Neutrosophic Sets and Systems, Vol. 61, 2023
University of New Mexico

A Novel Classroom Teaching Evaluation Method for Assessing Learning Effectiveness Based on Machine Vision and Neutrosophic Sets

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Abstract: With the development of intelligent technology, machine vision is gradually applied to classroom teaching. Considering the uncertainty of students' class status, the application of neutrosophic sets provides a novel way for classroom evaluation. In this context, this study proposes a novel classroom teaching evaluation method based on machine vision and neutrosophic sets to better evaluate students' learning effectiveness. The main innovation of this study is to construct a temporal neutrosophic evaluation model that considers students' concentration. Specifically, machine vision technology first is used to detect students' status so as to construct temporal neutrosophic evaluation matrices on students' class status. Thereafter, this study proposes a novel time weight function considering students' concentration based on the Pearson correlation coefficient. Then, this study introduces evaluation based on distance from average solution to address multi-criteria decision-making issues. Finally, the validity and feasibility of the proposed evaluation model are illustrated through a case study and comparative analyses. The results indicate that the ranking of the proposed method is $1 \succ 3 \succ 4 \succ 2$, which is consistent with comparative analyses. The aforementioned study further validates the practical value and provides valuable insights for teaching evaluation methods.

Keywords: learning effectiveness evaluation; neutrosophic sets; machine vision; evaluation based on distance from average solution; multi-criteria decision-making

1. Introduction

With the continuous advancement of intelligent technology, colleges are progressively adopting intelligent classroom devices, incorporating cameras and sensors, for monitoring students' activities and emotional status in the classroom [1]. These intelligent devices not only capture some information such as students' facial expressions, movements, and postures, but also provide feedback on students' classroom engagement and emotional status [2]. In this context, machine vision technology has become crucial in enhancing education quality. Analyzing students' classroom behaviors, it accurately captures students' class learning status, concentration, participation, and even emotional states. It is obvious that machine vision provides educators with powerful tools to better comprehend students' needs, facilitating personalized adjustments in teaching methods. Despite remarkable progress in machine vision technology for classroom monitoring, challenges arise due to the diverse nature of students' participation, understanding of subjects, and learning patterns. To tackle this complexity, neutrosophic sets (NSs), a method for handling uncertainty, typically provide decision-makers in educational work with tools to make education decisions more discerningly [3].

To address the aforementioned challenges, teaching evaluation plays a crucial role as a key component in achieving high-quality education. The Global Education Monitoring Report emphasizes the necessity of establishing effective student assessment and monitoring mechanisms to track students' learning efficiency, thereby enhancing teaching quality [4]. This further underscores the vital role of teaching evaluation in achieving high-quality education, particularly in assessing students' learning effectiveness. However, traditional evaluation processes are often subjective and limited, lacking widely accepted methods [5]. In practical scenarios, teaching evaluation requires careful consideration of multidimensional factors, including subject characteristics, student diversity, and the allocation of teaching resources. Consequently, assessing teaching is treated as a multi-criteria decision-making (MCDM) problem, involving a comprehensive balance among diverse pivotal factors [6]. To ensure that the assessment of students' learning effectiveness is effective, equitable, and meaningful, it is essential to develop and adhere to a high-quality evaluation methodology, thereby promoting education quality.

Aiming at the above issues, this study proposes a quantification classroom teaching evaluation method that combines machine vision with NSs to better evaluate students' learning effectiveness. Specifically, the following summarizes the main contributions of this study.

First, this study uses machine vision technology to identify and process the data on students' class status. According to the identified data, this study constructs temporal neutrosophic evaluation matrices on students' class status.

Second, a novel weight calculation method considering students' concentration is proposed based on the Pearson correlation coefficient. It not only reflects students' class status over time, but also measures the correlation between time and students' concentration. Moreover, the proposed weight function is objective, avoiding subjective influences.

Third, a classical single-valued neutrosophic Dombi weighted arithmetic average (SVNDWAA) operator is introduced. In addition, a similarity function is presented to implement the evaluation problems based on distance from average solution (EDAS), facilitating a comprehensive assessment on students' learning effect.

The rest of this study is formed as follows. Section 2 introduces a series of literature on NSs, machine vision and MCDM. Section 3 introduces the related definitions of NSs, presents the process of machine vision recognition, and proposes a temporal neutrosophic evaluation model. Section 4 provides an example and comparative analysis to verify the practical value of the proposed model. Section 5 generalizes the work and future prospects. The research framework is shown in Figure 1.

2. Literature Review

Scholars have spent much effort exploring and investigating NSs, machine vision and MCDM for achieving high-quality education. This section reviews relevant previous research on assessing education quality, providing an overview of existing deficiencies that require attention.

To evaluate university courses, classroom learning effectiveness is usually an explicit indicator for assessing teaching quality. In this regard, some scholars have delved into the application of NSs in exploring the evaluation of classroom learning effectiveness [7]. For example, Tang et al. [8] established a compromise solution using single-valued neutrosophic measurement of alternatives for enhancing students' learning outcomes. Subsequently, Wu and Fang [9] constructed an innovation multilevel teaching quality evaluation framework in higher education, integrating the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) with single-valued neutrosophic sets (SvNSs). At the same time, Mamites et al. [10] presented an analysis method on a neutrosophic decision-making trial and evaluation laboratory to study causal relationships affecting teaching quality in universities. Later, Rao and Xiao [11] proposed a novel generalized 2-tuple linguistic neutrosophic power Heronian mean operator applied in the MCDM algorithm, thereby better evaluating physical education quality. Then, Xie [12] presented a triangular fuzzy neutrosophic numbers grey relational analysis method, which expands the traditional classroom teaching mode and provides a novel insight for evaluating students' blended teaching effectiveness in colleges.

