical for teachers to understand their own behavior, the signals they transmit to students, and the influence of those signals on student responses.

Traditionally teachers acquire and enhance their behavior management skills by attending seminars or workshops, where they are guided and given strategies for managing challenging behaviors. In one example of such teacher professional development, for more than twenty years, teachers in Queensland, Australia have been coached in micro-skills for behavior management to assist them with developing more effective behavior management strategies (Davidson & Goldman, 2004; Goldman, 2007). The effectiveness of the process, which involves intensive observation and feedback, has been validated by research. However, in common with other similar approaches to teacher professional development the resource requirements such as facilities, travel, teacher time, and the availability of experienced coaches to provide feedback to trainees are substantial.

Hence there is inevitable interest in finding more economically efficient ways to provide what are known to be effective forms of professional development for teachers at all career stages from pre-service to experienced. That includes exploring the possible applications of digital technologies for delivery of teacher professional development in formats that enable more flexible access at times convenient to teachers and without the requirement to travel to a distant venue. Where that might once have involved printed materials or software packages on optical disks, in most locations broadband networks now allow for delivery entirely online.

Understandably, a good deal of the existing research about online teacher professional development has focused on developing teachers' capabilities for the pedagogical application of digital technologies (Prestridge & Tondeur, 2015) but the same general principles will be applicable to teacher professional development more broadly. In comparison with seminar or workshop-based programs, the use of digital technologies provides a more flexible solution, allowing learners to work at their own pace and providing opportunities to accommodate learner preferences.

Teachers at all levels of experience can learn much from each other through sharing experiences in teams, communities, and networks (Prestridge & Main, 2018) but there are also opportunities for provision of the online equivalents of seminars and workshops using either synchronous or asynchronous formats. Moreover, well designed learning packages can offer immediate feedback as the learning progresses, usually in an interactive manner that can be used in dialogic learning discussions (Harro-Loit, 2019). Such a style of feedback enables learners to review specific sections of the materials as often as needed, without causing embarrassment as might occur in face-to-face teacher professional development.

In this paper we introduce a system that applies digital technologies to facilitate the development of teachers' skills for behavior management. It is a video-based system that uses machine learning to assist teachers in developing their micro-skills for managing classroom behaviors. The system will ingest recorded video of a teacher and then segment and label the actions of the teacher in the video. The action labels will be delivered to teachers for use in ongoing coaching and reflection (Dann & Richardson, 2015), enabling each teacher to use the system to foster their behavior management skills based on analysis of their own performance.

This paper presents an overview of the proposed system and the results of some preliminary trials that demonstrate the potential of such a system. Following this introduction is a brief review of prior research that has informed the project. That review is followed by a description of the proposed machine learning system and results of experimental trials. The final section summarizes progress to date and suggests future directions.

Literature review

Classroom behavior management

Teaching typically entails substantial management skills. Teachers are responsible for preparing and handling the resources necessary to support their presentation of lesson content and the activities through which students practice skills and commit content to memory, all within constrained time periods. Management of student behavior, both directing and reinforcing on-task actions and forestalling or redirecting off-task actions, is an important element of overall classroom management (Nagro et al., 2020) and one that, depending upon circumstances and learner characteristics, teachers at all stages of experience sometimes find challenging. Misalignment between teacher preparation programs and the need of teachers for appropriate classroom management skills has been identified as contributing to problems in schools and attrition of the teaching workforce (Stevenson et al., 2020).

Davidson and Goldman (2004) noted that there are numerous different approaches to behavior management or discipline in school and classroom contexts. The approaches range from autocratic through authoritarian and democratic to liberal or laissez-faire and have different goals including maintaining order, ensuring compliance, and developing cooperation and personal integrity. There is no universally preferred approach and what is effective is dependent upon goals and circumstances.

