Research on the Reform of Film and Television Production Courses and Their Student Achievement Evaluation in Colleges and Universities in Shanxi Province Based on Random Forest Algorithm

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Abstract
This paper classifies the data of the original data set by random forest algorithm, selects the nodes in the attribute space for iteration, and gets the number of decision trees in the random forest. Based on the decision tree, the information gain rate in the sample set of student achievement is calculated, the spatial distance matrix of the sample set is defined, and the centroids of each cluster of the matrix indicators are separated to get the evaluation results of indicators in the student achievement evaluation reform as superior. The indicator weights of student learning achievement are evaluated through five assessment indexes, in which the teacher rating weight is the highest 10. It shows that active use of the Internet is conducive to cultivating and delivering excellent film and television production professionals to society.

Keywords: Random forest algorithm; Decision tree; Sample set; Performance evaluation; Information gain rate.
AMS 2010 codes: 97Q70
1 Introduction

1.1 Background of the study

In the context of the Internet era, the rapid development of the Internet, big data, and cloud computing technologies brought by new media technology has changed the world’s information landscape, and film and television works have become the most effective form of information dissemination through the combination of visual and auditory senses [1-2]. The Internet influences the film and television industry and the direction of professional talent training [3-5]. In the context of the Internet era, film and television-related industries have been transformed and upgraded by network technology, highlighting better requirements for talent in the industry. Although there are many types of work in the film and television art industry and the flow of personnel within the industry is small, the quality of industrial talents is not effectively improved in the new market environment, so the professionalism of film and television production students cannot meet the needs of the modern development of the industry [6-8]. In response to such problems, film and television-related industries have put forward new requirements for talent.

First, the development of the industry in the Internet environment requires talents with innovative consciousness and ability, and based on advocating the strengthening of the training of bi-creative talents, industries are paying more and more attention to the tapping of the innovativeness of industry professionals [9-10]. In the face of the changes in the industry’s talent needs, the teaching of film and television production courses to introduce new concepts and technologies for colleges and educators, there is a certain amount of talent training pressure and difficulty in teaching implementation [11-14]. Second, film and television art professionals should have good practical skills, and the content of film and television works is closely related to people’s lives, which requires people to take into account both professional and life in the creation to guarantee the authenticity and integrity of the content of the works [15]. Third, students need to have multidisciplinary knowledgeability, film and television creation design multi-professional and multidisciplinary knowledge, requiring creators to have cross-border awareness and proficiency in multiple fields of knowledge, understanding the differences that exist between different cultures so that film and television works are richer in connotation, more infectious and expressive, and gain more audience recognition and support [16].

1.2 Methodology of this paper

This paper constructs a model for evaluating student achievement based on the Internet and uses the Random Forest algorithm to calculate the index evaluation of student achievement evaluation reform. Firstly, the data set is classified, the decision tree is constructed for node splitting, the entropy value of the sample set before the division is calculated, the sample set in the node is selected for iteration, the construction of the decision tree is completed, and the decision tree data is combined and analyzed. Next, the feature variables in the random forest are evaluated, the number of autonomous sample set categories is extracted for variables, and the number of decision trees in the random forest is obtained. The student achievement sample set's continuous attributes are discretized by local merit, and the information gain rate of the corresponding attributes is calculated. Different values are taken to divide the student achievement samples, the spatial distance matrix of the sample set is defined, and the squared sum of the distance between the centroid of each cluster and the mean center of the sample set is taken as the separation of the data set, and the evaluation result of the index is obtained as superior. The experimental results show that the evaluation results of the reform indexes of the proposed method are excellent, and the reform of the performance evaluation of college film and television production courses in the background of the Internet era is conducive to enriching learners’
knowledge of film and television screenwriting, improving learners’ screenwriting ability and enhancing the quality of film and television screenwriting talents.