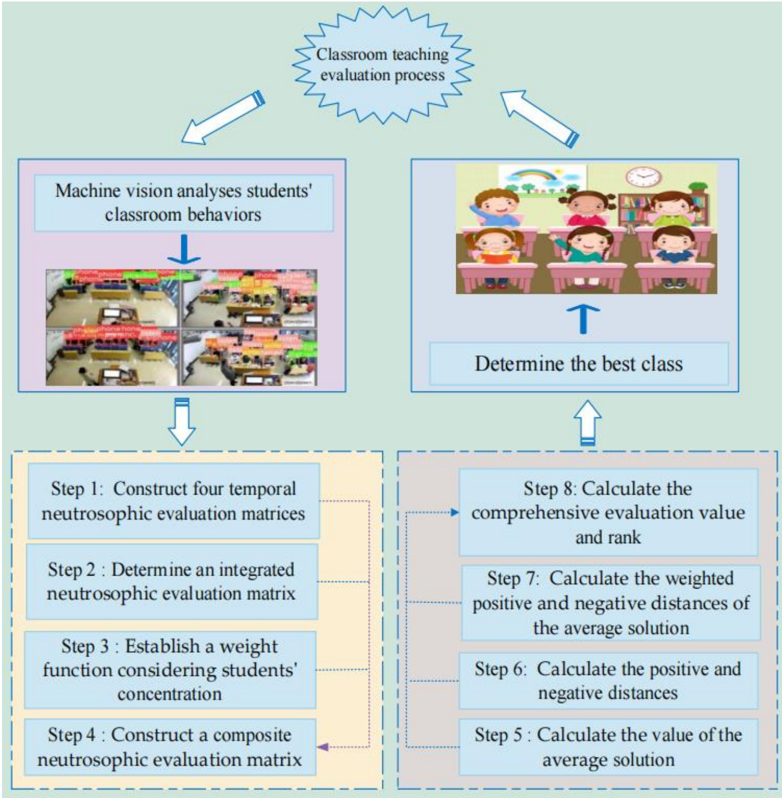

Figure 1. Research framework

According to evaluation on teaching quality in higher education, machine vision usually provides feedback on students' class learning behaviors. Currently, the application of machine vision technology in evaluating classroom teaching effectiveness has attracted widespread attention [13]. For example, Arashpour et al. [14] applied the YOLO algorithm in facial motion detection to predict students' engagement in the classroom, facilitating teachers in optimizing their instructional strategies. Subsequently, Shen et al. [15] delved into facial expression recognition to capture learners' emotional changes over time. On this basis, a domain-adaptive facial expression recognition method applied to the MOOC scenario was proposed to verify the effectiveness of students' learning engagement. Then, Pabba and Kumar [16] introduced a real-time system employing convolutional neural networks (CNN) for facial expression recognition related to students' status. At the same time, Liu [17] employed multi-task CNN and a quantitative evaluation method-class focus index to detect learners' facial features for determining students' status. Later, Gollapalli et al. [18] proposed a sustainable university field training framework and used machine vision technology to extract educational data to elucidate students' learning outcomes.

Meanwhile, the application of MCDM in education is gaining increasing attention. In this context, scholars are dedicated to exploring the practical application of MCDM models in classroom teaching to address its uncertainties effectively [19]. For example, Martin et al. [20] developed an MCDM method on Plithogenic contradictions, presenting a novel optimal decision-making method. Then, Priyadharshini and Irudayam [21] investigated a unique MCDM method using Plithogenic single-valued fuzzy sets, emphasizing the proposed method's effectiveness and practical adaptability to societal needs. At the same time, Abdel-Basset et al. [22] proposed a multi-stage approach integrating the application of the analytical network process method and TOPSIS to address information uncertainty within a hybrid technique. Additionally, Gamal et al. [23] presented a novel framework that integrated the α-discounting MCDM and the VlseKriterijumska Optimizacija I Kompromisno Resenje method, which was applied to address uncertain and fuzzy conditions under a neutrosophic environment. Later, Gamal et al. [24] extended a reliable MCDM approach based on the elimination effects of criteria and the combined compromise solution utilizing type-2 neutrosophic numbers for criteria assessment.

Based on the aforementioned, the introduced research shows some issues need to be settled in the teaching evaluation field. Firstly, the traditional evaluation methods mainly rely on subjective evaluation, leading to inconsistent evaluation criteria and difficulty in quantifying evaluation results. Secondly, although machine vision has been used in students' status assessment in recent studies, it has not yet been integrated with teaching evaluation methods. Thirdly, although NSs provide new ideas on students' learning effectiveness, they have not yet established a unified framework to solve various complexities and challenges in classroom teaching evaluation. Regarding the above issues, this study proposes a novel evaluation method based on NSs with machine vision, so as to better evaluate students' learning effectiveness.

3. Materials and Methods

For convenience, this section is segmented into several parts. The first part briefly introduces essential definitions regarding this study. The second part introduces the process of machine vision recognizing students' in-class status. The third part proposes a weight calculation method considering students' concentration. The fourth part proposes a temporal neutrosophic evaluation model considering students' concentration.

3.1. Preliminaries

Definition 1. [25] Let X be a set, and the elements of X are represented by x. If $\tilde{A} = \{< x, \alpha_1(x), \alpha_2(x), \ \alpha_3(x) > | x \in X\}$, $\tilde{A}$ is denoted as an SvNS, where $\alpha_1(x): X \to [0,1]$, $\alpha_2(x): X \to [0,1]$, $\alpha_3(x): X \to [0,1]$ depict the truth, indeterminacy and falsity membership degree, respectively. For simplicity, a single-valued neutrosophic number (SvNN) is expressed as the element $< x, \alpha_1(x), \alpha_2(x), \ \alpha_3(x) >$ in $\tilde{A}$.

Definition 2. [26] Presume that there exist two SvNNs, namely $\alpha_1 =< \alpha_{11}, \alpha_{21}, \ \alpha_{31} >$ and $\alpha_2 =< \alpha_{12}, \alpha_{22}, \ \alpha_{32} >$. Then, there are the following algorithms:

(1) $\alpha_1 \oplus \alpha_2 = \langle \alpha_{11} + \alpha_{12} - \alpha_{11} \cdot \alpha_{12}, \alpha_{21} \cdot \alpha_{22}, \alpha_{31} \cdot \alpha_{32} \rangle$;

(2) $\alpha_1 \otimes \alpha_2 = \langle \alpha_{11} \cdot \alpha_{12}, \alpha_{21} + \alpha_{22} - \alpha_{21} \cdot \alpha_{22}, \alpha_{31} + \alpha_{32} - \alpha_{31} \cdot \alpha_{32} \rangle$;

