Developing a Video-Based Discussion Platform with Emotion Detection Deep Learning to Increase Online Learning Engagement

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Abstract
This study discusses the development of Videmo platform. Videmo is a prototype online learning platform grounded in the Community of Inquiry framework and andragogical principles. It integrates Video-Based Discussion (VBD) and Emotion Detection Deep Learning (EDDL) technology to promote deeper learning and emotional engagement. Videmo Platform is a response to the limitations of Text-Based Discussion, which often miss capturing the students' emotions needed for interaction and understanding. Videmo recognizes emotional expressions such as happy, sad, angry and surprise using EDDL technology through facial analysis in videos discussion. Technical test results showed that the platform achieved an F1-score detection accuracy of 95% for MobileNet V1 SSD, followed by Tiny Face Detector F1-score of 92.0% and Face Expression Model F1-score of 88.0% in various lighting conditions and viewing angles. Surveys with 34 students found 86.27% of students said that Videmo engaged them more in the discussion and 75% of lecturers felt they understood the students' emotional engagement better. These findings illustrate the ability of Videmo Platform to transform the online learning experience into one that is more interactive and personalized. These initial findings suggest that Videmo may enhance social presence and provide instructors with richer insights into learner engagement, indicating potential for creating more interactive and personalized online learning experiences.

Keywords: Video-based discussion, emotion detection, deep learning, engagement, online learning

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In the digital age, online learning has become a core aspect of education, particularly after the COVID-19 pandemic, which forced numerous online learning platforms to be launched in many parts of the world (Almahasees et al., 2021; Camargo et al., 2020; Zhang et al., 2022), including in Indonesia. The platforms that enable online learning, not only allow better access to educational content but also can potentially facilitate the collaborative nature of teaching and learning (Almahasees et al., 2021; Camargo et al., 2020). A study by Musthofa et al. (2024) stressed that although teachers in Indonesia have been open to adopting online learning technologies during the pandemic, a gap still exists in optimizing these technologies to design effective and personalized learning for their students. Personalized learning involves not only tailoring academic content to individual students, but also supporting their emotional and social needs during the learning process. This support is especially critical in online environments where physical presence and face-to-face interactions are limited. Thus, there is a growing need for online learning systems that can respond to the social-emotional needs of users, particularly in online learning systems where physical interaction is reduced.

Most online learning platforms still rely on Text-Based Discussion (TBD), which many times misses out on the nuances of emotions and non-verbal communication. On the other hand, these components of emotion and non-verbal communication play an essential role in facilitating understanding and motivating learners regarding learning (Farsani et al., 2022; Mendzheritskaya & Hansen, 2019). Emotional engagement is an essential dimension of student engagement, and is recognized as a key component that can help create quality and impactful learning environments by having a strong effect on students' motivation, satisfaction, and learning results. Emotional engagement refers to the positive and negative emotional responses students exhibit during learning activities, including curiosity, joy, boredom, and worry (Fayanto et al., 2024). By recognizing and addressing these emotional dimensions, educators can create learning environments that are more supportive and personalized. The use of technology that supports non-verbal interaction in online learning is significant for developing adaptive learning environments. The technology integration in 21st-century learning is essential to foster students' soft skills and adaptability, enabling more engaging and effective classroom experiences. It had been demonstrated that technology-enhanced environments in learning contribute greatly to the critical skills needed for modern education (Oktaviani et al., 2019).

To ground this study, adult learning principles offer an essential theoretical perspective. Knowles' (1984) andragogical approach states that adults learn best when they are self-directed, goal-oriented, problem-centered, and have a clear understanding of how the learning experience is directly related to their professional or personal context. They bring previous experience as resources for understanding, interpreting new information, and constructing meaning. In the context of online learning, these characteristics suggest that an online platform must offer more than content, it must provide autonomy, relevance, and opportunities for active participation. Research on student initiative and engagement in online environments suggests that when students are afforded autonomy and can contribute meaningfully, their cognitive and affective investment rises, thus resulting in more positive learning outcomes (Heflin & Macaluso, 2021; Martin & Bolliger, 2018). Videmo addresses these needs by allowing learners to take part in asynchronous Video-Based Discussions (VBD), allowing them to respond in their own time, and to make a meaningful contribution to the collective learning experience. This design also is congruent with the online engagement frameworks that emphasize social presence, learner agency, and emotional connectedness as core dimensions of quality learning experiences

(Redmond et al., 2018, 2023). Moreover, the integration of Emotion Detection Deep Learning (EDDL) enables Videmo to provide emotion-sensitive information about learners' affective states during video-based discussions. This information can help instructors better understand students' emotional engagement and provide more responsive feedback. In this way, Videmo has the potential to support a more personalized and supportive online learning environment. Recognizing and responding to emotional presence has been shown to lead to stronger online learning communities and participation (Jiang & Koo, 2020; Lowenthal & Moore, 2020), and further validates the justification for EDDL inclusion in Videmo. This also accords with Media Richness Theory (Daft & Lengel, 1986), which argues that rich media such as video are more effective for complex communication, and with Social Information Processing Theory (Walther, 1992), which claims that meaningful interpersonal connections can be developed online if enough social cues are available.

To address this issue, we created an online learning platform called "Videmo" that uses Video-Based Discussion (VBD) which is also equipped with emotion detection feature based on Emotion Detection Deep Learning (EDDL) technology. With emotion detection, Videmo delivers a personalized experience that provides the student a more meaningful discussion. This level of personalization in line with the research of Ulfa et al. (2024), which develops adaptive instructional scaffolding on online discussions to support personalization and enhance engagement in MOOCs learning environments. Adaptive Instructional Scaffolding refers to a dynamic support mechanism in online learning environments, where instructional assistance is adjusted based on learners' individual needs, cognitive progress, and even emotional feedback. This approach allows students to receive timely guidance, explore multiple perspectives, and stay engaged in meaningful ways throughout the learning process. Adaptive Instructional Scaffolding is a great way to encourage students to explore, analyze, and understand diverse perceptions and to be challenged in their learning with a more in-depth understanding of their learning space relevant to Videmo's aim to be adaptive and emotional in their video-based discussions.

In this study, Videmo was specifically applied in the context of asynchronous video-based discussions, where students respond to online discussion by recording and uploading video. This context emphasizes student autonomy and the opportunity to express ideas through verbal, facial, and emotional communication. Through Videmo, students can give feedback via videos recorded directly on the platform, while EDDL technology automatically detects students' expressions during video recording. Videmo is a video-based discussion platform that allows content sharing, but it also detects and displays students' emotions during online discussions. It is crucial to employ EDDL technology in online learning because emotional expressions of students often reflect their understanding, motivation, and engagement about a specific subject (Mercer, 2019; Cheng et al., 2022; Ekström et al., 2020). The evidence is clear that positive emotions play a crucial role in maintaining motivation and attention, resulting in better learning outcomes over time (Dao & Sato, 2021; Denovan et al., 2020; Reinhold et al., 2021). Videmo bridges the gap for richer interaction during online learning using deep learning- based emotion analysis technology. This technology can recognize seven primary emotions such as happiness, sadness, anger, surprise, neutrality, fear, and disgust captured from students' facial expressions in discussion videos. This analysis enables instructors to provide more personalized feedback and gain deeper insights into students' emotional involvement during online discussions. In this way, Videmo offers a more holistic approach to online discussion by combining video-based interaction, discussion content, and emotion analysis.