As outlined by Davidson and Goldman (2004), research from multiple sources (Glasser, 1990; Richmond, 1996; Rogers, 1995) has supported identification of ten micro-skills (Richmond, 1996) associated with effective management of student behavior. They range from initially *establishing expectations* so that students understand the boundaries of acceptable behavior in a context to *following through* on responses to disruptive behavior and *defusing* tensions following an incident. Since the mid-1990s, those micro-skills have been promoted for teachers in Queensland schools with extensive support through structured teacher professional development programs.

One significant example of such a teacher professional development program developed from 1996 is 'classroom profiling' in which a trained profiler observed a teacher in the classroom and offered structured feedback (Davidson & Goldman, 2004). The process is relatively intensive, involving initial presentations to teaching staff in a school about the 10 micro-skills, unobtrusive observation of a 40-minute class for participating teachers recorded using a formatted observation sheet, and a subsequent meeting of about 20 minutes between the profiler and individual teachers to provide specific comments about what the team working on this project describe as *suggestible moments* around which adjustments can make an appreciable difference to behavior management. Although originally developed for K-12 schools, the process has been adapted for use in vocational education and has been demonstrably successful in both contexts (Davidson & Goldman, 2004; Goldman, 2007).

Despite the acknowledged success of teacher professional development based on direct observation of teachers in their classrooms the significant costs of such a program tend to limit the breadth and frequency of its application. Skilled profilers need to be identified and trained before travelling to widely dispersed sites to spend substantial blocks of time with each participating teacher. Although teachers might benefit from opportunities for repeated observations with feedback over time to enable follow-up and refinement of skills, the costs prevent widespread adoption of such practices and there would clearly be value in developing more cost-effective techniques.

Video applications in teacher professional development

Developments in digital technologies over recent decades have simplified the capture, editing, distribution, and playback of video to the point where teachers can readily arrange recording of their own selected classroom performances for subsequent reflection as part of an ongoing program of personal professional development. Recent developments include Swivl (swivl.com), which places a camera on a rotating base so that it can follow the teacher who wears a tracking device that contains a microphone thus ensuring that the video captures teacher activity around the classroom. A recent study comparing reflections of preservice teachers (PSTs) with and without the use of Swivl (McCoy & Lynam, 2021) reported strong evidence for the value of video for supporting reflection and encouraged the authors to advocate for the use of such video to support teacher professional development at all career stages.

Numerous other studies have attested to the value of video in supporting reflection for teacher learning through identification of suggestible moments. In a study in the USA, PSTs recorded a sample of their teaching, reflected on it, sent it to their university supervisor, and then met with the supervisor to review the video and their reflections (Gibbons & Farley, 2020). There was a positive impact on their pedagogical practices, classroom management, and learner engagement as their teaching experience progressed confirming reflection on video as a useful addition to teacher preparation. In another US study with inservice teachers, video analysis accompanied with coaching by trained teachers was successful in developing the teachers' skills for culturally responsive classroom management (Lane et al., 2020). A study of video analysis accompanied by expert feedback found that it could enhance PSTs professional vision of classroom management in an online learning environment but that the availability of the expert feedback was critical to success (Prilop et al., 2021).

Video-based reflective practice has frequently been reported as a beneficial tool for teacher learning but the process can be complex and teachers often require support with technical aspects and effective observation (Yuan et al., 2020). A doctoral study in Finland found that video enhanced observation enabled PSTs to apply a more analytical viewpoint to their teaching (Körkkö, 2020). However, the process was complex and time consuming, requiring new skills of PSTs and supervisors, and leading to the conclusion that the process has promise for teacher professional development but needs refinement.

Ideally teachers should be assisted to develop the skills to undertake their own reflective processes, thereby making it more conveniently available for them and reducing the dependence upon external resources. One approach to self-led video analysis of instruction for reflection outlined a four-step process to record, review, reflect on, and revise instruction using a checklist of evidence-based strategies with video exemplars, a structured observation tool, and guide for self-reflection (Nagro et al., 2020).