(3) $w\alpha_1 = (1-(1-\alpha_{11})^w, (\alpha_{21})^w, (\alpha_{31})^w), \ w > 0.$

Definition 3. [27] Let $S(\alpha_1)$ be the cosine similarity of an SvNN $a_1 =< \alpha_{11}, \alpha_{21}, \alpha_{31} >$. Then $S(\alpha_1)$ is denoted as

$$S(\alpha_1) = \frac{\alpha_{11}}{\sqrt{(\alpha_{11})^2 + (\alpha_{21})^2 + (\alpha_{31})^2}}. \tag{1}$$

Definition 4. [28] Suppose F: $\mathbb{U}^q \to \mathbb{U}$ is a function of q. Then, an ordered weighted averaging (OWA) operator is as follows

$$F(a_1, a_2, \cdots, a_q) = \sum_{\sigma=1}^{q} w_\sigma b_\sigma, \tag{2}$$

where b_σ is the jth element of the descending sort in $\{a_1, a_2, \cdots, a_q\}$, and $w = \{w_1, w_2, \cdots, \ w_q\}^T$ is the weighted vector associated with F, satisfying $w_q \in [0,1]$ and $\sum_{\sigma=1}^{q} w_\sigma = 1$.

Definition 5. [29] Let $\alpha_1, \alpha_2, \cdots, \alpha_n$ be SvNNs. Let $\eta = (\eta_1, \eta_2, \cdots, \eta_n)$ be the weight vector of α_n with $\eta_n \geq 0$ and $\sum_{k=1}^{n} \eta_k = 1$. Then, an SVNDWAA operator is obtained as

$$SVNDWAA(\alpha_1, \alpha_2, \cdots, \alpha_n) = \sum_{k=1}^{n} \eta_k \alpha_k. \quad (3)$$

3.2. The process of machine vision recognition

In this study, the Yolov5 object detection model is employed to identify and classify in-class status of students, so as to objectively evaluate students' learning effectively in different classes and periods [30]. In the introduced process, the data on the students' class learning status is derived from classroom teaching videos, which are divided into image sequences. Here, 2000 images are selected as the datasets. The Labelimg software is then employed to detect the status of different students, which are categorized into 6 types: listen, write, distraction, talk, sleep, and phone. The specific identification process of Yolov5 is shown in Figure 2. And the effect of Yolov5 detection is illustrated in Figure 3.

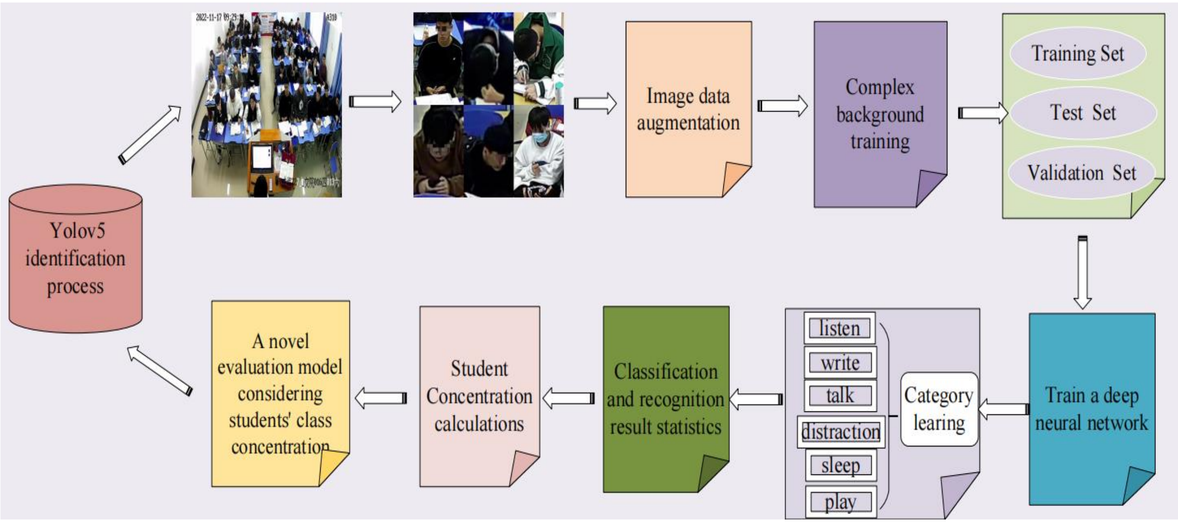

Figure 2. The identification process of Yolov5

For convenience, assume an SvNN exists, namely $\alpha_1 =< \alpha_{11}, \alpha_{21}, \ \alpha_{31} >$. Then, the calculation method of $\alpha_{11}, \alpha_{21},$ and α_{31} are as follows:

$$\alpha_{11} = \frac{A}{A + \sum_{p=1}^{3} B_p + \sum_{p=1}^{2} C_p}, \alpha_{21} = \frac{\sum_{p=1}^{3} B_p}{A + \sum_{p=1}^{3} B_p + \sum_{q=1}^{2} C_q}, \alpha_{31} = \frac{\sum_{q=1}^{2} C_q}{A + \sum_{p=1}^{3} B_p + \sum_{q=1}^{2} C_q}, \quad (4)$$

where α_{11} represents the truth-membership degree of 'listen' in machine vision recognition; α_{21} represents the indeterminacy-membership degree of 'distraction', 'write' and 'talk'; whereas α_{31} represents the falsity-membership degree of 'sleep' and 'phone'. A represents the count of students 'listen' in class, and $B_p (p = 1,2,3)$ represents the count of students 'distraction', 'write' and 'talk' in class. Whereas $C_q (q = 1,2)$ represents the count of students 'sleep' and 'phone' in class. Consequently, α_1 is obtained.