The purpose of this study is to investigate how Videmo's features, specifically Video-Based Discussion (VBD) and Emotion Detection Deep Learning (EDDL), enhance student engagement and understanding in online learning environments. This study also evaluates the accuracy of the emotion recognition technology under different usage conditions and examines user satisfaction with the integrated VBD and EDDL features. Based on these objectives, this study addresses the following research questions:

RQ1: How effective is the Video-Based Discussion (VBD) feature in Videmo at enhancing student engagement in online learning?

RQ2: How well does the Emotion Detection Deep Learning (EDDL) technology detect key emotions (such as happiness, sadness, anger, surprise, neutrality, fear, and disgust) from students' facial expressions in Videmo?

RQ3: What is the satisfaction level of instructors and students regarding the emotion analysis feature in Videmo in supporting evaluation and feedback processes in online learning?

RQ4: What technical challenges does Videmo face in implementing emotion detection, especially in relation to variations in lighting and facial viewing angles?

Through these questions, we hope this research will help advance current online learning technology, especially in establishing a more interactive and personalized learning environment among the students.

Literature Review

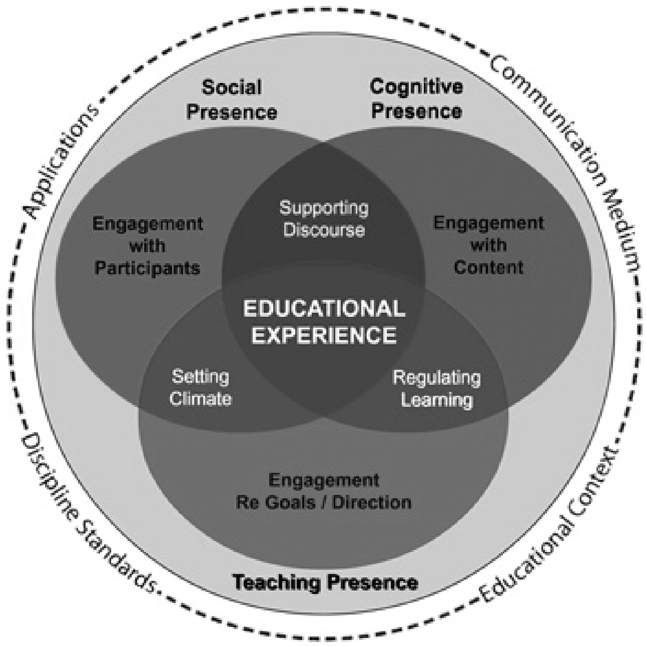
Video-Based Discussions in Online Learning

The online education literature identifies Video-Based Discussion (VBD) as an effective approach to increase student engagement. VBD allows students to give expressions, feelings, and body language directly, adding an element of communication that is harder to establish in a discussion that is only text-based. Milovic and Dingus (2021) showed that video-based discussions allowed students to feel more connected to classmates and lecturers and the interaction felt more meaningful. These findings demonstrate that VBD was able to mitigate isolation, an emotion prevalent in online learning, and heighten social presence, which contributes to the construct of inclusive learning.

Video-based discussions (VBD) offer a rich communication environment with the availability of verbal and non-verbal cues, which is consistent with Media Richness Theory (Daft & Lengel, 1986). The theory argues that rich media, in this case video, are more effective than text to convey socially complex information. In addition, Social Information Processing Theory (Walther, 1992) posits that interpersonal connections can become meaningful when relational messages are conveyed effectively in online communication. In the context of VBD, these relational cues include facial expressions, tone of voice, eye contact, and visible gestures. Recent studies have confirmed that VBD increases social presence, mitigates feelings of isolation, and enhances learner satisfaction (Milovic & Dingus, 2021; Swartzwelder et al., 2019). Research on learner presence and online engagement also emphasizes that social presence and emotional presence of the learners are key predictors of engagement, making VBD a critical strategy for online education (Jiang & Koo, 2020; Redmond et al., 2023).

Figure 1

Model Community of Inquiry (CoI)



Social presence is vital for the creation of an effective-learning experience according to the Community of Inquiry (CoI) model (Garrison et al., 1999). This model places a great emphasis on non-verbal modes of communication, including facial expressions and body movements, in developing positive social interaction in online educational settings. While applying CoI provides an opportunity for students to interact more deeply - helping to promote an inclusive and participatory learning environment (Syarifuddin et al., 2020). Compared to other theories such as Social Constructivism or Self Determination Theory, the CoI model offers a more structured lens for understanding how social presence and cognitive engagement work together in online learning settings. This theory is particularly relevant for Videmo because it emphasizes the importance of non-verbal communication, emotional cues, and social presence, all of which are enhanced through video-based discussions (VBD).

VBD inherently caters to this aspect of communication, enabling lecturers and students to share richer and more affective messages than they did in text. Swartzwelder et al. (2019) found that video-based discussions increased student engagement and interaction compared with text-based discussions. In particular, students who participated in video-based discussions were more willing to contribute, respond to peers, and communicate their understanding of the discussion material. Similarly, Lowenthal and Dunlap (2010) argued that virtual presence can strengthen the emotional connection between learners and instructors. Video-Based Discussion (VBD) can therefore stimulate social interaction in online learning settings by giving learners a way to express their thoughts and feelings through video, which may serve as an initial step toward deeper cognitive engagement.

The Importance of Emotions in the Learning Process

Emotions play a pivotal role in learning, and even more so in the context of online environments, where face-to-face interaction is restricted. Positive emotions, such as excitement, motivates and engages the student, and negative emotions, such as anxiety or frustration, detracts from learning according to the Control-Value Theory of Achievement Emotions by Pekrun (2006). Detecting emotions is critical in these online learning contexts for measuring the students' engagement, and allows for timely instructor intervention. The Control-Value Theory by Pekrun (2006) was selected because it explains the causal relationship between perceived control, value appraisals, and achievement emotions. Unlike basic motivation theories, the Control-Value Theory directly addresses how emotion influences learning outcomes. In Videmo, emotion detection is framed through the Control Value Theory to identify how students' emotional states such as anxiety or enjoyment reflect their perceived mastery and engagement. Research by Immordino-Yang and Damasio (2007) further evidence that emotional engagement in learning improves recall and strengthens memory of learning subject matter for the long term. Their study found that positive emotions can enhance learning resilience, increasing the retention of information over long periods of time. As a result, in the scenario of online education, technologies that can determine and modify emotions can significantly assist in facilitating personalized and adaptive learning experiences (Calvo & D'Mello, 2010).

Emotions during online learning always reflect important signals about students' cognitive activities. According to Artino (2012), emotions like confusion and frustration are good early indicators in understanding whether or not students are having difficulty with parts of the material. When instructors are aware of how their students are feeling, they can better tailor their support to the areas that need it most, in a timely manner.