Taken together, the findings from these studies confirm the value of video-based reflection for teacher professional development in a variety of contexts. However, it is also clear that PSTs or teachers engaging in this practice may require support with technical aspects and will certainly benefit from a carefully structured process and, ideally, the availability of expert feedback and coaching to identify and guide learning around suggestible moments. Hence it becomes important to consider what might be done to reduce dependence upon the immediate presence of an expert and to maximize the value of available expertise.

Research on teacher 'noticing'

Teachers' ability to respond appropriately to classroom events depends upon their ability to 'notice' and interpret student actions and thinking as a basis for enacting an appropriate pedagogical response. In a systematic review of 43 articles selected from 611 identified articles about prospective teacher noticing, Amador et al. (2021) traced the lineage of relevant research back as far as the 1990s. They noted that 'noticing' is learnable and described different approaches to developing the relevant skills among prospective teachers with increasing use of recorded video as the technology has developed.

A recent study explored the use of standard video and a newer 360 format video for developing PST noticing and found that there were benefits deriving from the richer content of the new format (Kosko et al., 2020). PSTs using the 360 video attended to more student actions and produced richer descriptions of those actions. The PSTs in the study had been prepared through a prior noticing activity and engagement with the mathematics task being undertaken by the students in the video they viewed. This preparation was consistent with the literature reviewed in the study which revealed that PST noticing developed with experience and was enhanced by richer representations of the classroom activity they observed.

Although the concept of teacher noticing is directed toward attending to and interpreting student behavior, similar considerations are applicable to interpretation of teacher actions in the classroom. Whether an observer views teacher activity directly or in recorded video, the ability to identify and interpret significant actions is learned rather than innate. As evidenced by the literature (Davidson & Goldman, 2004; Gibbons & Farley, 2020; Goldman, 2007; Körkkö, 2020; Lane et al., 2020; Prilop et al., 2021; Yuan et al., 2020) the involvement of experienced observers with relevant expertise has been crucial to the success of both direct and video-mediated observation of teaching for teacher professional development. The processes entailed in such programs tend to be demanding of the limited and expensive time of teachers and observers.

Hence the work described in this paper seeks to develop a digital technologies system that can assist PST noticing of suggestible moments in their own video recorded instructional performance. Assisting teachers to recognize and interpret their own actions in self-recorded video of teaching will support them in reflecting on their performance and developing relevant skills. It should enable them to do so in a timelier fashion and without the requirement for access to an expert observer.

Machine learning and human action recognition

Recent decades have seen rapid developments in digital technologies for artificial intelligence and machine learning. Advances in pattern recognition have underpinned developments such as voice driven interfaces and facial recognition for security applications ranging from accessing personal devices to crowd surveillance. Some applications have aroused concerns for privacy but the ongoing increase in capability is apparent and such systems have valuable applications when deployed with appropriate safeguards.

Developments in pattern recognition by digital technologies are not confined to static objects but are making inroads into the more challenging area of human action recognition, which requires the combination of recognizing objects with temporal dynamics. The success of such systems depends largely upon the capability to extract and recognize relevant cues and various methodologies have been devised to facilitate that process.

Das Dawn and Shaikh (2016) surveyed research on the use of spatio-temporal interest point (STIP) detection for human action recognition. They noted that prior researchers had used complexity and numbers of body parts involved to identify four categories of activity: gestures (showing meaning using hand, head or face), actions (collected gestures by one person such as walking, waving, or running), interactions (collections of actions involving two humans or a single human and some object), and group activities (where there are more than two actors). STIP methods have been found to work well with video by identifying features and tracking their movement across a series of frames, leading to development of established techniques for use in algorithms. The accuracy of techniques can be improved using methods to account for factors such as camera motion by adjusting trajectories of features in a video to account for it (Wang & Schmid, 2013).

