How Does Analysis of Handwritten Notes Provide Better Insights for Learning Behavior?

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ABSTRACT

Handwritten notes are one important component of students' learning process, which is used to record what they have learned in class or tease out knowledge after class for reflection and further strengthen the learning effect. It also helps a lot during review. We hope to divide handwritten notes (Japanese) into different parts, such as text, mathematical expressions, charts, etc., and quantify them to evaluate the condition of the notes and compare them among students. At the same time, data on students' learning behaviors in the course are collected through the online education platform, such as the use time of textbook and attendance, as well as the scores of the online quiz and course grade. In this paper, the analysis of the relationship between the segmentation results of handwritten notes and learning behavior are reported, as well as the research on automatic page segmentation based on deep learning.

CCS CONCEPTS

• **Computing methodologies** → **Image segmentation**; • **Applied computing** → **Computer-assisted instruction**.

KEYWORDS

learning behavior, page segmentation, handwritten note

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1 INTRODUCTION

Note-taking is a common learning method in the student's learning activities. The process of taking notes requires students to have higher concentration and effort than simply listening to lectures and reading [24]. Students also have better effect when reviewing their own notes[1, 3]. In terms of input methods, handwriting is more convenient to record formulas, diverse diagrams, and custom marks, than the keyboard. It is especially more convenient in subjects with more non-text content such as mathematics or chemistry. The reading habit is followed by note-taking habit as the second most significant contributor to achievement in chemistry[6, 20]. At the same time, handwritten notes are more helpful for learning than using the keyboard, since the process of handwriting makes it easier for the recorder to reorganize the information in his own language[18, 27]. Taking pictures of critical information via cell phones is more likely to cause absenteeism and adversely affect student attendance[15, 30].

It is more common practice to evaluate the content of the notes through teacher involvement[2]. It is very helpful for teachers and students to understand the extent of how handwritten notes can facilitate students in their studies, and what kind of notes can better let students achieve better learning results[6, 20]. Further, it also allows teachers to check students' notes and understand their learning progress. However, reviewing all students' notes manually imposes a heavy burden on teachers and it is difficult to quantify. Therefore, an automatic quantifying method is required. It is necessary to establish a method to automatically extract and analyze information from the electronic data of handwritten note images.

It would be the best case if the complete handwritten text could be recognized by OCR and analyzed by NLP and other means. However, the performance of complete OCR is still difficult to Recognize handwritten text, we chose the second-best method to analyze the notes by counting the area of the handwritten area and the number of characters, for which there was no similar study before. However, the composition of handwritten notes is not the same, different types of content require to be analyzed differently. For example, text and schematic diagrams will have different learning effects[16]. Many studies have shown that notes taken solely through transcription are not always effective in improving learning[12]. Compared with the pure text recording, the schematic diagram will require students' comprehension of the learning content and extract the essence. At the same time, for different courses, the importance of texts and formulas will also be different. The type and position

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of the note content are not fixed. For further extracting features, different types of content areas need to be segmented.

It is possible to split the pages of a neatly laid out electronic document in the traditional way[4, 23], but it is quite difficult to split the text and formulas in a handwritten document. However, with the recent developments in machine learning methods, such as deep learning the performance of page segmentation is enhanced[9, 13, 17, 31], which can be used to extract the Content areas while judging the attributes of each area. In addition, the number of words of the note can reflect the workload of the note[5, 21], more words in the note can reflect more content it may contain. On the other hand, through the online education platforms, we could acquire additional student learning behavior data in addition to the regular test scores and course results. For example, the use time of teaching materials, and students' using status some functions of the online platform[10, 19]. If the correlation between notes and learning behaviors can be verified, the student learning behaviors can also be inferred by evaluating their notes without the records of online education platforms.

In this research, we use page segmentation, which is a method based on the field of deep learning, to quantify handwritten notes. We hope that this automated quantitative approach will help teachers understand how well their students are taking notes as a way to assess student learning. We also wished to use the results of the page segmentation to verify whether different note content produces different learning effects and to use this result to give better guidance to students in note-taking. In this experiment, we perform character segmentation based on the result of page segmentation, and the correlation between the area of different contents and the number of characters in different areas, and their learning behavior data. The results obtained showed that the amount of note-taking correlated with learning time and learning outcomes, and found that the area of the graph area had a greater effect on performance compared to other content.

2 PAGE SEGMENTATION OF HANDWRITTEN NOTES

In this study, U-Net[25] is taken as the neural network model to automatically classify the content areas of handwritten notes images, such as areas with formula and text. For character segmentation, another U-Net network is used to segment characters, then the output of the two networks will be combined to obtain the final result of character segmentation and classification (Fig.1).