Affective learning theory highlights that emotions influence attention, motivation, and memory, and thus how they impact learning depth (Bloom & Krathwohl, 1956; Immordino-Yang & Damasio, 2007). In online learning, where physical presence are limited, encouraging emotional presence can be important in maintaining participation and preventing disengagement. According to Redmond et al. (2023), students who feel a sense of emotional support and presence in online courses demonstrate higher levels of persistence and engagement. This underscores the value of designing platforms that can recognize and respond to learners' affective states.

Emotion Detection in Educational Contexts Using Deep Learning Technology

The evolution of AI technology, notably deep learning, facilitates automatic and accurate identification of students' emotions based on their facial expressions. This technology enables learning platforms to identify and interpret the emotional state of students in real time, thus making the learning journey more adaptive. According to Bagane et al., (2022) major emotions like happiness, sadness, anger, surprise, fear, disgust and neutral feature matches can be achieved by convolutional neural network (CNN) in up to 85% accuracy rate. In some cases, this could involve, for example, teachers and learning systems that will be able to track the emotional state of a student while learning, so as to give more adequate feedback.

A few of the studies also discuss the effectiveness of deep learning algorithms that have proved successful in warning emotions with highest accuracy. Anbananthan Pillai Munanday et al. (2023) showed that transfer learning-optimized CNNs improved detection accuracy in various lighting conditions and face viewing angles. This is especially true in online learning where the conditions of video and expressions are different, and platforms like Videmo can offer people more accurate emotional feedback. Online learning can be greatly promoted by emotion detection deep learning technology. Furthermore, the inclusion of emotion detection and a video discussion feature would enable Videmo to assist lecturers in developing an understanding of the emotional needs of students, thereby allowing them to tailor teaching methods for a more inclusive and adaptive environment.

Although emotion detection systems have demonstrated some potential, performance could be affected by environmental factors such as lighting, camera angles, and visibility of participants faces (Bagane et al., 2022). These technical limitations should be considered in educational settings, and the results here must be understood as preliminary until confirmed by studies on larger, more diverse samples. Videmo must hence be regarded as an early-stage prototype and evaluated as such, in line with the suggestion of a neutral research position.

Methodology

This research uses a system development-based experimental approach. There are three stages, namely: 1) platform development, 2) technical testing, 3) implementation and user evaluation.

In the first stage, *the Videmo platform was developed* using PHP, JavaScript and the face-api.js library to detect faces, analyze emotions, and record discussion videos. The main tools, VBD and EDDL, were integrated to support online discussions with real-time emotion analysis.

The second stage involved *technical testing of the emotion detection model*. The models used are SSD MobileNet V1 for initial face detection, Tiny Face Detector for detailed facial feature detection, and Face Expression Model for detecting emotion classifications (happy, sad, angry, surprised, neutral, fear, and disgusted). The three models are then tested and evaluated using customized datasets with Precision, Recall, and F1-score metrics. Environmental factors such as lighting and camera angle were monitored but noted as potential variables influencing detection accuracy.

The third stage is *implementation and user evaluation*. The Videmo platform was implemented in an online discussion forum with 34 students and 2 lecturers. Participants were recruited through convenience sampling from two classes, and all provided informed consent prior to participation. There are two classes, namely class A guided by Lecturer 1 with 17 students and class B guided by Lecturer 2 with 17 students. Emotion data was collected from each student in each class A and B when conducting video-based discussions through the Videmo platform. In class A, the discussion was about light topics, namely “The benefits of group discussion in online learning” and “A pleasant online learning experience.” While in class B, they discussed complex topics such as “The effectiveness of online learning in building 21st century skills” and “Ethical challenges in the use of artificial intelligence for education.” Surveys were conducted to measure the level of user satisfaction and learning effectiveness. The emotional data obtained was then analyzed quantitatively to determine the pattern of students’ emotional engagement. This study was performed as a so-called controlled simulation in a non-course context to be able to focus on the platform functionality and user experience, an aspect that must be taken into account when interpreting results. While the sample size was sufficient for this study, it represents a limitation in terms of generalizing the findings.

The diagrams below demonstrate Videmo's use case diagram and feature workflows to give a better insight into how the system works and how users interact with it. Here is the diagram which shows how different modules of the platform interact to provide real-time emotion detection and demonstrate video-based discussions.

Figure 2

Use Case Diagram

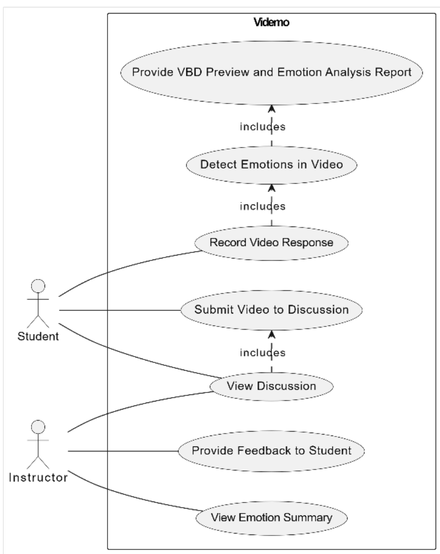
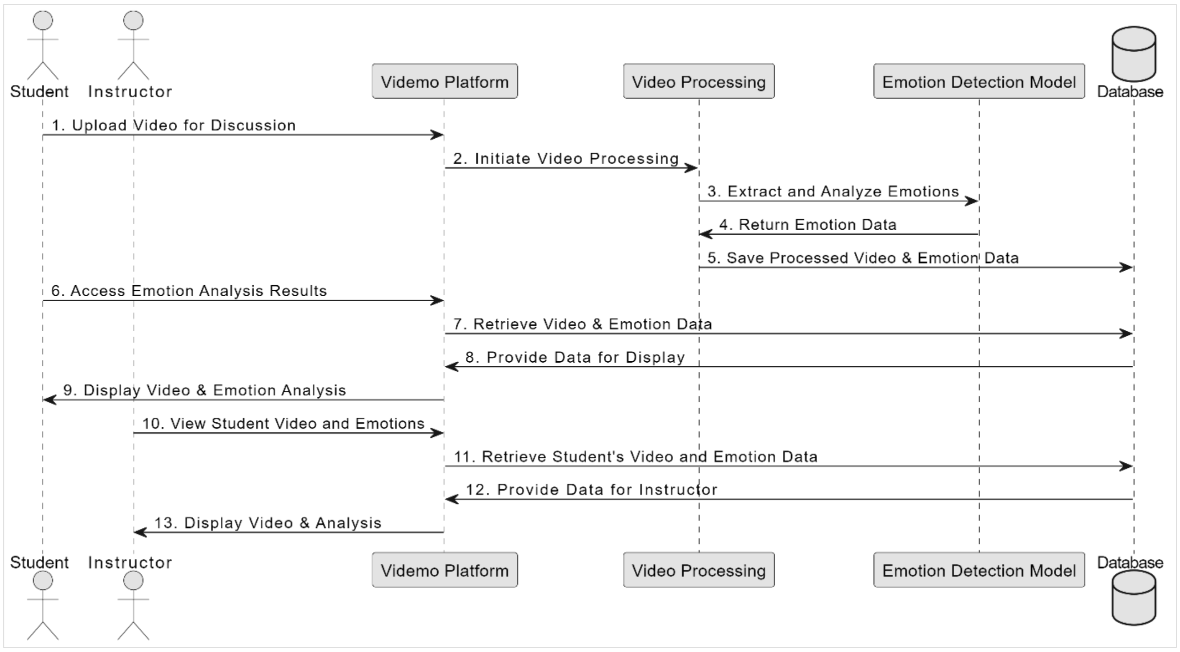


Figure 3

Feature Workflow Diagram



Videmo utilizes various models and algorithms to support emotion analysis in video discussions:

a) SSD MobileNet V1
This model is used as an initial filter to detect faces in the video. With an efficient object detection algorithm, the MobileNet V1 SSD provides accurate face position estimation.

b) Tiny Face Detector
The model is optimized to detect facial features in detail, even under varying lighting conditions and face orientation. Tiny Face Detector ensures accuracy of detection, especially in non-ideal environments, while maintaining performance.

c) Face Expression Model
The model classifies facial expressions into seven major emotion categories (happy, sad, angry, surprised, neutral, fear, and disgust) using deep learning algorithms. The model has been tested and optimized to classify facial expressions with high accuracy.