Digital technologies systems for video analysis rely upon deep learning models using convolutional neural networks (CNNs) which have been validated through research including the classification of a million YouTube videos using spatio-temporal methods as described above (Karpathy et al., 2014). The use of 3-dimensional rather than 2-dimensional CNNs has been found to improve performance of the machine learning systems (Tran et al., 2015) and other work has improved the speed of analysis by an order of magnitude using techniques related to video compression (Zhang et al., 2016). The system described in this paper draws upon these research results and the algorithms they have pioneered.

Proposed Methodology

Richmond (1996) identified 10 essential skills for classroom behavior management. However, in this paper the focus is on the first 4 skills shown in Table 1, as they are considered essential for improving student engagement and are the most frequently used in the classroom.

Class	Description
Establishing expectations	Making rules
Giving instructions	Telling students what to do
Waiting and scanning	Stopping to assess what is happening
Cueing with parallel acknowledgment	Praising a particular student to prompt others

Table 1: The 4 Essential Skills for classroom behavior management

The proposed Teacher Reflection Suggestion System (TRSS) will accept video recorded by a teacher or PST and automatically label video segments exhibiting the skills with varying degrees of success as suggestible moments. The labels will be provided to the teacher, with or without links to exemplars or other aids, as suggestions to assist in reflection on relevant aspects of their teaching. Figure 1 represents the workflow of the TRSS.

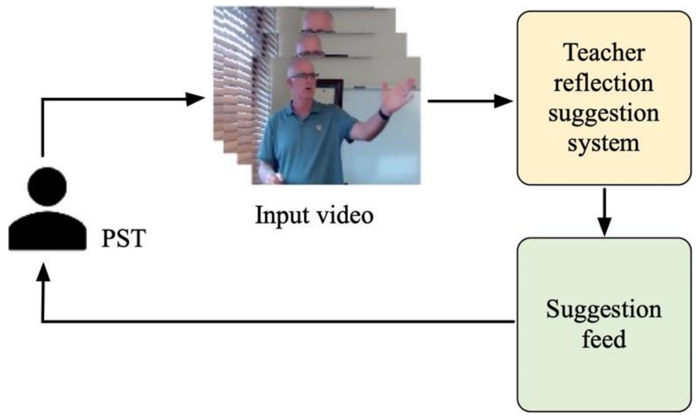

Figure 1: Workflow of the teacher reflection suggestion system

The process of labeling teacher actions in the video can be viewed as a human action recognition task for which there is an extant body of research demonstrating the possibilities (Das Dawn & Shaikh, 2016; Karpathy et al., 2014; Tran et al., 2015; Wang & Schmid, 2013; Zhang et al., 2016). Hence the core of the TRSS will use machine learning to recognize and label teacher actions in recorded video to alert teachers to suggestible moments most appropriate for reflection.

The TRSS consists of two main components, namely: the facial feature extractor module and the temporal modelling module. A person's face can provide a lot of information about their personal behavior (Ricciardelli et al., 2016) and the facial feature extractor is responsible for acquiring face-related representations of each frame from the input sequence. On the other hand, the temporal modelling module will be responsible for processing the input sequence of facial features and thence modeling the temporal dependency between frames in the facial features sequence. For this module, the TRSS will rely on one of the most successful and well-adopted deep recurrent neural network architectures for modelling sequential data, Long Short-Term Memory (LSTM) (Hochreiter & Schmidhuber, 1997). The following sections describe the two building blocks of the proposed approach and how they are interconnected.

Facial Features Extractor Module

The facial features extractor module will be based on one of state-of-the-art facial behavior analysis toolkits, OpenFace 2.0 (Baltrusaitis et al., 2018), in order to extract the interpersonal facial features of the teacher in a given input sequence video. OpenFace 2.0 provides a variety of features related to head, face, and eyes of human subjects.