2 Literature review

Poza-Lujan, J. L. et al. Assessed whether a computer engineering degree program, a first-year foundation course, required additional work when implementing continuous assessment at the Technical University of Valencia, Spain. It evaluated whether there was an increased instructor workload in various scenarios and if it impacted student performance. The standard and intensive continuous evaluation methods were analyzed, with the latter resulting in an increase in the number of tests and exams on top of the former. The test results illustrate that continuous evaluation can improve students' performance, but it tends to be burdensome for teachers, and students' scores were not significantly affected. Yan, Q et al. Designated a performance survey evaluation for non-English majors based on the Roche multidirectional tree clustering method. The evaluation results showed that the scores of the Roche multidirectional tree clustering for non-English major college students were distributed at an intermediate level. Overall, English performance and Roche multidirectional tree clustering did not correlate significantly. Classroom English requires teachers to develop a pluralistic teaching evaluation model that teaches students according to their abilities to promote overall development [17]. Romero C et al. proposed an essential and challenging task when predicting students' performance in traditional teaching [18].

On the one hand, the number of status factors that influence student performance is a critical issue in the education field; on the other hand, it is a critical issue. Lower graduation rates, a decline in the school's reputation among those involved, and overall financial loss can be caused by students in poor standing. One of the important tasks in educational data mining and learning analytics is to predict student performance, which has been successfully applied in evaluating student performance.

Asiah M et al. tested students' academic performance to improve the quality of learning to help students excel in their studies. Predictive analytics can help educational institutions make better decisions. Reviewed current research activities related to academic analytics used to predict students’ academic performance, and staff has proposed various methods to develop optimal achievement models using students’ data. The models used to predict student achievement are related to many learning classification tasks and to optimize the models, they are tested using variables to find the most influential attributes for prediction. Correct performance prediction helps guide students through the process and prevents them from receiving low scores. The model aids the instructor in detecting the level of student course completion and final grade linked to student performance [19]. Gao, Z et al. The key aspects of improving teaching improvement are student evaluation of teaching effectiveness and monitoring of teaching quality. An integrated framework was used to develop a multi-level student performance evaluation system based on online student evaluation practices. A new Internet-based evaluation model is employed to enhance students' learning efficiency and teaching motivation. Also, based on the Internet platform, student teaching evaluation was analyzed to obtain support for improving students' learning and optimizing teaching evaluation. [20].

3 Internet-based student performance evaluation model

3.1 Student evaluation model

In the Internet background, educational resources have changed from closed to open, educational modes from single to multiple, teaching from indoctrination to interaction, and learning from passive to independent. Teaching practical courses in film and television education requires open resources,
independent learning for students, and diversified and interactive teaching modes. By combining the teaching method of Internet practice in film and television production courses, high-quality media talents with theoretical knowledge and practical skills can be developed.

The model of student performance evaluation is shown in Figure 1. The sharing of Internet resources allows students to be informed of the specific information and details in their grades, which can motivate them. At the same time, through the process of grade evaluation, teachers can timely find and correct certain parts of the teaching process that deviate from the expected teaching goals, thus ensuring better achievement of teaching goals. Multimedia teaching has become a crucial method of teaching in the Internet era. Teachers must screen and refine Internet information and incorporate cutting-edge information, cases, and videos into their teaching. By integrating text, sound, pictures, and videos in a teaching form, the teacher can enhance students' learning attention by activating their senses. According to the market demand for film and television production professionals, students in film and television should have both artistic and technical skills and should understand the pre-production planning and shooting of film and television, as well as be proficient in post-production editing and special effects. Stimulating students’ innovation is the ultimate goal for education, so the comprehensive combination of education and the Internet is the future education trend. The internet won't replace traditional education, but it will give it a new vitality and become a useful supplement.

![Figure 1. Student performance evaluation model](image)

3.2 Random Forest Algorithm

3.2.1 Selection of decision tree attributes

The random forest algorithm is an integrated learning method, which means that it is composed of many small models to be constructed, and the outputs of the individual small models are combined to form the final output [21]. The random forest algorithm is a typical machine learning algorithm for classification, regression, or other learning tasks. In this paper, the random forest algorithm is based on the random forest algorithm to evaluate student performance evaluation reform for index calculation. The data are grouped from the original dataset, the corresponding decision tree models are obtained after training for each group, and finally, all the decision data results are combined and analyzed to obtain the final random forest model.