All these models are integrated with the face-api.js library, which enables JavaScript-based analysis directly in the web environment.

Figure 4

Model Processing Flow for Emotion Detection

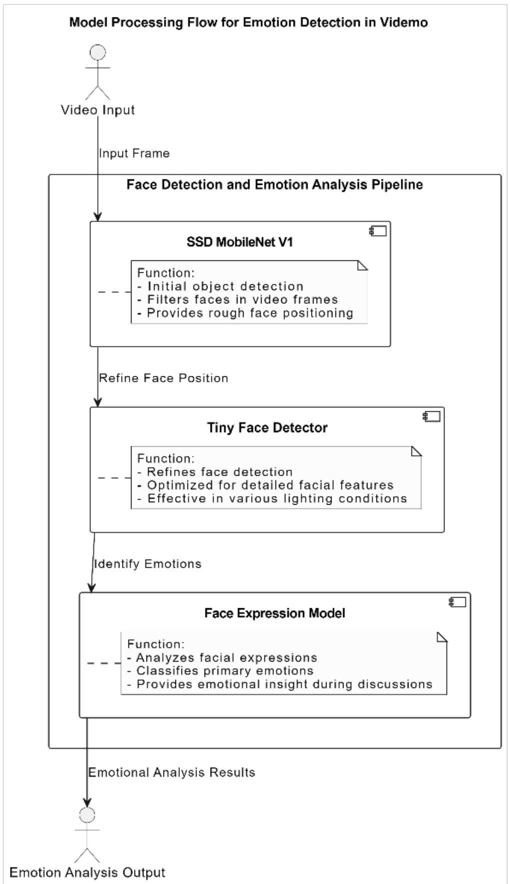
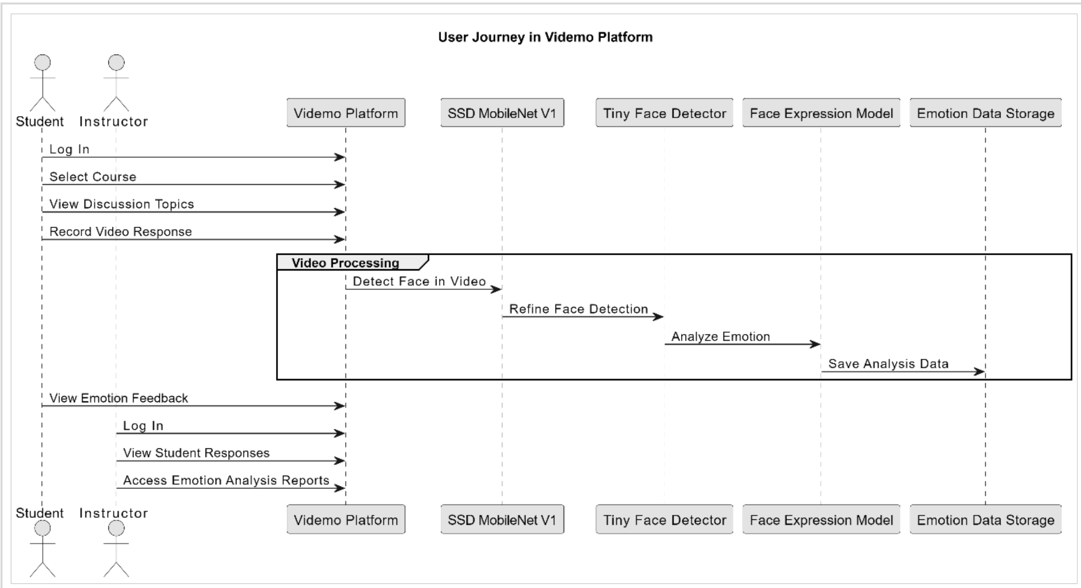


Figure 5

User Journey in Videmo Platform



The Videmo development process consists of several key stages:

a) *Requirement Analysis*
The development of Videmo started with identifying the need for a platform that supports video-based discussions and provides emotion analysis. This approach was taken to enhance more in-depth and emotional learning interactions.
b) *Model Integration and Fine-Tuning*
Each model was integrated and matched with student recorded data to ensure the accuracy of emotion analysis. Model parameters were incrementally adjusted to optimize the accuracy of emotion detection and classification.
c) *User Testing and Feedback.*
At this stage, users participated in initial testing, providing feedback on the accuracy and relevance of the emotion analysis results. This feedback was used to make adjustments to the detection algorithm to make the analysis results more relevant to the learning context.
d) *Validation and Iteration*.
Validation is done by applying Videmo to real discussions to ensure the accuracy of the model under various conditions (light, face angle). Iterations were conducted to address shortcomings and ensure the system is able to provide consistent emotional analysis.
e) *Data Storage and Security Compliance*.
Videmo uses strict data storage and security policies, ensuring that every video and emotion analysis result is stored securely. Access rights are restricted to authorized parties to maintain student privacy.

These methodological choices restrict the generalizability of the findings, which are intended as preliminary and guiding evidence to design larger studies.

Result

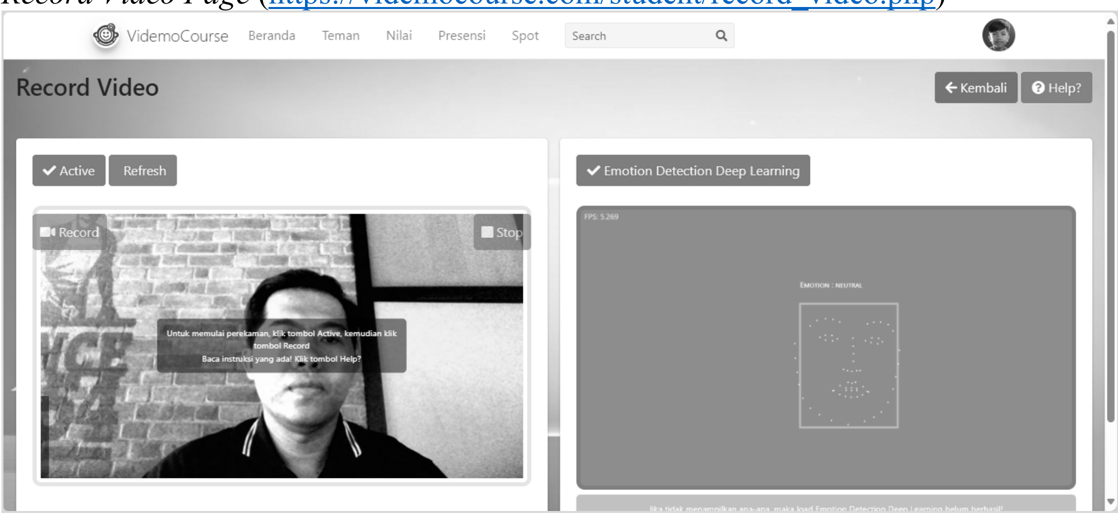
Description of Videmo Feature

<u>Video-Based Discussions (VBD)</u>

The VBD feature in Videmo provides a video-based discussion platform that allows students to record their discussion responses on video. VBD enables asynchronous interaction, allowing lecturers and students to engage in a more meaningful discussion than text-association. When students record video responses to the discussion on the Videmo platform, they are able to view real time emotion data which offers deep insights as to their emotional engagement during the recorded discussion.