Figure 3. The effect chart of Yolov5 recognition

3.3. A calculation method of weight considering students' concentration

In classroom learning, students' listening effectiveness exhibits a transition from concentration to distraction as the class time extends [31]. In this context, this study proposes a novel time weight function $\omega(t)$ that considers students' concentration based on the Pearson correlation coefficient. The proposed $\omega(t)$ is a combination of decay and correlation. The decay factor signifies a gradual decline in students' concentration over time, reflecting that fatigue and distractions arise during extended study sessions. Conversely, the correlation factor evaluates the relationship between class duration and students' concentration, assessing variations in attention levels during different periods. In this study, the duration of a class is taken as $T-$ minute, in which each 10-minute is divided into a period and each period is further subdivided into 2-minute as a time node. The following $\omega(t)$ is defined as

$$\omega(t)=\frac{\exp\left[\dfrac{\sum_{j=1}^{t_i}(x_{ij}-\overline{x_i})\,|\,y_{ij}-\overline{y_i}\,|}{\sqrt{\sum_{j=1}^{t_i}(x_{ij}-\overline{x_i})^2\sum_{j=1}^{t_i}(y_{ij}-\overline{y_i})^2}}\cdot\left(w_s-\dfrac{w_s-w_e}{t_{\max}}\cdot t\right)\right]}{\sum_{j=1}^{n}\exp\left[\dfrac{\sum_{j=1}^{t_i}(x_{ij}-\overline{x_i})\,|\,y_{ij}-\overline{y_i}\,|}{\sqrt{\sum_{j=1}^{t_i}(x_{ij}-\overline{x_i})^2\sum_{j=1}^{t_i}(y_{ij}-\overline{y_i})^2}}\cdot\left(w_s-\dfrac{w_s-w_e}{t_{\max}}\cdot t\right)\right]}, \tag{5}$$

where $x_{ij}(i,j=1,2,\cdots,n)$ denotes the jth time node in the ith period, $\overline{x_i}$ represents the average time in the ith period, y_{ij} is on behalf of the number of students paying attention at the jth time node in the ith period, $\overline{y_i}$ means the average number of students listening attentively in the ith period, t denotes unit moments in a class divided into 10-minute periods, whereas t_{max} represents the maximum unit moment in class divided into 10-minute periods. In this study, w_s indicates the initial weight set to 1, while w_e represents the final weight set to 0.

Theorem 1: The $\omega(t)$ considering students' concentration satisfies the following properties.

(E1) For $t\in[0,T]$, $\omega(t)$ is a monotonically decreasing function.

(E2) When $t=0$, $\omega(t)$ has the maximum value.

(E3) When $t=a$, $\omega(t)$ has the minimum value.

Proof:

To prove the proposed properties, two fundamental functions are constructed as

$$f(t)=\exp\left[r\cdot(1-\frac{t}{T})\right],t\in[0,T],$$

$$F(t)=\frac{\exp\left[r\cdot(1-\frac{t}{T})\right]}{\sum_{t=0}^{T}\exp\left[r\cdot(1-\frac{t}{T})\right]},t\in[0,T].$$

Then, it gets

$$f'(t)=\frac{df(t)}{dt}=\left[\exp\left[r\cdot(1-\frac{t}{T})\right]\right]\cdot(-\frac{r}{T}),t\in[0,T], \tag{6}$$

where $r(r>0)$ represents the Pearson correlation coefficient.

Calculations indicate that $f'(t)$ is always less than 0. Then, it gets $f(t)$ is a monotonically decreasing function. Since Eq. (3) is a normalization of Eq. (2), $F(t)$ also monotonically decreases. Then, (E1) holds.☑

When $t=0$, $f(t)$ takes the maximum value $f_{max}(t)=e^{r}$. Then, (E2) holds.☑

When $t=T$, $f(t)$ takes the minimum value $f_{min}(t)=1$. Then, (E3) holds.☑

3.4. A temporal neutrosophic evaluation model considering students' concentration

To better evaluate students' learning effectiveness, this subsection proposes a novel temporal neutrosophic evaluation model that considers students' concentration. First, this study constructs four temporal neutrosophic evaluation matrices on students' class status over time and aggregates the proposed four matrices as one using a classical OWA operator. Second, a novel $\omega(t)$ considering students' concentration is proposed based on the Pearson correlation coefficient. Third, this study applies the EDAS method by introducing a classical SVNDWAA operator and a similarity function for comprehensive assessment and optimization of students' learning effectiveness. Specifically, the evaluation steps are as follows.

Step 1: Construct temporal neutrosophic evaluation matrices. This study focuses on ϕ classes, with l courses within a month as the research objects. By processing the data from students' class videos, a neutrosophic evaluation matrix $K_{l\times\phi i}$ is established for ϕ classes in the ith period by using Eq. (4). Taking the evaluation matrix $K_{l_1}^{\phi i}$ of a course within a month as an example, the following $K_{l_1}^{\phi i}$ is defined as

$$K_{l_1}^{\phi i}=\begin{bmatrix} <\alpha_{11}^{11},\alpha_{21}^{11},\alpha_{31}^{11}> & <\alpha_{11}^{12},\alpha_{21}^{12},\alpha_{31}^{12}> & \cdots & <\alpha_{11}^{1i},\alpha_{21}^{1i},\alpha_{31}^{1i}> \\ <\alpha_{11}^{21},\alpha_{21}^{21},\alpha_{31}^{21}> & <\alpha_{11}^{22},\alpha_{21}^{22},\alpha_{31}^{22}> & \cdots & <\alpha_{11}^{2i},\alpha_{21}^{2i},\alpha_{31}^{2i}> \\ \vdots & \vdots & \ddots & \vdots \\ <\alpha_{11}^{\phi 1},\alpha_{21}^{\phi 1},\alpha_{31}^{\phi 1}> & <\alpha_{11}^{\phi 2},\alpha_{21}^{\phi 2},\alpha_{31}^{\phi 2}> & \cdots & <\alpha_{11}^{\phi i},\alpha_{21}^{\phi i},\alpha_{31}^{\phi i}> \end{bmatrix},$$

where $\alpha_{11}^{\phi i},\alpha_{21}^{\phi i},\alpha_{31}^{\phi i}$ represent the truth-membership degree, indeterminacy-membership degree, and falsity-membership degree of class $\phi(\phi=1,2,\cdots,\varepsilon)$ in the ith period of the $K_{l_1}^{\phi i}$, respectively, whereas $i=1,2,\cdots,n$.