2.1 Use U-Net to Conduct Area Segmentation on the Page Content

U-Net is a fully convolutional neural network, which is often used as an effective method in semantic segmentation tasks. By skipping connection, the manifested features obtained close to the input layer in the neural network is integrated with the features close to the output layer, which can effectively segment the text and formula areas that are similar locally but different overall[29]. By inputting the original image, the predicted classification of each pixel can be directly obtained. Fig.1(a,b,c) shows the result of U-Net segmentation of the content on the page of an input image, as well as the corresponding Ground Truth image. It can be seen that U-Net can segment the page content and quantify the area occupied by each type of content on the page. In this study, for analyzing the number of characters in the text, in addition to using U-Net for area segmentation and post-processing results, the characters are also segmented to count the number of characters on each page of notes.

2.2 Post-processing Through Morphological Transformation of the Segmentation Result

Since the dataset is designed to classify regions, some of the text regions are labeled with entire paragraphs rather than lines of text, so we also need a post-processing method to further optimize the segmentation results. Recognition of text lines can be achieved by using the rapidly developing techniques related to scene text detection, which focuses more on detecting independent text lines in complex environments and avoiding missed detection as much as possible. In a simple environment like handwritten notes, where there is no interference from other elements, segmentation by deep pixels methods hardly miss detection and can also classify different contents including images at the same time. There are some other studies on line detection for handwritten text[26], but our study focuses more on the area of the region.So we consider using deep pixels to segment the text line area.

As the note we processed in this study are generally white backgrounds, the description area is composed of pixels with colors other than white, such as black and red. In order to avoid misidentification caused by darker shadows, maximum and minimum filters are adopted to eliminate shadows, such characters can extract the maximum and minimum pixel values of each local area in the page. In the case of shadows, it is assumed that image pixels can be roughly divided into three types: background pixels without shadows, pixels with shadows, and pixels of and written characters. The relationship between the brightness values of each pixel,P_o, P_s, P_w can be considered as the following.

$$255 \geq P_o > P_s > P_w \geq 0 \tag{1}$$

First, a background image B composed of, P_o, P_s is generated by using a max filter with the size of 20×20. The max filter extracts the maximum brightness of the handwritten note image compared with the surrounding area. However, the P_s pixels around P_w in B are hard to be extracted (since the camera's sharpening process makes the background pixels next to the text pixels tend to have higher brightness), so the shadowed areas are easy to be neglected. Therefore, a min filter with the same size as the max filter is applied to B to extract the shadow area properly. In this way, a shadowed background image B' is obtained. Finally, B' is subtracted from the original image and normalized to $[0, 255]$. Fig.2 shows an example under the operation with the aforementioned sequence, it can be seen that the shadow is properly eliminated.

After the shadows are eliminated, a single-channel image is obtained, which can be binarized to achieve non-background areas. Considering that handwritten notes usually contain underlines that are grid lines, a Sobel filter is used to extract vertical edges. The binarized pixels are first dilated and then the noise is removed by a single erosion operation. Finally, an accurate text line is obtained by another contraction. For the filter size in morphological