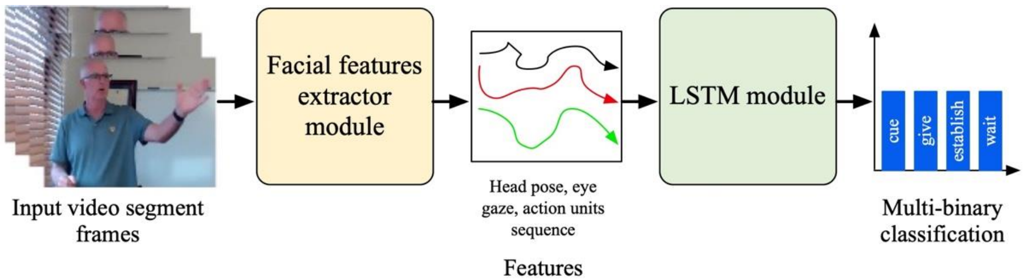

Figure 2: The Proposed Hybrid Network

Analysis in the TRSS will rely on only three types of features, namely head pose translation and rotation in 3D, eye gaze vectors and angles in 3D and presence and intensity of facial action units. The rationale behind choosing these specific features, is that head pose may provide some discriminative features between the different micro-skills actions which are the focused of TRSS. Eye gaze on the other hand can be beneficial when it comes to certain micro-skills action such as waiting and scanning. Facial action units/expressions can be viewed as complementary features that may help in differentiating between some correlated micro-skills such as establishing expectation and giving instructions. OpenFace 2.0 (a facial behavior analysis toolkit) is used at the base feature extraction stage. The extracted features are a combination of eye gaze location/direction in 3D, head pose and facial expression features (which total 76 features). Given a short sequence *v* of video frames (1 second in duration), the following features are calculated based on the output from the OpenFace 2.0 toolbox:

- **Head Pose:** The system will calculate both the mean and standard deviation of the translation and the rotation vectors of the head position in the world coordinates around the X, Y and Z axis. The total number of these features is 12.
- **Eye Gaze:** The system will calculate both the mean and standard deviation of the two eyes gaze direction vector in the world coordinates around the X, Y and Z axis. Additionally, it will calculate the mean and standard deviation of the eye gaze direction in radians in the world coordinates which is the average of the two eyes. The total number of these features is 16.
- **Facial Action Units:** As mentioned above, facial action units are a mechanism to encode human facial movements based on their appearance on the face. OpenFace 2.0 toolbox can recognize the intensity levels of 17 action units. For this feature, the system will calculate both the mean and standard deviation of the 17 actions units which results in a total of 34 features.

LSTM Module

LSTM networks have shown great success in multiple sequential modelling tasks such as natural language translation and summarization. The reason for their resilient performance is their capability for capturing the temporal dependency between consecutive observations. As a result, it makes the job of the following stage (classification/regression) easier due to the rich representations captured and provided by LSTM.

The LSTM module of TRSS consists only of two layers namely, LSTM layer and a dense layer. The LSTM layer contains 16 hidden units, while the dense layer contains 2 hidden units. Since the target task is a classification task, the loss function used for training the LSTM model is the softmax loss function which is

$$L = -\frac{1}{N}\sum_{n=1}^{\mathrm{N}} \log \frac{e^{f_{yn}}}{\sum e^{fm}} \quad (1)$$

where N is the total number of training samples, f_{yn} is the target value of the n-th sequence training sample and fm is m-th element of the class predictions vector f.

Experiments

Dataset

The total number of videos available for the four micro-skills actions was 21, each with duration ranging from 20 seconds to 1 minute. The videos were divided as follows: 4 videos for cueing with parallel acknowledgement skill (cue), 4 videos for establishing expectation skill (establish), 8 videos for giving instruction skill (give) and 5 videos for waiting and scanning skill (wait).