Figure 6

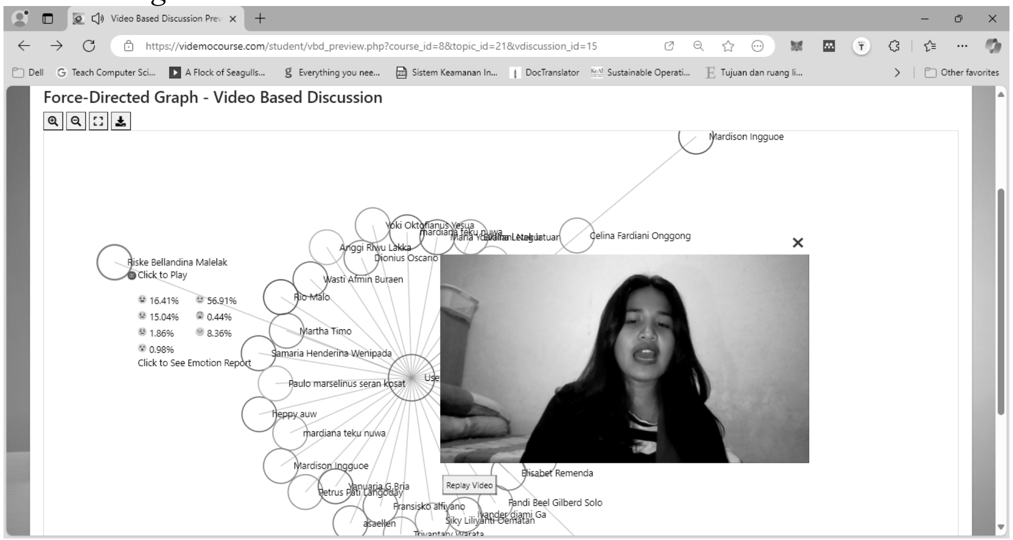
Record Video Page (https://videmocourse.com/student/record_video.php)



<u>Emotion Detection Deep Learning (EDDL)</u>

EDDL utilizes deep learning algorithms to automatically detect emotions from students' facial expressions in videos. It is built to identify seven basic emotional states: happiness, sadness, anger, surprise, neutrality, fear, and disgust. EDDL works in the same time the discussion video is being recorded, where the overall percentage of emotions calculated during the recording is stored on the database in addition to the discussion video information. The results of this emotion analysis are displayed on the VBD preview which can provide lecturers with information about the emotional dynamics that occur during online discussions.

Figure 7
Preview Page Video-Based Discussion



Technical Testing Results

Technical testing has been conducted before it was used in real online learning to see if the model used in Emotion Detection Deep Learning is working well. The technical tests conducted in the development of Videmo are as follows:

<u>Accuracy and Reliability of Emotion Detection Model</u>

The emotion detection model was tested under a range of conditions, including different lighting levels, facial angles, and types of emotional expressions. The technical test involved taking video samples from university students under varying lighting conditions and using three main models: SSD MobileNet V1 for initial face detection, Tiny Face Detector for detailed facial feature detection, and Face Expression Model for emotion classification. The accuracy and robustness data was tested using Precision, Recall, and F1-score metrics, which are standard in the evaluation of detection and classification models.

$$Precision = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Positive\ (FP)}$$

$$Recall = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Negative\ (FN)}$$

$$F1 - Score = 2 \text{ x } \frac{Precision \text{ x } Recall}{Precision + Recall}$$

Testing included 34 student video samples selected thematically by lighting, facial angles, and emotional expressions. The dataset has been labelled with ground truth in the form of bounding boxes for face detection and emotion categories for classification. Face detection in the video is achieved using the MobileNetV1 SSD model. Intersection over Union (IoU) use to compare the bounding box of model detection results and the ground truth bounding box for evaluation. Detection is considered correct if IoU > 0.5 (True Positive). If there is no face but the model detects, it is a False Positive, where as if there is a face but is not considered by the model, it is a False Negative. Tiny Face Detector is a tool that finds facial features more specifically and under adverse environmental situations, like not very bright light or face alignment. The bounding box model results are compared with the ground truth using the same method as MobileNet V1 SSD Model. For the Face Expression Model, performance was evaluated based on emotion classification accuracy rather than bounding box detection or IoU. The Face Expression Model is responsible for classifying facial expressions. We quantitatively compare the emotion hypothesis predictions given by the model with the ground truth labels. Therefore, the evaluation did not involve bounding boxes or IoU; instead, it measured the proportion of predictions that matched the ground-truth labels. The accuracy of each model test is summarized in Table 1:

Table 1

Face and Emotion Detection Model Accuracy

Model	**Precision (%)**	**Recall (%)**	**F1-score (%)**
SSD MobileNet V1	94.8	95.2	95
Tiny Face Detector	91.3	92.8	92
Face Expression Model	88.1	87.9	88

From the table, it can be seen that SSD MobileNet V1 out of all achieves a better accuracy with the F1-score of 95.0%, and this is followed by Tiny Face Detector with an F1-score of 92.0% and Face Expression Model with an F1-score of 88.0%. From these results, we can conclude that combining these three models we can detect faces and emotional expressions in less-than-optimal environments.

<u>Evaluation of System Robustness to Lighting and Angle Variations</u>

Additional tests were carried out to assess the system's robustness across various lighting conditions and face viewing angles. These experiments involved adjusting lighting intensity (low, medium, and high) and face orientation (facing the camera at 0°, as well as at 30° and 45° angles from the camera). Each condition was tested with 34 samples to assess the stability of the system. Each sample is analyzed by the MobileNet V1 SSD model and Tiny Face Detector, resulting in a prediction bounding box. This bounding box is compared to the ground truth bounding box using Intersection over Union (IoU), with detection considered true positive if IoU > 0.5. Accuracy was calculated for each combination using the formula:

$$Accuray = \frac{Number\ of\ Correct\ Detections\ (True\ Positives)}{Total\ Number\ of\ Faces\ in\ Ground\ Truth}\ x\ 100\%$$

The test results are shown in Table 2.