A decision tree is a method in machine learning with a tree-like structure that approximates a discrete value structure, where each internal node represents a judgment on an attribute, each branch
represents the output of each judgment result, and finally, each leaf node represents the result of a classification. Figure 2 shows the concept diagram of the decision tree. The rectangle is used to represent the internal nodes and the root node of the decision tree, while the ellipse is used to represent the leaf node of the decision tree. The structure as a whole is presented as a tree structure, where A and B represent different judgment attributes, a1, a2, b1, and b2 represent the decision conditions, and d1, d2, and d3 represent the results of the classification. As depicted in Figure 2, the root node has no incoming edges and only outgoing edges. The inner node has a single incoming edge and at least two outgoing edges. The leaf node has a single incoming edge and no outgoing edge.

![Decision tree concept diagram](Figure 2)

When building a decision tree, it is crucial to determine the principle of splitting each node, that is, to select the 'optimal' attributes. The more commonly used methods to select the 'optimal' attribute are information gain, Gini coefficient, information gain ratio, and so on. In the calculation process, the entropy value of the whole sample set before the division is calculated, and then the entropy value of each sub-sample set after the division is calculated separately by dividing the overall sample space of performance reform according to each different attribute. The optimal attribute is the one that ensures that the divided sample set has the minimum entropy value. Let the sample set be \( T \) and \( \alpha_n \) be the \( n \)th attribute in \( T \), then the formula for calculating the information gain is:

\[
Gain(\alpha_n) = \text{Entropy}(T) - \sum_{i=1}^{m} \left[ \frac{|T_i|}{|T|} \times \text{Entropy}(T_i) \right] m
\]

In equation (1), the number of samples for \( T \) is \( |T_i| \), the number of samples for \( T \) is \( |T| \), and the entropy \( \text{Entropy}(T) \) is calculated as:

\[
\text{Entropy}(T) = -\sum_{i=1}^{s} \text{freq}(C_j, T) \times \log_2 \left( \text{freq}(C_j, T) \right)
\]

In Eq. (2), \( s \) denotes the number of categories in \( T \), and \( \text{freq}(C_j, T) \) is the frequency of samples in \( T \) belonging to the category of \( C_j \). That is, the difference between the entropy of the sample set \( T \) and the expected value of the entropy of the \( m \) subcategories obtained after using \( \alpha_n \) for classification is the information gain. The larger the value, the better the \( \alpha_n \) selection and the better the classification effect.
The attribute selection metric of the algorithm mainly uses the information gain ratio. Its definition formula is:

\[
\begin{align*}
\text{GainRatio}(\alpha_n) &= \frac{\text{Gain}(\alpha_n)}{\text{Split}(\alpha_n)} \\
\text{Split}(\alpha_n) &= \sum_{i=1}^{m} \frac{|T_i|}{|T|} \times \log_2 \left( \frac{|T_i|}{|T|} \right)
\end{align*}
\]

In equation (3), \(\text{Split}(\alpha_n)\) represents the splitting information, i.e., the information generated when \(T\) is divided into \(m\) parts, i.e., the entropy when each sample is treated as an equal possibility, and \(\text{Gain}(\alpha_n)\) represents the information gain.

In the split selection, the entropy value of the candidate attributes is calculated first, and the attribute with the maximum entropy value is selected as the split attribute, and the above process is iterated continuously to build a good decision tree model.

Let there be a sample set \(T\) at node \(m\), which contains \(k\) categories, and the \(Gini\) coefficients are defined as:

\[
Gini(m) = 1 - \sum_{i=1}^{k} p_i^2
\]

Where \(p_i^2\) denotes the probability that category \(i\) is at node \(m\). When \(Gini(m)\) is equal to 0, the samples at this node all belong to the same category, and there is a maximum sample purity at this time. When \(Gini(m)\) is maximum, the samples at this node are of equal probability, and there is a minimum sample purity at this time.