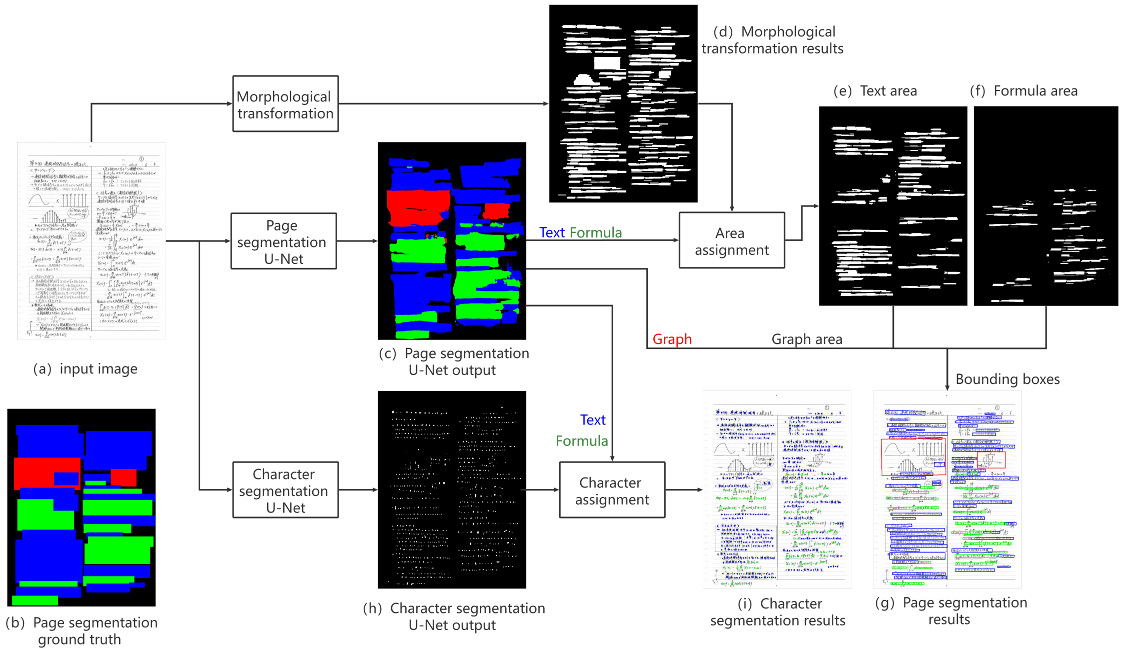
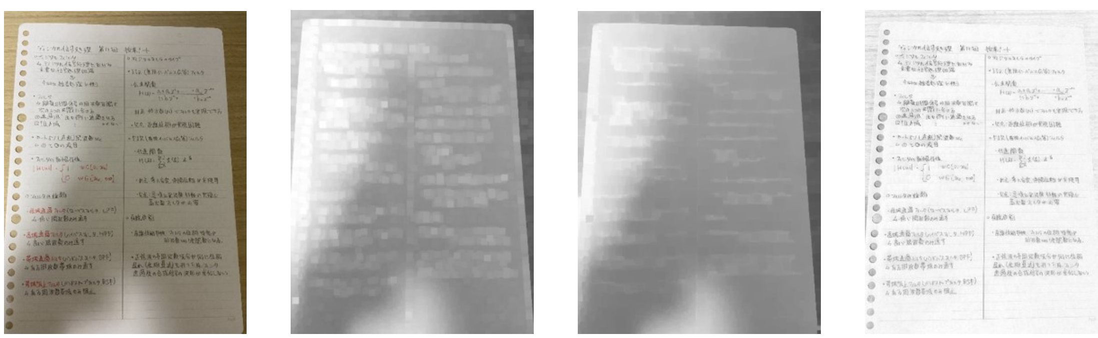


Figure 1: Flow of page segmentation and character segmentation



(a) Input (b) B (c) B' (d) Output

Figure 2: Shadow Elimination

transformation[11], vertical size is set to be far smaller than the horizontal size to prevent adhesion between lines, which is 20×2 in the experiment. The result of morphological transformation is shown in Fig.1(d). The text and formula regions detected by page segmentation U-Net and the binarized image obtained by the above method are combined by AND operation(text:Fig.1(e),formula:Fig.1(f)). By using the minimum outside rectangle of each connected region as the text region, more accurate segmentation results :Fig.1(g) are obtained.

2.3 Character Segmentation

Due to the need to count the number of characters and prevent sticking between detected text areas, by referring to [28], we cropped the rectangular GT of a single character as a new label. Specifically, there is a small rectangular area in the middle of the annotation text area, whose length and width are only half of the text size and serves as the kernel of a single character. In the model output, connected regions are found for pixels classified as pairs of core regions, and each connected region is counted as one character. The obtained text segmentation result must be used in combination with the page segmentation result. On the one hand, it can filter out the misidentification of non-text areas, and on the other hand, it can distinguish text and formula. The number of kernels in the text area and the formula area are counted as the number of text characters and the number of formula characters.

3 EXPERIMENT

3.1 Data Description

Student notes and learning behavior data from a total of 11 lectures in the course of Digital Signal Processing of the College of Engineering were collected. Among them, 83 students submitted their notes and completed their courses, with a total note page number of 1682. Students can complete notes during or after class by using the online textbook and submit photos of any number of pages of notes by uploading them. In a single lecture, some students submit up to 10 pages of handwritten notes, and some students also just submitted notes for partial lectures. The images in the data set mainly consist of photos of handwritten notes on A4 size notebooks, as well as pictures of electronic notes handwritten with a tablet or other tools. Their size and length-width ratio are not uniform, and some images are not clear. The page segmentation Ground Truth of handwritten notes includes text, formulas, and labels for numbers. It is created by the manually selected rectangular area where text, formulas, and graphs are located.