Step 2: Determine an integrated neutrosophic evaluation matrix. Introducing a classical OWA operator to integrate one-month courses from different classes into a course is to obtain a comprehensive evaluation matrix $L_{l\times\phi i}$, enhancing the depth and accuracy of students' performance assessment. Due to the same type of courses in each class, $w_\sigma = \frac{1}{l}(\sigma = 1,2,\cdots,l)$ is taken in this study. By using Eq. (2), the $L_{l\times\phi i}$ is defined as

$$L_l^{\phi i} = w_\sigma \times K_l^{\phi i}$$
$$= \begin{bmatrix} <\alpha_{12}^{11},\alpha_{22}^{11},\alpha_{32}^{11}> & <\alpha_{12}^{12},\alpha_{22}^{12},\alpha_{32}^{12}> & \cdots & <\alpha_{12}^{1i},\alpha_{22}^{1i},\alpha_{32}^{1i}> \\ <\alpha_{12}^{21},\alpha_{22}^{21},\alpha_{32}^{21}> & <\alpha_{12}^{22},\alpha_{22}^{22},\alpha_{32}^{22}> & \cdots & <\alpha_{12}^{2i},\alpha_{22}^{2i},\alpha_{32}^{2i}> \\ \vdots & \vdots & \ddots & \vdots \\ <\alpha_{12}^{\phi 1},\alpha_{22}^{\phi 1},\alpha_{32}^{\phi 1}> & <\alpha_{12}^{\phi 2},\alpha_{22}^{\phi 2},\alpha_{32}^{\phi 2}> & \cdots & <\alpha_{12}^{\phi i},\alpha_{22}^{\phi i},\alpha_{32}^{\phi i}> \end{bmatrix}.$$

Step 3: Establish a time weight function considering students' concentration. The overall effect of students' class status is evaluated through the $\omega(t)$ considering students' concentration constructed in Section 3.1. The proposed $\omega(t)$ not only reflects students' class status over time, but also measures the correlation between class time and students' concentration. Here, the $\omega(t)$ is shown in Eq. (5).

Step 4: Construct a composite neutrosophic evaluation matrix. By combining the proposed $\omega(t)$ with the $L_{l\times\phi i}$, a composite neutrosophic evaluation matrix $G_{l\times\phi i}$ is obtained. Integrating $L_{l\times\phi i}$ and $\omega(t)$, the $G_{l\times\phi i}$ is defined as

$$G_l^{\phi i} = \omega(t) \times L_l^{\phi i}$$
$$= \begin{bmatrix} <\alpha_{13}^{11},\alpha_{23}^{11},\alpha_{33}^{11}> & <\alpha_{13}^{12},\alpha_{23}^{12},\alpha_{33}^{12}> & \cdots & <\alpha_{13}^{1i},\alpha_{23}^{1i},\alpha_{33}^{1i}> \\ <\alpha_{13}^{21},\alpha_{23}^{21},\alpha_{33}^{21}> & <\alpha_{13}^{22},\alpha_{23}^{22},\alpha_{33}^{22}> & \cdots & <\alpha_{13}^{2i},\alpha_{23}^{2i},\alpha_{33}^{2i}> \\ \vdots & \vdots & \ddots & \vdots \\ <\alpha_{13}^{\phi 1},\alpha_{23}^{\phi 1},\alpha_{33}^{\phi 1}> & <\alpha_{13}^{\phi 2},\alpha_{23}^{\phi 2},\alpha_{33}^{\phi 2}> & \cdots & <\alpha_{13}^{\phi i},\alpha_{23}^{\phi i},\alpha_{33}^{\phi i}> \end{bmatrix}.$$

Step 5: Calculate the value of the class average solution. To calculate the average solution for each class, a classical SVNDWAA operator is introduced. It is used to convert the ranking results of all classes into a standard scoring scale for comparison and evaluation, effectively reducing errors in the final evaluation results. By using Eq. (3), the class average solution is obtained as

$$\overline{AF_\phi} = SVNDWAA(\alpha_1,\alpha_2,\cdots,\alpha_n) = \sum_{k=1}^{n}\eta_k\alpha_k, \tag{7}$$

where $\overline{AF_\phi}$ represents the class ϕ average solution, and η_k means the weight vector in α_k.

Step 6: Calculate the positive and negative distances. To evaluate the learning outcomes of each class compared to other classes, a similarity function is introduced. According to Eqs. (1) and (7), the positive distances $PDC_{\phi i}$ and negative distances $NDC_{\phi i}$ of class ϕ in the ith period are denoted as

$$PDC_{\phi i} = \frac{\max(0, S(\alpha_3^{\phi i}) - S(\overline{AF_\phi}))}{S(\overline{AF_\phi})}, \tag{8}$$

$$NDC_{\phi i} = \frac{\max(0, S(\overline{AF_\phi}) - S(\alpha_3^{\phi i}))}{S(\overline{AF_\phi})}, \tag{9}$$

where $S(\alpha_3^{\phi i})$ represents similarity calculation for each SvNN in $G_{l\times\phi i}$, whereas $S(\overline{AF_\phi})$ represents the similarity calculation of $\overline{AF_{\phi}}$.

Step 7: Calculate the weighted positive and negative distances. According to definition 2, the weighted $PDC_{\phi i}$ and $NDC_{\phi i}$ of class ϕ in the ith period are denoted as

$$SP_{\phi}=\sum_{i=1}^{n}\lambda_i PDC_{\phi i}, \tag{10}$$

$$SN_{\phi}=\sum_{i=1}^{n}\lambda_i NDC_{\phi i}, \tag{11}$$

where SP_{ϕ} and SN_{ϕ} indicate the weight sums of $PDC_{\phi i}$ and $NDC_{\phi i}$, respectively, whereas λ_i is treated as the weighted of the ith period.

Step 8: Calculate the comprehensive evaluation value. CS_{ϕ} is defined as

$$CS_{\phi}=\frac{1}{2}\left[\frac{SP_{\phi}}{\max SP}+(1-\frac{SN_{\phi}}{\max SN})\right]. \tag{12}$$

Rank according to CS_{ϕ} and the highest CS_{ϕ} is the optimal one.

4. Results and Discussion

This section is mainly divided into three parts. 1) Give a practical example for the model used to illustrate the effectiveness. 2) Present a comparison of the proposed model with others to demonstrate the consistence. 3) Discuss the obtained results.