When attribute \(\alpha\) divides sample \(T\) into \(l\) categories, the average \(Gini\) coefficient obtained is:

\[
GiniE(\alpha) = \sum_{i=1}^{l} \frac{|T_i|}{|T|} \times Gini(i)
\]

Where \(|T_i|\) indicates the number of samples at child node \(i\), \(l\) indicates the number of child nodes \(d\), and \(|T|\) indicates the number of overall samples before disaggregation.

The \(Gini\) coefficients are similar to the first two metrics. To perform node splitting, the \(Gini\) coefficients of all attributes are calculated by traversing the attribute space, and the attribute corresponding to the smallest \(GiniE(\alpha)\) of them is selected for splitting, and the process is iterated to complete the construction of the decision tree.

### 3.2.2 Measures of importance of feature variables

The random forest has two measures of variable importance, a \(Gini\) importance value and a replacement importance value.
Assuming that there is $M$ variable $X_1, X_2, X_3, L, X_M$, the importance score statistic for $M$ variables needs to be calculated. According to the $Gini$ index, the score statistic of variable $X_i$ is expressed as $VIM^{(Gini)}_i$. The statistic $VIM^{(Gini)}_i$ represents the average change in the impurity of node splitting in the random forest tree for the $i$th variable. The $Gini$ index is calculated by the formula:

$$GI_m = \sum_{k=1}^{K} \tilde{p}_{mk} (1 - \tilde{p}_{mk})$$  \hspace{1cm} (6)

$K$ is the number of self-help sample set categories, $\tilde{p}_{mk}$ is the probability that node $m$ belongs to category $k$, and the index of node $m$ when the sample belongs to the dichotomous category data, i.e., $K = 2$, is:

$$GI_m = 2\tilde{p}_m (1 - \tilde{p}_m)$$  \hspace{1cm} (7)

Where $\tilde{p}_{mk}$ is the probability estimate of the sample belonging to either class at node $m$.

The importance of variable $X_i$ at node $m$, i.e., the amount of change in the $Gini$ index before and after branching at node $m$, is:

$$VIM^{(Gini)}_{im} = GI_m - GI_l - GI_r$$  \hspace{1cm} (8)

In Eq. (8), $GI_l$ and $GI_r$ denote the $Gini$ indices of the two new nodes split by node $m$, respectively.

If variable $X_i$ appears $M$ times in the $j$nd tree, then the importance of variable $X_i$ in the $j$th tree is defined as:

$$VIM^{(Gini)}_{ji} = \sum_{m=1}^{M} VIM^{(Gini)}_{im}$$  \hspace{1cm} (9)

The $Gini$ importance of variable $X_i$ in the random forest is defined as:

$$VIM^{(Gini)}_i = \frac{1}{n} \sum_{j=1}^{n} VIM^{(Gini)}_{ji}$$  \hspace{1cm} (10)

In equation (10), $n$ is the number of decision trees in the random forest.

### 3.2.3 Attribute information gain rate calculation

The calculation of the information gain rate of the corresponding attributes is particularly important when performing local merit-based discretization of continuous attributes in a student achievement sample set and in the process of creating student achievement analyses. In a known student achievement sample set $S = \{x_1, x_2, ..., x_n\}$, it is assumed that each student achievement sample can contain multiple attributes and the student achievement sample category attributes have different values. Then the student achievement sample set $S$ can be divided into $m$ subsets $\{s_1, s_2, ..., s_m\}$ according to the different taken values, which results in the information entropy required to classify the given student achievement sample as:
$$I(s) = -\sum_{i=1}^{m} P_i \log_2 P_i$$  \hspace{1cm} (11)

$P_i = \frac{|s_i|}{|s|}$ is the concept of an arbitrary student achievement sample category, and $|s_i|$ and $|s|$ are the number of tuples in $s_i$ and $s$, respectively.