Table 2

Effect of Lighting Conditions and Viewing Angle on Face Detection Accuracy

Condition – Angles From the Camera	Low Lighting (%)	Medium Lighting (%)	High Lighting (%)
Angles 0°	91.2	95.3	96.8
Angles 30°	88.4	93.7	95.1
Angles 45°	82.7	89.5	91.4

Description:

a. Low Lighting: Dim or minimal light
b. Medium Lighting: Standard light (normal lighting)
c. High Lighting: Bright or excellent light
d. 0°: The face is directly facing the camera
e. 30°: The face is tilted by 30°
f. 45°: The face is tilted more sharply by 45°.

The results demonstrate that the high illumination with a viewing angle of 0° detects the optimally good-face accuracy of 96.8%. At low illumination, the accuracy was as low as 82.7% when the angle was 45°, which suggest that it is more difficult to detect the face when the illumination is less and the face angle is sharper. But, the results were still around 80% accuracy in all situations, which tells the high stability of the MobileNet V1 SSD with Tiny Face Detector combination going through different situations.

<u>Evaluation of Face Expression Models for Emotion Classification</u>

Face Expression model-testing on seven core emotions or facial expressions to determine how accurate results are for predicting emotions alone. The prediction accuracy of the model was obtained for each emotion using 34 samples. The model will output the emotion for every sample. Testing compares the model prediction with ground truth. If the predicted value in the model differs from the ground truth, it is false. If it is the same then it is correct (Correct Prediction). Accuracy is calculated for each emotion based on the percentage of correct predictions against the total samples of that emotion. The accuracy formula used:

$$Accuray = \frac{Number\ of\ Correct\ Prediction}{Total\ Number\ of\ Samples}\ x\ 100\%$$

The characteristics for recognizing facial expressions include the mouth, eyes, and eyebrows. Happy expressions are characterized by a smile, raised lip corners, and narrowed eyes due to raised cheeks. Sad expressions are characterized by lowered lips, raised inner eyebrows, and eyes that appear haggard. Angry is characterized by downward furrowed eyebrows, narrowed eyes, and compressed or tightly pursed lips. Surprised shows a wide open mouth, raised eyebrows, and dilated eyes. Neutral is characterized by a relaxed face with no particular expression. Fear is characterized by eyes wide open, eyebrows raised to the center, and mouth slightly open or pulled back. Disgust is characterized by pursed lips, raised nose, and narrowed eyes, indicating discomfort or disgust.

The results of this emotion accuracy test are shown in Table 3.

Table 3

Prediction Accuracy of Face Expression Model Based on Emotion

Emotion	Prediction Accuracy (%)
Happy	91.2
Sad	85.5
Angry	84.9
Surprised	89.3
Neutral	92.1
Fear	80.7
Disgusted	82.5

The table shows that the highest accuracy was reached for the emotions "Neutral" (92.1%) and "Happy" (91.2%), while the lowest accuracy was recorded for "Fear" (80.7%). This variation may be attributed to the complexity of facial expressions associated with certain emotions, like "Fear" and "Disgust."

User Testing Results

User Satisfaction Level

User testing involved 34 students and 2 lecturers to evaluate the VBD and EDDL features on the Videmo Platform. Testing was conducted in three stages: (1) participants engaged on the platform with two types of discussion topics, namely light topics such as "The benefits of group discussion in online learning" and "An enjoyable online learning experience," as well as complex topics such as "The effectiveness of online learning in building 21st century skills" and "Ethical challenges in the use of artificial intelligence for education," (2) emotion data from discussions were recorded using the EDDL feature and analyzed based on emotion categories, and (3) participants filled out a satisfaction survey to evaluate the ease of use of the platform and the benefits of the emotion feature in discussions.

Table 4

Survey Results for Students

No.	Survey Question	Agree	Disagree	Percentage Agree (%)
1	Did the VBD and EDDL features help you engage more actively in the discussion?	30	4	88.24%
2	Do you feel comfortable using the VBD and EDDL features?	29	5	85.29%
3	Did the VBD and EDDL features improve your understanding of the discussion material?	28	6	82.35%

4	Do the VBD and EDDL features make it easier for you to express your opinions?	31	3	91.18%
5	Did the VBD and EDDL features help you co-operate with other participants?	29	5	85.29%
6	Did the VBD and EDDL features help you keep your focus during the discussion?	27	7	79.41%
7	Does the emotion data from VBD affect the way you interact?	28	6	82.35%
8	Are VBD discussions more efficient than regular discussions?	30	4	88.24%
9	Do the VBD and EDDL features increase your confidence in speaking?	28	6	82.35%
10	Do the VBD and EDDL features motivate you to be more active in discussions?	29	5	85.29%
11	Did the VBD and EDDL features help you understand other participants' perspectives?	31	3	91.18%
12	Do you feel that the VBD and EDDL features improve the quality of discussions?	30	4	88.24%
13	Do the VBD and EDDL features make discussions more enjoyable?	28	6	82.35%
14	Is the VBD and EDDL interface of Videmo Platform easy to use?	32	2	94.12%
15	Do VBD and EDDL features make online learning more engaging?	30	4	88.24%
	Total	**440**	**70**	**86.27%**

The survey showed that the majority of students felt that Video-Based Discussion (VBD) and Emotion Detection Deep Learning (EDDL) feature in Videmo Platform had a positive impact on their engagement in online discussions. A total of 86.27% of students expressed satisfaction with the various features offered by this platform. There are several important points that emerged from this survey:

a. *Improving the quality of discussion*
Total 91.18% of students felt that VBD and EDDL feature, helped them better understand their peers' points of view. Not only that, but the online discussions were also more enjoyable and richer because students could express their opinions in a more expressive way. Overall, they also felt that the quality of the discussion improved.
b. *Making it easier to express opinions*
The VBD feature, according to 91.18% of respondents, made it very easy for them to convey their ideas. Compared to text-based discussions, they felt that videos allowed emotions and body language to be better conveyed. VBD and EDDL feature in the Videmo platform helped them feel more confident in discussions.
c. *Ease of user interface*
Total 94.12% of students agreed that Videmo's interface was very easy to use. The platform is intuitively designed, so it does not take long for students to understand how it works. They even felt comfortable when accessing the available features.
d. *The emotion data effect for students in video-based discussion.*

> Item 7 student survey question: “Does the emotion data from VBD affect the way you interact?” Responses revealed a various answers or perceptions. Total 82.35% of students agreed that emotion data affected their interaction, follow-up interviews highlighted mixed perceptions. Some students stated that knowing their emotions were being analyzed encouraged them to engage more seriously and reflectively in online discussions. Others, however, admitted feeling mildly self-conscious, particularly in expressing negative emotions or controversial views. These varied responses suggest that while emotion data may positively increase awareness and reflection, it could also introduce a sense of performance pressure.

From the results of this survey, it appears that students feel more free and comfortable when sharing ideas through video. They also felt that the emotional expressions and body language captured in the online discussion helped to create a more interactive atmosphere and supported deeper engagement.