Class	**Precision**	**Recall**	**F_1-score**
Cueing with parallel acknowledgement	92%	69%	79%
Giving instructions	81%	95%	88%
Establishing expectations	92%	75%	83%
Waiting and scanning	84%	95%	89%

Table 2: Performance evaluation of the proposed framework

Results

The performance of the proposed approach was evaluated using small chunks of videos. Specifically, each video was further split into small chunks of 1 second duration without overlapping, resulting in roughly 60 videos for training and 70 videos for testing. Given the imbalanced nature of the processed dataset and the correlation between the four classes of essential skills, two separate binary classifiers were trained for each pair of the essential skills, namely (Establishing expectation, Waiting and Scanning) and (Giving instructions, cueing with parallel acknowledgment).

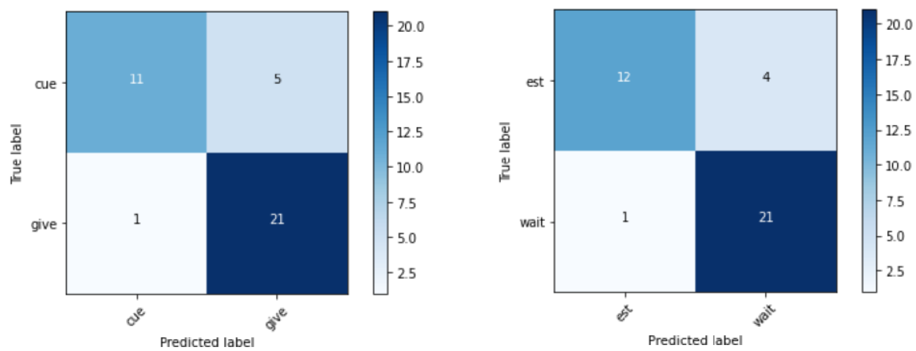

Figure 3: The confusion matrices of the two classifiers

Table 2 reports the results of the two trained classifiers of the proposed framework. As can be noticed, the two classifiers have achieved resilient results in terms of precision, recall and F_1-score.

To further investigate the performance of the two binary classifiers, confusion matrices were constructed as illustrated in Figure 3. In a confusion matrix, the stronger the color of the matrix diagonal, the higher accuracy that the model achieves. Also, the lighter the color of the off-diagonal cells, the lower the false positive rate of the model. Additionally Figure 4 visualizes some of the outputs from the classifiers. As can be noticed, on the left image the framework correctly identified the giving instructions action and on the left image it also accurately identified the establishing expectation action.

Figure 4: Sample results from the proposed framework.

Conclusion and future work

Teachers' capabilities for effective management of classroom behavior are important both for the successful promotion of students' learning and for the wellbeing of the teachers themselves (Nagro et al., 2020). Stress arising from difficulties with classroom management is a significant contributor to attrition of the teaching workforce (Stevenson et al., 2020). Appropriate programs of teacher professional development in behavior management can contribute to improve learning outcomes for students and reduced stress and attrition among teachers (Davidson & Goldman, 2004; Goldman, 2007).

There is ample evidence that teachers' behavior management capabilities can be improved through reflection and coaching following expert observation of teaching either directly in the classroom (Davidson & Goldman, 2004; Goldman, 2007) or using recorded video (Gibbons & Farley, 2020; Lane et al., 2020; Prilop et al., 2021). However, the restricted availability of expert observers and other resources limits the application of such methods.

Hence, this paper has described preliminary work on the development of a digital technologies solution that could provide a more cost-effective approach to identifying key elements of teacher behavior in their classrooms and supporting reflection directed toward developing appropriate behavior management skills. By assisting (pre-service) teachers to 'notice' their own behaviors (Walkoe et al., 2020) through identifying *suggestible moments* and providing additional relevant information such a system would support development of the necessary skills through enhanced reflection (Berenato, 2020).

Initial trials of a machine learning system for identifying and tagging actions relevant to classroom behavior management in recorded video have demonstrated the feasibility of such a system. Further research with more expansive collections of recorded video will refine the action recognition system and improve its accuracy in identifying relevant teacher actions. The inclusion of video recordings of a wider range of cultural and ethnic groups will be necessary to reduce the risk of bias in the recognition system.

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