The decision tree construction process of random forest algorithm based on local merit-based discretization technique is the process of making the uncertainty gradually decrease after the division. Choosing any discrete attribute $A$, assuming that there exist $V$ different values of $A$, dividing $S$ into $V$ subsets $\{S'_1, S'_2, \ldots, S'_V\}$, the entropy or expectation information according to the division into subsets by $A$ is:

$$I_A(s) = \sum_{j=1}^{V} \frac{|s_j|}{|s|} I(s'_j)$$ \hspace{1cm} (12)

$\frac{|s_j|}{|s|}$ is the right of the $j$th subset, and the information increment of attribute $A$ is:

$$Gain(A) = I(s) - I_A(s)$$ \hspace{1cm} (13)

The information gain rate is used to determine the attribute classification, and the formula for calculating the information gain rate is:

$$Gainratio(A) = \frac{Gain(A)}{Spliti(A)}$$ \hspace{1cm} (14)

$$Spliti(A) = \sum_{j=1}^{V} \frac{|s_j|}{|s|} \log_2 \left( \frac{|s_j|}{|s|} \right)$$ \hspace{1cm} (15)

$Spliti(A)$ for the calculation steps of information entropy, set information entropy, information expectation, information gain, split information, and information gain rate split information in the process of constructing a decision tree for student achievement analysis.

Let $X$ be the set containing $n$ student samples, $X = \{X_1, X_2, \ldots, X_i, \ldots, X_n\}$, each student sample consists of $p$ course grades, and the $i$th sample object can be expressed as: $X_i = \{X_{i1}, X_{i2}, \ldots, X_{ip}\}$.

Now the set is divided into $k$ clusters, each containing $m$ student samples, then $X = \{C_1, C_2, \ldots, C_k\}$, the set of cluster centers $V = \{v_1, v_2, \ldots, v_k\} (k < n)$.

Normalization is a linear transformation of the original data so that the result falls into the interval $[0, 1]$ with the following transformation function:

$$x' = \frac{x - \text{min}}{\text{max} - \text{min}}$$ \hspace{1cm} (16)
is the raw score of the film production course, \( \text{max} \) is the highest score of the course, and \( \text{min} \) is the lowest score of the course.

The Euclidean distance between two points in space is defined as:

\[
d(X_i,X_j) = \sqrt{\sum (X_i^n - X_j^n)^2}
\]  

(17)

Where \( i = 1,2,...,n; j = 1,2,...,n; w = 1,2,...,p \).

Define the spatial distance matrix \( X' \) of the sample set \( X \) as

\[
X' = \begin{bmatrix}
0 & d(X_1,X_2) & \cdots & d(X_1,X_n) \\
d(X_2,X_1) & 0 & \cdots & d(X_2,X_n) \\
\vdots & \vdots & \ddots & \vdots \\
d(X_n,X_1) & d(X_n,X_2) & \cdots & 0
\end{bmatrix}
\]  

(18)

In Eq. (18), the intra-cluster distance of \( X_i \) sample is defined as the sum of the distances between \( X_i \) and the samples of the same cluster to which it belongs, i.e:

\[
\text{DistSum}(X_i) = \sum_{i,j \in C_i} d(X_i,X_j)
\]  

(19)

Where \( i = 1,2,...,n; j = 1,2,...,n \).

The sample \( X_i \) with the smallest sum of intra-cluster distances of the \( k \) th cluster is taken as the center and the sum of squared clustering errors \( E \) is defined as:

\[
E = \sum_{i=1}^{k} \sum_{j=1}^{m} |X_{ij} - V_i|^2
\]  

(20)

Where \( X_{ij} \) is the \( j \)th data object of the \( i \)th cluster and \( V \) is the center of the \( i \)th cluster. \( \text{CH} \)

The indicators are:

\[
\text{CH}(k) = \frac{\sum_{i=1}^{k} m_i d^2(v_i,c)/(k-1)}{\sum_{i=1}^{k} \sum_{x \in C_i} d^2(x,v_i)/(n-k)}
\]  

(21)

\( \text{CH} \) metric takes the squared sum of the distance between the centroid of each cluster and the mean center of the sample set as the separation of the data set, the squared sum of the distance between each point in the cluster and the cluster center as the tightness within the cluster, and the ratio of separation to tightness as the final metric of \( \text{CH} \). The larger the metric indicates, the higher the degree of dispersion among the clusters, the tighter the clusters, and the better the evaluation result. It indicates that the indicator is better than the others in most cases.
4 Analysis of student performance evaluation reform of film and television production courses in Shanxi Province universities