4.1. Case study application

In this subsection, the proposed model is applied in a case study. This study defines the duration of a class as 50 minutes, consisting of five periods, with each period further divided into 2-minute as time nodes. Besides, this study focuses on four Professional English courses in four classes over five periods within a month, where $i(i=1,2,3,4,5)$ is considered the ith period. l_1, l_2, l_3 and l_4 correspond to the four Professional English courses. Moreover, $\phi(\phi=1,2,3,4)$ represents Marine Engineering classes 221, 222, 223, and 224, respectively. For the above four classes, this study collects four videos of four Professional English courses from each class within a month, detects students' class status and processes the identification data. Based on the identified data, students' learning status in class is evaluated. The specific evaluation procedures are as follows.

Step 1: This study establishes four evaluation matrices ($K_{l_1}^{\phi i}$,$K_{l_2}^{\phi i}$,$K_{l_3}^{\phi i}$,$K_{l_4}^{\phi i}$) for four Professional English courses in four classes over five time periods within a month. By using Eq. (4), $K_{l_1}^{\phi i}$, $K_{l_2}^{\phi i}$, $K_{l_3}^{\phi i}$ *and* $K_{l_4}^{\phi i}$ are given as

$$K_{l_1}^{\phi i}=\begin{bmatrix}(0.87,0.06,0.07) & (0.85,0.07,0.08) & (0.88,0.05,0.07) & (0.78,0.13,0.09) & (0.87,0.12,0.01)\\(0.94,0.06,0.00) & (0.98,0.02,0.00) & (0.98,0.02,0.00) & (0.94,0.06,0.00) & (0.94,0.06,0.00)\\(0.94,0.06,0.00) & (0.93,0.07,0.00) & (0.84,0.08,0.08) & (0.83,0.10,0.07) & (0.85,0.08,0.07)\\(0.39,0.50,0.11) & (0.47,0.37,0.16) & (0.40,0.41,0.19) & (0.35,0.52,0.13) & (0.34,0.52,0.14)\end{bmatrix},$$

$$K_{l_2}^{\phi i}=\begin{bmatrix}(0.80,0.19,0.01) & (0.87,0.13,0.01) & (0.87,0.13,0.01) & (0.80,0.18,0.01) & (0.71,0.28,0.01)\\(0.90,0.10,0.00) & (0.91,0.09,0.00) & (0.91,0.09,0.00) & (0.86,0.14,0.00) & (0.82,0.18,0.00)\\(0.89,0.06,0.05) & (0.90,0.05,0.05) & (0.91,0.05,0.04) & (0.95,0.05,0.00) & (0.96,0.04,0.00)\\(0.37,0.48,0.15) & (0.31,0.54,0.15) & (0.29,0.47,0.24) & (0.29,0.56,0.15) & (0.29,0.56,0.15)\end{bmatrix},$$

$$K_{l_3}^{\phi i}=\begin{bmatrix}(0.63,0.34,0.03) & (0.55,0.35,0.10) & (0.72,0.25,0.03) & (0.72,0.28,0.10) & (0.67,0.28,0.05)\\(0.85,0.15,0.00) & (0.78,0.22,0.00) & (0.75,0.25,0.00) & (0.75,0.25,0.00) & (0.73,0.27,0.00)\\(0.97,0.03,0.00) & (0.96,0.04,0.00) & (0.94,0.04,0.02) & (0.86,0.04,0.10) & (0.83,0.06,0.11)\\(0.32,0.54,0.14) & (0.30,0.53,0.17) & (0.23,0.53,0.24) & (0.25,0.57,0.18) & (0.29,0.52,0.19)\end{bmatrix},$$

$$K_{l_4}^{\phi i}=\begin{bmatrix}(0.62,0.32,0.06) & (0.70,0.24,0.06) & (0.68,0.22,0.10) & (0.60,0.20,0.20) & (0.51,0.27,0.22)\\(0.76,0.24,0.00) & (0.79,0.21,0.00) & (0.75,0.25,0.00) & (0.73,0.27,0.00) & (0.64,0.36,0.00)\\(0.84,0.05,0.11) & (0.79,0.04,0.17) & (0.83,0.07,0.10) & (0.85,0.07,0.08) & (0.87,0.06,0.07)\\(0.26,0.55,0.19) & (0.26,0.56,0.18) & (0.25,0.56,0.19) & (0.25,0.53,0.22) & (0.29,0.44,0.27)\end{bmatrix}.$$

Step 2: A classical OWA operator is introduced to integrate four courses into a course within a month. Since the four courses are the same type, the same weight value $w_\sigma=\frac{1}{4}(\sigma=1,2,3,4)$ is taken throughout the study. By using Eq. (2), $L_{l\times\phi i}$ is obtained as

$$L_{l\times\phi i}=\begin{bmatrix}(0.75,0.24,0.04) & (0.77,0.20,0.06) & (0.81,0.17,0.05) & (0.74,0.20,0.10) & (0.72,0.24,0.08)\\(0.88,0.14,0.00) & (0.90,0.14,0.00) & (0.90,0.16,0.00) & (0.85,0.18,0.00) & (0.82,0.23,0.00)\\(0.92,0.05,0.04) & (0.91,0.05,0.06) & (0.89,0.06,0.06) & (0.88,0.07,0.06) & (0.89,0.06,0.06)\\(0.34,0.52,0.15) & (0.34,0.51,0.17) & (0.30,0.50,0.22) & (0.29,0.55,0.10) & (0.30,0.51,0.19)\end{bmatrix}.$$

Step 3: By using Eq. (5), the proposed $\omega(t)$ considering students' concentration is calculated. Specifically, the weight calculation results are shown in Table 1. The correlation between students' concentration and time is presented in Figure 4.