Table 5

Survey Results for Lecturers

No.	Survey Question	Agree	Disagree	Percentage Agree (%)
1	Does the emotion data generated by the Videmo platform make it easier for you to understand student engagement?	2	0	100.0%
2	Does the emotion data generated by the Videmo platform provide new insights into student responses?	2	0	100.0%
3	Does the emotion data generated by the Videmo platform help you identify struggling students?	1	1	50.0%
4	Does the emotion data generated by the Videmo platform help you plan learning interventions?	1	1	50.0%
5	Is the emotion data generated by the Videmo platform relevant for learning evaluation?	2	0	100.0%
6	Does the emotion data generated by the Videmo Platform improve the quality of student discussions?	1	1	50.0%
7	Does the emotion data generated by the Videmo platform make it easy for you to provide feedback?	2	0	100.0%
8	Do you find the emotion data generated by the Videmo platform helpful in understanding group responses?	1	1	50.0%
9	Does the emotion data generated by the Videmo platform support decision-making in learning?	2	0	100.0%
10	Does the emotion data generated by the Videmo platform enhance your online teaching experience?	1	1	50.0%
	Total	**15**	**5**	**75.0%**

A total of 75% of lecturers’ statements expressed that the EDDL feature helped them to better understand how students engage in online discussions. The emotion data generated through this feature allows lecturers to be more sensitive to students’ emotions in online discussions. It also helps lecturers to provide feedback that feels more relevant and personalized.

However, there is an important caveat. For the question of whether this emotion data can help lecturers in developing learning interventions, only 50% agreed. This result, in fact, signals that while this feature is quite useful, its use may not be optimal as it requires a deeper understanding of how emotion data can be applied directly in learning strategies.

In addition, this study itself still has limitations that need to be recognized. This study only involved two lecturers, and did not actually test the Videmo platform in real course learning. On the contrary, the online discussion conducted in this study was only a simulation, focusing on two types of topics: light and complex. Therefore, the findings obtained are more representative of the initial potential of Videmo's features, and cannot be used as a complete picture of how this platform works in real learning situations. As such, the results of this study are promising, but wider implementation in real learning contexts is needed to test and validate its potential.

Analysis of Engagement and Learning Effectiveness

The test was conducted on two classes, each consisting of 17 students, with the division based on the lecturer and the type of discussion topic. Class A (17 students), supervised by Lecturer 1, discussed light topics. Meanwhile, class B (17 students), supervised by Lecturer 2, discussed complex topics. In class A, the emotion data showed the dominance emotions is "happy" (40%) and "neutral" (35%) emotions. The emotion data detected in class A reflected a sense of comfort and good understanding of the discussion material. In class B, the dominating emotions were "fear" (31%) and "surprise" (30%) emotions. This result shows that in class B there is a cognitive challenge and curiosity of students towards more difficult material.

Table 6

Students' Emotion Distribution on Light Topics and Complex Topics

Emotions	**Mean of Light Topic 1**	**Mean of Light Topic 2**	**Mean of Light Topic**	**Mean of Complex Topics 1**	**Mean of Complex Topics 2**	**Mean of Complex Topic**
Happy	42%	38%	40%	20%	18%	19%
Sad	8%	6%	7%	12%	10%	11%
Angry	5%	7%	6%	14%	16%	15%
Surprised	12%	16%	14%	28%	32%	30%
Neutral	34%	36%	35%	22%	18%	20%
Fear	10%	12%	11%	30%	32%	31%
Disgusted	3%	5%	4%	8%	6%	7%

The emotion data generated from EDDL provides a clearer picture of the level of student engagement in the discussion. From the analysis of the video-based discussions, it was found that "happy" and "neutral" emotions dominated student responses on light topics, while on complex or critical topics, “fear” and “surprise” emotions were more common. This suggests that emotional engagement is in line with students' level of understanding of the discussion material.

The dominance of “happy” and “neutral” emotions on light topics reflects a supportive discussion environment and provides a sense of comfort for students. Meanwhile the high emotions of “fear” and “surprise” on complex topics show the cognitive challenges students face in understanding more difficult discussion topics, and also trigger curiosity. Emotions on complex topics indicate the need for support strategies, such as scaffolding or additional clarification, to help students overcome challenges.

These results reveal the preliminary evidence for that Videmo’s VBD and EDDL features supported student engagement and may provide instructors with useful emotional insights, but needs further validation in the settings of real courses.

Discussion

Relevance and Effectiveness of Video-Based Discussion (VBD) in Online Learning

The study of this feature shows an impact on the student experience in Videmo via the Video-Based Discussion (VBD) method. The majority of students perceived that video-based discussions enabled them to interact on a deeper level than text-based discussions. With video, they can express emotions and body language that get lost in plain text.

Research by Milovic and Dingus (2021) supports this finding, where video-based discussions were used to mitigate the feelings of isolation that are common with online learning. Relatedly, the Community of Inquiry (CoI) model presented by Garrison et al. (1999), highlights the importance of social presence in creating meaningful learning experiences. In this case, Videmo helps students to feel more emotionally connected in the online learning environment.

There are some additional interesting aspects on the lecturer’s perspective, that the VBD feature provides additional benefits. Due to the recording of students’ facial expressions and body language, lecturers can better determine whether or not students actually comprehend with what they are teaching. The survey showed that 91.18% of students felt that VBD helped students to state their opinion more effectively, while 94.12% felt that Videmo’s interface was easy to use. This shows that overall, VBD not only enhances the quality of discussions, but also provides a supportive environment for collaborative learning. It is at the same time supporting Media Richness Theory (Daft & Lengel, 1986), which argues that video provides a richer medium for exchanging complex information compared to text. Additionally, according to Social Information Processing Theory (Walther, 1992), being able to see the facial expression and hear the tone of voice of peers can aid in developing interpersonal relationships even through a computer-mediated environments.

Emotion Detection to Support Learning Evaluation

The Emotion Detection Deep Learning (EDDL) feature in Videmo makes an important contribution in measuring students’ emotional engagement, which is often an indicator of learning comprehension and motivation. The EDDL feature in Videmo has been shown to accurately detect seven discrete emotions (happiness, sadness anger, surprise, neutrality, fear, and disgust) with a high degree of accuracy. Particularly the emotions “neutral” (92.1%) and “happy” (91.2%), while the lowest accuracy was recorded for “fear” (80.7%). This capability enables lecturers to understand how topics resonate with students emotionally, thus informing more tailored and meaningful feedback.

In the survey, 75% of lecturers responded that the emotion data helps them to understand student engagement better. For example, the dominant emotions of “fear” and “surprise” on complex topics indicate the cognitive challenges students’ experience. This aligns with the theory of Pekrun (2006), which theorizes that joy is a positive emotion that relates to an increase in motivation to learn, whereas fear is an emotion describing the need for further intervention or support. These results also resonate with findings from Jiang and Koo (2020), who reported that fostering emotional presence in online courses strengthens community and engagement. By making emotions visible, Videmo supports timely scaffolding, which is consistent with Control-Value Theory’s emphasis on regulation of achievement emotions. Teachers also can provide students with more personalized support by understanding their emotional states, which enhances the overall learning process. This functionality allows lecturers to give feedback not only on the content but also to consider emotional issues, which leads to a more comprehensive evaluation.

However, we should exercise caution regarding the interpretation of certain emotions like “fear” or “disgust.” These feelings don’t always relate directly to what’s being learned and may be impacted by external forces: environmental conditions, the students’ mood throughout the discussion, etc. Thus, even if this feature has potential, its use must be further refined in a more realistic and matched way with emotion data.