4.1 Decision tree precision rate test

The algorithm's accuracy was tested using the ten-fold cross-validation method. Under this method, the sample data set was divided into ten parts, and nine of them were used each time as training data and one as test data for testing, and the corresponding accuracy rates were finally derived. Measured decision tree accuracy is used to make judgments, and Table 1 displays the decision tree accuracy test results. The ten-fold cross-validation evaluation algorithm is closely related to the setting of the number of leaves of the decision tree, and the accuracy of the model changes with the number of leaves. When the setting of the number of leaves of the decision tree is greater than 9, the accuracy rates are all above 90%, indicating a good accuracy rate.

<table>
<thead>
<tr>
<th>Number of leaves</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy (%)</td>
<td>62.8</td>
<td>75.1</td>
<td>82.6</td>
<td>82.2</td>
<td>84.7</td>
<td>85.1</td>
<td>87.2</td>
<td>89.1</td>
<td>91.0</td>
<td>90.6</td>
</tr>
</tbody>
</table>

The number of sampled student achievement training sample sets, i.e., the number of growing trees in the random forest algorithm-based student achievement evaluation model, was tested for sample set accuracy. Figure 3 shows the results of the effect of the number of growing trees on the accuracy of out-of-bag data for each classification. The out-of-bag data error tends to stabilize for each classification case, with the excellent-growth trees gradually increasing from 0.2 accuracies to about 0.8. The improvement in each evaluation index is greater, the advantage in classification accuracy is greater, and the accuracy of classification is higher.

Figure 3. Effect of the number of growing trees on the accuracy

After getting the decision tree accuracy rate to evaluate the teaching of film and television production courses, the Internet era, film and television production courses according to the different learning levels of students, and combined with the teaching characteristics of the course divided the teaching objectives into two major parts of cognitive and skills, each objective designed and designed in different teaching stages of specific teaching objectives. Table 2 presents an analysis of the film and television production course teaching indicators scoring, combined with the Internet to film and television production course scoring, which is set to 1-5 points. The course rating for camera action skills and digital video production fundamentals in cognitive rating is 5 points. The content of the film and television production course is extensive, including theoretical knowledge, photography, video operations, post-editing, and so on. Students must prioritize mastering a skill that aligns with their interests and finish a complete work through group work. The current course teaching is more focused on requiring the performance of higher-order thinking skills, such as creative thinking skills.
based on divergent thinking and perceptual experience. It requires students to integrate the theoretical knowledge of digital video production into the entire creative process of work planning, script writing, on-site shooting, post-editing, etc. and to effectively solve various complex problems and achieve innovations in perspective, structure, and artistic expression.

Table 2. Rating of teaching indicators for film and television production courses

<table>
<thead>
<tr>
<th>Cognitive</th>
<th>Movement skills</th>
</tr>
</thead>
<tbody>
<tr>
<td>Digital Video Production Fundamentals</td>
<td>Composition of audiovisual language</td>
</tr>
<tr>
<td>5</td>
<td>3</td>
</tr>
</tbody>
</table>

4.2 Analysis of student performance reform in Film and television production courses

Students majoring in educational technology and digital media technology in universities in Shanxi Province were selected for the experiment, with 2 large classes, each divided into two small classes. The course consisted of 55 students majoring in educational technology and 60 majoring in digital media technology, resulting in 115 students. The overall goals to be achieved by the teaching activities of the film and television production course in Shanxi Province colleges and universities are divided into three major areas: cognition, motor skills, and emotion. The teaching objectives of the film and television production course include cognition, mastering the basic theory of film and television, such as the foundation of digital video production, the composition of audiovisual language, and the grammar of the audiovisual language. Familiar with the video production process and the production staff's work, master the principles of digital video editing, and so on. Action skills for the practice of camera, video editing, studio programs and live production, and other experiments, master the basic elements of the camera, master the basic methods of video editing, master the basic skills of studio programs and live production. Emotional development involves adapting to work and society, independent thinking and creativity, teamwork, and higher-order thinking skills such as critical and creative thinking.