Table 1. Weight calculation results

time	10min	20min	30min	40min	50min
r	0.73	0.42	0.69	0.30	0.74
$\omega(t)$	0.25	0.22	0.19	0.18	0.16

Step 4: Integrating $L_{l\times\phi i}$ and $\omega(t)$, $G_{l\times\phi i}$ is given as

$$G_{l\times\phi i}=\begin{bmatrix}(0.29,0.70,0.45) & (0.28,0.70,0.54) & (0.27,0.71,0.57) & (0.22,0.75,0.63) & (0.18,0.80,0.67)\\(0.41,0.61,0.00) & (0.40,0.65,0.00) & (0.35,0.71,0.00) & (0.29,0.73.0.00) & (0.24,0.79,0.00)\\(0.47,0.47,0.45) & (0.41,0.52,0.54) & (0.34,0.59,0.59) & (0.32,0.62,0.60) & (0.30,0.64,0.64)\\(0.10,0.85,0.62) & (0.09,0.86,0.68) & (0.07,0.57,0.71) & (0.06,0.90,0.74) & (0.06,0.90,0.77)\end{bmatrix}.$$

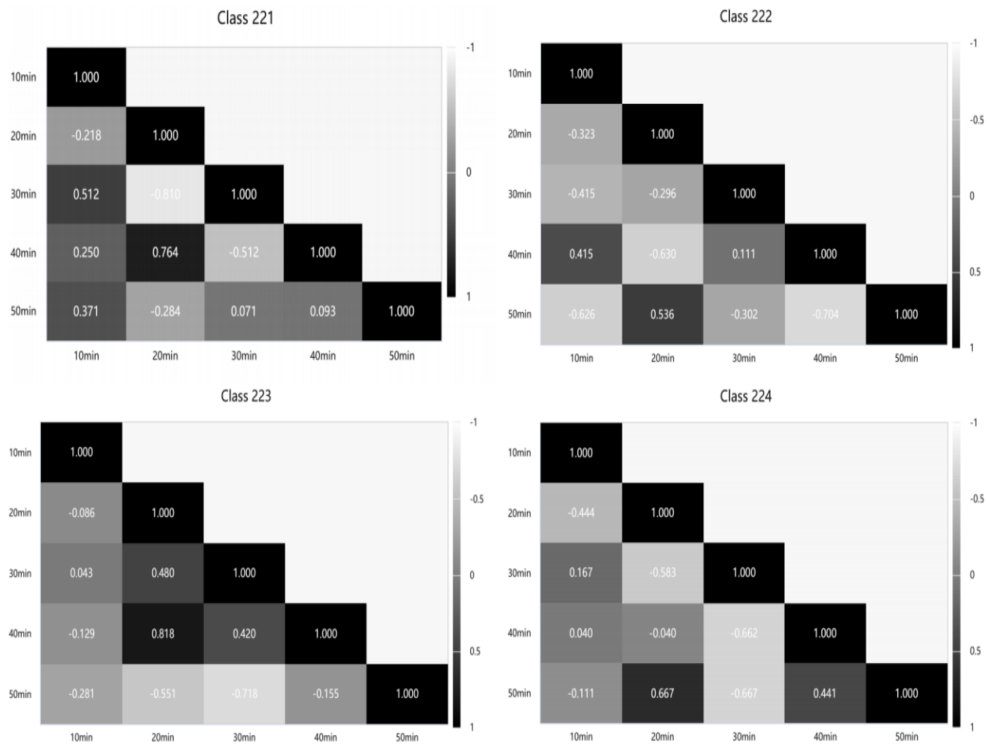

Figure 4. Correlation between students' concentration and time

Step 5: By using Eq. (7), $\overline{AF_1}$, $\overline{AF_2}$, $\overline{AF_3}$ and $\overline{AF_4}$ are obtained as

$$\overline{AF_1} = \frac{1}{5}\alpha_3^{11} + \frac{1}{5}\alpha_3^{12} + \frac{1}{5}\alpha_3^{13} + \frac{1}{5}\alpha_3^{14} + \frac{1}{5}\alpha_3^{15} = \langle 0.25, 0.73, 0.57 \rangle,$$

$$\overline{AF_2} = \frac{1}{5}\alpha_3^{21} + \frac{1}{5}\alpha_3^{22} + \frac{1}{5}\alpha_3^{23} + \frac{1}{5}\alpha_3^{24} + \frac{1}{5}\alpha_3^{25} = \langle 0.34, 0.70, 0.00 \rangle,$$

$$\overline{AF_3} = \frac{1}{5}\alpha_3^{31} + \frac{1}{5}\alpha_3^{32} + \frac{1}{5}\alpha_3^{33} + \frac{1}{5}\alpha_3^{34} + \frac{1}{5}\alpha_3^{35} = \langle 0.37, 0.57, 0.56 \rangle,$$

$$\overline{AF_4} = \frac{1}{5}\alpha_3^{41} + \frac{1}{5}\alpha_3^{42} + \frac{1}{5}\alpha_3^{43} + \frac{1}{5}\alpha_3^{44} + \frac{1}{5}\alpha_3^{45} = \langle 0.08, 0.82, 0.70 \rangle.$$

Step 6: By using Eqs. (8) and (9), $\mathrm{PDC}_{\phi i}$ and $\mathrm{NDC}_{\phi i}$ are obtained in Table 2 and Table 3.

Step 7: By using Eqs. (10) and (11), SP_ϕ and SN_ϕ are calculated. It gets

$$SP_1 = 0.10,\ SP_2 = 0.09,\ SP_3 = 0.11,\ SP_4 = 0.11,$$

$$SN_1 = 0.05,\ SN_2 = 0.11,\ SN_3 = 0.09,\ SN_4 = 0.12.$$

Step 8: By using Eq. (12), CS_ϕ is obtained. It gets

$$CS_1 = 0.75,\ CS_2 = 0.45,\ CS_3 = 0.63,\ CS_4 = 0.50.$$

Based on the above sorting results, the priority order of four classes is $1 \succ 3 \succ 4 \succ 2$, indicating that class 221 performs the best overall, while class 222 shows the worst performance. Specifically, the detailed analysis shown in Figure 5 presents the truth-membership degree for each class over time.