Advantages of Videmo Compared to Other Platforms

This unique combination of VBD and EDDL offers potential benefits over many existing platforms. Besides offering a video-based discussion area, Videmo also provides lecturers with emotional insights that they can use to adapt their approach to the learning environment. For instance, when emotions like “confusion” or “frustration” are detected, the lecturers can immediately explain additional details to prevent students from losing understanding about the material. This advantage is reinforced by the overall student satisfaction rate of 86.27%, with 91.18% feeling that VBD improved the quality of discussions. This implies Videmo is not just a communication tool for online learning platform, but also a more comprehensive human assessment tool. Utilizing the content and emotion data, Videmo creates a more experimental style of learning for the student on an online learning platform. However, as noted by Redmond et al. (2023), engagement strategies should be verified empirically for different contexts; accordingly, the benefits of Videmo need to be demonstrated in longitudinal studies before we can generalize its effect or impact.

Although Moodle, being one of the most popular learning management systems (LMS) available today, already includes the features to create discussion forums and some basic interactive resources, these tools are text-based for the majority and do not offer native emotion analysis or video-based discussion integration. Therefore, Moodle forums may fail to capture students’ emotional expressions, which are relevant in order to understand engagement and social presence. Videmo does not rather replace Moodle, but provides an additional emotional layer of interaction with a video-based discussions and real-time emotion detection capabilities. In this way teachers can not only assess the cognitive value of what students contribute, but also follow their emotional engagement. The future addition of Videmo into other LMS systems, such as Moodle or as a plug-in or an external activity, could result in a more complete solution where both the robust course management capabilities from other LMS and the emotionally detection feature of Videmo is offered.

Technical Limitations and Challenges

Videmo platforms do have a lot of potential, but there are certainly some technical limitations to take into account. One of the problems discovered is that the detection sensor for emotions fails when lighting conditions are poor and/or the student's face is not turned towards to the camera. For example, from the tests conducted, the face detection accuracy reached 96.8% in bright lighting, but decreased to 82.7% in low lighting. Such conditions are a clear challenge, particularly in online learning, where users' conditions of the environment can differ radically. In addition, the interpretation of certain emotions, such as “fear” or “disgust,” can sometimes be confusing. These emotions may not always be directly related to the topic of discussion, but can be influenced by other factors, such as the student's mood or distractions from the surrounding environment. Therefore, it is important for developers need to ensure that these emotion detections are both accurate and relevant with respect of the educational context, to avoid introducing bias on their usage.

This study was performed on a relatively small scale. The discussions tested were still simulations, not real learning situations. The study only involved 34 students and 2 lecturers, and focused on two types of discussion topics, namely light topics and complex topics. This is so small scale that the observed results represent more the initial potential of Videmo rather than the real impact in daily exploitation. Future studies involving larger, more diverse samples and controlled comparisons across instructional contexts are necessary to validate and extend these initial findings.

This limitation opens up a possible area of future research. Future studies may recruit larger samples in real learning environments. These might focus on testing across different environmental settings such as lighting and hardware to increase validity and efficacy across different contexts. Taken together, these limitations suggest that the current results must be considered as preliminary evidence and not definitive conclusions. This work represents the first phase of our research which will continue with a quasi-experimental design with control and experimental groups to go deeper in the investigation about the affirmative impact on teaching a course by means of Videmo.

Future Implications and Recommendations

Future development of Videmo should focus on improving the technical reliability of emotion detection, expanding validation in authentic course settings, and preparing instructors to interpret emotion data pedagogically. Similar to the suggestions of Martin and Bolliger (2018), future research should consider the role of such tools in supporting learner autonomy, faculty presence, and cognitive engagement across diverse online learning environments. To make Videmo a more reliable and educationally meaningful tool for online learning, several important steps can be taken:

a. Improve the Accuracy of the Technology

In this study, one of the biggest challenges was the decrease in emotion detection accuracy in low lighting conditions or when students' faces were not fully visible. This is a very common occurrence in online learning, where the user's environmental conditions are often difficult to control. By utilizing techniques such as transfer learning or more advanced deep learning models, Videmo can be more adaptive to these conditions. This will certainly strengthen its reliability in various learning situations.

b. Integration of NLP-based Sentiment Analysis

The future research is to develop a sentiment analysis based on Natural Language Processing (NLP). This feature enables deep analysis of students' verbal responses that can be analyzed to understand their emotions more deeply. By merging emotion data from video and text, it can provide lecturers with a much more holistic view. However, this would surely enhance the learning assessment mechanism.

c. Improved Validation with a Broader Study

Given that this was a small-sample study, the next step will be to conduct a larger scale study. Testing Videmo with real courses, and bigger numbers of students, will give a more accurate picture of how the system functions in the wild. Future studies should also examine whether Videmo aligns with learners' needs, instructional goals, and authentic online course practices.

d. Training for Lecturers

Educational technologies such as Videmo are effective only when instructors understand how to use them appropriately. As would training on using Videmo platform, and reading emotion data from the platform. This training not only must include how to identify emotion data but also how to connect that data with learning strategies to enhance activity relevance to student needs.

Ethical Considerations and Privacy

The integration of video-based discussion and emotion detection in Videmo raises important concerns regarding user privacy, ethical data use, and psychological comfort. Although Videmo collects emotional data strictly for educational research purposes, the recording of students' videos and the analysis of emotional data may still lead to discomfort or self-consciousness. To address these concerns, all participants were informed in advance about how their videos and emotional data would be used, and only those who provided consent were eligible to participate in this study. Data storage in Videmo follows strict access and encryption protocols, and emotional data are not used for purposes beyond this research.

Conclusion

Through the development of our Videmo platform which integrates VBD and EDDL technologies, we present a new option for online learning with a more in-depth and meaningful approach. Students are able to use the VBD feature to express feelings and emotions and body language which are not normally expressed in text-based discussions, improving their social presence in the online learning environment. EDDL technology enables lecturers to gain insight into students' emotional responses to topics of discussion, offering a more comprehensive view of student engagement. The survey results indicate that Videmo has been successful in improving user engagement and satisfaction as 86.2% of students stated that they have participated more often in discussions and 75% of lecturers agreed on finding it easier to understand student responses with Videmo. Technical tests also showed a high level of emotion detection accuracy, especially for "happy" and "neutral" emotions, despite challenges in certain lighting conditions and viewing angles. While the platform still faces some technical challenges, particularly in less-than-ideal video conditions, further development of the emotion detection technology and integration of Natural Language Processing (NLP)-based sentiment analysis could improve the reliability of the system. This study adds to a growing literature on online learning by combining emotion analytics with video-based discussion and provides empirical support that emotional presence can be predictably measured and used for adaptive instruction. Next steps are to introduce a quasi-experimental design, including control and intervention conditions in actual course contexts, in order to rigorously test the impact of Videmo on engagement, learning achievement, and emotional regulation over time.

Declarations

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Ethics Approval and Consent to Participate

This study was approved by the Research Ethics Committee of Universitas Citra Bangsa (No: A.0221/SU/FKIP/UCB/VIII/2024). All participants provided written informed consent prior to data collection, and all procedures were conducted in accordance with institutional ethical standards for research involving human subjects.

Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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