The film and television production courses in Shanxi Province colleges and universities are oriented to industrial development needs, so the curriculum should start from these practical abilities of material management, audio and video editing, special effects compositing, lens processing, and microfilm creation. Combined with new technologies, concepts, and methods in the Internet era, students learn film and television production processes, audiovisual creative thinking, visual effect production, script writing, and sub-screen design. Table 3 displays the weighting of the evaluation indexes for the student learning achievement assessment reform. 5 kinds of course evaluation content, the teacher’s rating weight is the highest 10, and the weighting of students’ mutual evaluation and self-evaluation are both 5. This way, students can find out more and more timely problems and receive more comprehensive feedback, which is more effective than a single teacher's evaluation and can promote their progress.
Table 3. Weighting of Indicators for Evaluation of student learning achievement reform  

<table>
<thead>
<tr>
<th>Indicators (%)</th>
<th>Theory</th>
<th>Capabilities</th>
<th>Course assessment and evaluation content</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Film and Video Production Process</td>
</tr>
<tr>
<td>Teacher Rating</td>
<td>20</td>
<td>25</td>
<td>10</td>
</tr>
<tr>
<td>Student mutual evaluation</td>
<td>30</td>
<td>20</td>
<td>5</td>
</tr>
<tr>
<td>Student Self-Assessment</td>
<td>25</td>
<td>20</td>
<td>5</td>
</tr>
</tbody>
</table>

According to the setting of the performance evaluation model, 115 students were tested on the performance evaluation reform, and a percentage system calculated each score; 5 points were calculated for each score, and the total score of the three items was 15 points. The distribution of experimental scores is shown in Figure 4.

Figure 4(a) shows the distribution of students’ experimental scores before the reform. Most of the students’ scores are distributed in 1-3 points, among which 40 people have scores of 2 points distributed in Assignment 1, and the average number of people with 4-5 points is about 10. The content of the film and television production course is extensive, including theoretical knowledge, photography and camera operations, post-editing, and so on. Students must concentrate on mastering a skill aligned with their interests and complete work through group division of labor. The current course teaching is more focused on requiring the performance of higher-order thinking skills, such as creative thinking skills based on divergent thinking and perceptual experience. It requires students to integrate the theoretical knowledge of digital video production into the entire creative process of work planning, script writing, on-site shooting, post-editing, etc. and to effectively solve various complex problems and achieve innovations in perspective, structure, and artistic expression.

Figure 4(b) shows the distribution of students’ experimental scores after the reform. After the reform, students’ scores are all distributed in 3-5, and there are no students with scores of 0. Compared with the number of students with scores of 5 before the reform, the number of students has improved by about 20. Therefore, teaching film and television production courses in the university curriculum system is a type of course system that pays more attention to practical teaching effects and practical teaching organization. When teachers organize and implement the relevant course teaching process, they should not only realize the reform of the course teaching dimension based on the technological innovation and technical reform of the relevant professions but also cultivate and improve students’ practical ability, advanced technology application ability and innovative thinking ability in many aspects according to the professional talents demand in the corresponding professional fields at the present stage. The reform of the school education dimension can ultimately lead to the cultivation of comprehensive technical talents that meet the needs of the relevant professions.
Figure 4. Grade distribution before and after grade evaluation reform

5 Conclusion

In this paper, we analyze student behavior data based on a random forest algorithm against the background of the Internet era and construct optimal evaluation indexes through the decision tree model. A total of 115 people in Shanxi province colleges and universities were selected to test the
performance evaluation reform, and the index weights were evaluated by five assessment indexes on students’ learning performance, in which teachers’ rating weights were the highest 10. To evaluate students' experimental performance before and after the reform, most of their performance before the reform was distributed in 1-3 points. The basic distribution is 3-5 points after the reform. In the Internet era, the practical part of film and television production courses in Shanxi universities is a significant aspect of teaching. In the teaching reform, we fully use the characteristics of the Internet to develop a suitable teaching mode and provide more resources and a broader platform for students’ practical learning so that we can cultivate real film and television talents with artistic quality, eyesight, technology, and creativity.

References