Table 2. Positive distances

ϕ	$PDC_{\phi 1}$	$PDC_{\phi 2}$	$PDC_{\phi 3}$	$PDC_{\phi 4}$	$PDC_{\phi 5}$
1	0.27	0.15	0.08	0.00	0.00
2	0.27	0.18	0.00	0.00	0.00
3	0.40	0.14	0.00	0.00	0.00
4	0.29	0.14	0.14	0.00	0.00

Table 3. Negative distances

ϕ	$NDC_{\phi 1}$	$NDC_{\phi 2}$	$NDC_{\phi 3}$	$NDC_{\phi 4}$	$NDC_{\phi 5}$
1	0.00	0.00	0.00	0.15	0.12
2	0.00	0.00	0.00	0.19	0.34
3	0.00	0.00	0.10	0.17	0.26
4	0.00	0.00	0.00	0.29	0.29

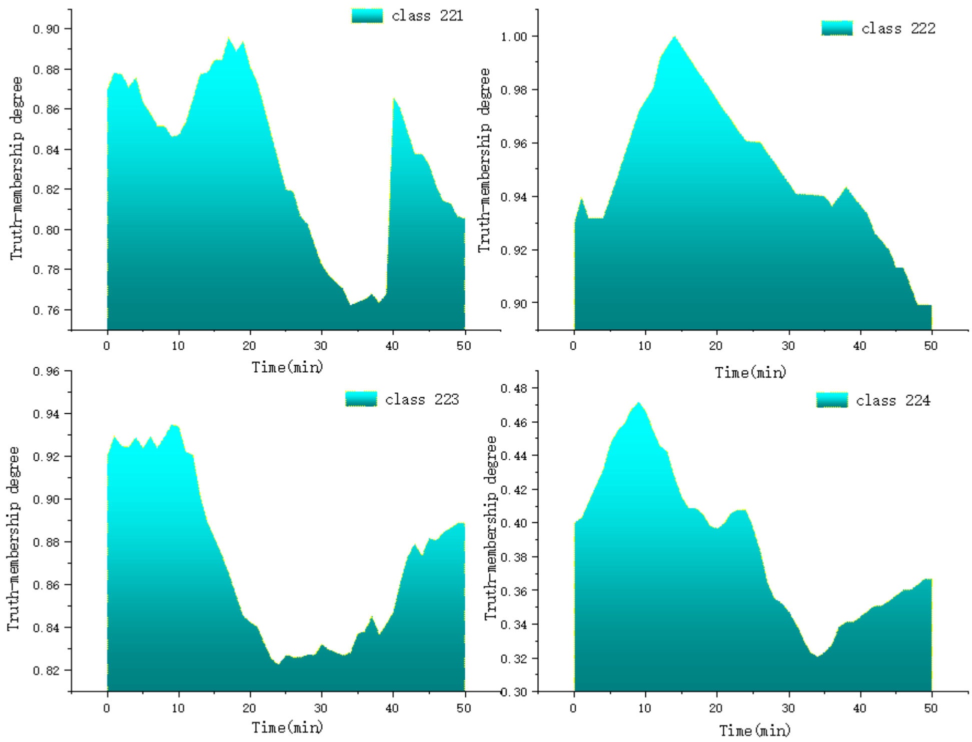

Figure 5. The truth-membership degree of the four classes over time

4.2. Comparative analysis

To further affirm the viability and practicability of the proposed method in assessing students' learning effectiveness, this study conducts comparative analysis with the traditional EDAS method, as well as the approaches introduced by Han et al. [32] and Biswas et al. [33]. Among them, the ranking results are presented in Table 4, which are consistent with those of existing methods. They all agree that class 221 is the optimal scheme. Based on this consistency, the proposed method is effective and reliable.

Table 4. Comparative analysis results

Method	Sorting results	Optimal scheme
The proposed method	$1 \succ 3 \succ 4 \succ 2$	1
Traditional EDAS method	$1 \succ 3 \succ 4 \succ 2$	1
Han et al.' method	$1 \succ 3 \succ 4 \succ 2$	1
Biswas et al.' method	$1 \succ 3 \succ 4 \succ 2$	1

4.3. Discussion

For convenience, a concise description of the experimental results is provided in this study. The details are as follows.

(1) This study utilizes machine vision technology to detect and analyze the videos on students' class state. Considering its uncertainty and diversity, this study proposes an SvNN calculation method to handle the obtained data. Compared to previous relevant research, the application of machine vision technology presents a more accurate and objective data analysis.

(2) This study proposes a novel classroom teaching evaluation method that combines machine vision technology with NSs. It is found that the ranking results are consistent with comparative analysis, indicating that the proposed method provides a novel idea and is suitable for solving the MCDM problem.

(3) This study proposes an objective weight function that considers students' concentration. Compared with other weight calculation methods (such as Analytic Hierarchy Process), the weight calculation method proposed in this study has reduced subjective challenges and a higher correlation performance on students' concentration.

As a result of the above, the proposed method presents a distinctive solution to address the subjectivity and inconsistency issues identified in previous research. This further expands the research depth in this field, providing a novel method for realizing high-quality education.

5. Conclusions and Prospects

To better evaluate students' learning effectiveness, this study proposes a novel classroom teaching evaluation method that combines NSs with machine vision technology, providing a reference for teaching quality evaluation. Specifically, the main contributions are summarized as follows.

First, this study identifies and classifies data on students' class status using Yolov5 detection mode, providing a novel idea to accurately and comprehensively evaluate students' class status. According to the obtained data, an SvNN calculation method is proposed, laying the foundation for constructing temporal neutrosophic evaluation matrices.

Second, this study proposes a novel time weight function on the basis of the Pearson correlation coefficient. The proposed weight function is a combination of decay and correlation that considers students' concentration. Moreover, the proposed weight function remains unaffected by subjective factors, enhancing the objectivity of the evaluation results.

Third, this study introduces a classical SVNDWAA operator to calculate class average solutions and utilizes a similarity function to implement the EDAS method. Besides, comparative analysis is given to verify the superiority of the model proposed, ensuring the accuracy and reliability of MCDM.

It is noteworthy that there is a relationship problem between samples and objects in the current accuracy of machine vision recognition. In some situations, the class status on the first three rows of students in the classroom is collected by the camera in this study, which fails to cover the learning status of the entire class. Therefore, future research should involve expanding the sample size to capture students' status more comprehensively, thus reducing potential sampling errors. Additionally, intuitionistic fuzzy sets can also be applied in this study. However, considering the specific context and requirements of this study, SvNSs are more suitable for effectively handling the uncertainties and fuzziness involved in the evaluation process, leading to more accurate assessment results.

Funding: The Fangwei Zhang's work is partially supported by the Special Key project of the Planning of Shandong Science of Education on Innovation Literacy (Titled: Research on the integration mechanism of innovation and entrepreneurship education and professional education in application-oriented universities under OBE mode, No. 2022CZD016)

Conflicts of Interest: The authors declare no conflict of interest.

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Received: Aug 20, 2023. Accepted: Dec. 21, 2023