In the course of digital signal processing, the online education platform Moodle and the digital textbook reading system BookRoll[7, 22] were used. In the last lecture, 5 multiple-choice questions were given as online tests on the Moodle platform, with the highest test score of 50 points for the analysis of this experiment. During the online test, students can use textbooks and the Internet. In addition, students' attendance records for a total of 14 lectures(11 lectures requiring submission of notes and 3 review lectures). The final course grade is graded A through D and a failing F (Quantified as 95,85...55). In addition, BookRoll automatically records the data of each student's reading on the textbook, such as opening and turning pages, as well as the marks made on the electronic textbook, the learning feedback through the "get it" and "not get it" buttons. By processing the operation records, the reading time of each student can be counted for analysis. However, for the reason of not closing the reading page of the e-textbook in time, or not reading while the textbook's opened, etc., although we have eliminated more than fifteen minutes of inactivity, the obtained time may still be much longer than the actual reading time.

For the training set of page segmentation, 518 note images from the first, second, and third lectures are adopted, where 160 note images from the 11th lecture are taken as the validation dataset. The reason for the choice is that the notes of these courses have a more balanced text, formula and graph, and have been tested to be largely unchanged in accuracy at 300 or more training data. Since the training data for character segmentation is difficult to be annotated, only 22 images from the first, second, and third lectures are selected for labeling and being used as training data. The validation dataset used for evaluation is the number of characters in the 18 pictures in Lecture 11. The batch size of training U-Net is 8, the learning rate is 10-3, and Adam[14] is used as the optimization method. The post-processed output of page segmentation using U-Net is shown in Table 1. After post-processing, the accuracy is increased from 85.08% to 86.16%. Since the GT of data is not for text lines, there are a lot of annotations for text paragraphs(Fig.1(b)), so in the text area and formula area, the accuracy will be reduced instead due to the elimination of the space between lines. As shown in Fig.1(g),the blue rectangle is the result of text line recognition, and the yellow part is the area of the remaining handwritten pixels,the bounding box of each text line can be clearly obtained.

It can be seen from OUT=1 in Table 1 that the recognition accuracy of the text area is higher, which may be because there are more text areas in the training set. In addition, 13.85% of the formula area was incorrectly identified as a text area, because misidentification often occurs in the area adjacent to the formula and the text. Since we use rectangles to mark GT, many blank areas are marked as graph areas when marking the graph area. Therefore, the model recognizes 23.46% of the graph area as the background. Since all areas of the page content are recognized by more than 50%, in this study, the output data of the model is used to quantify the area of handwritten notes.

The result of character segmentation is shown in Fig.1(i), with the characters of the text in blue and the characters of the formula in green. After counting the characters, the number of characters measured on each page is y, where the actual number of characters is t. After calculating the error rate for each image through $\frac{|y-t|}{t}$, the average error rate is 21.74%. Because there are many Chinese characters in Japanese that are easily recognized as two characters, the overall number of recognized characters is higher.The number of characters per page recognized by the model is on average 9.42% higher than the actual value. Although the accuracy of character segmentation varies slightly depending on the actual situation of the page, the original result of character segmentation with an error rate of 21.74% can basically describe the number of characters in a note.

3.2 Analysis of the correlation between the amount of note-taking and learning behavior

As a result of page segmentation and character segmentation, we obtained the area(number of pixels) of the text, formula, and graph areas, as well as the number of characters corresponding to the text and formula used to describe the amount of note-taking. The learning behavior data used are the number of attendance, the number of marker uses of the online textbook, and the number of times students' learning feedback (Getit and NotGetit) is used, as well as the online test scores and course grades. The correlation between the two sets of data is shown in the table.

Through the results in Table 2 we can observe that there are positive and significant correlations between textbook usage time, the online quiz scores and grades, and all characteristics of notes. With the data for each learning behavior, the correlation coefficient was highest for the total number of characters and slightly higher for the area and amount of characters of the formula compared to the other two contents, but there was no significant gap between the characteristics. To better understand the relationship between note-taking characteristics and learning data, we divided students into three groups according to grades A, BCD, and F. The average data of each group are shown in Table 3. Among the three groups, the largest gap in the total number of formula characters can be seen, while the gap in the number of pages of notes is smaller, which can indicate that the amount of note content after classification obtained by page segmentation can describe the actual note content in more detail to know the students' learning situation.

Table 1: Page segmentation model result
0:Background 1:Text 2:Formula 3:Graphs

	OUT = 0	OUT = 1	OUT = 2	OUT = 3
GT= 0	92.21%(90.46%)	4.18%(6.90%)	1.74%(1.94%)	1.86%(0.71%)
GT= 1	18.00%(14.59%)	76.85%(80.57%)	4.33%(4.63%)	0.82%(0.21%)
GT= 2	16.9%(16.14%)	13.85%(13.51%)	65.52%(69.30%)	3.72%(1.05%)
GT= 3	23.46%(35.37%)	2.42%(4.76%)	2.59%(2.96%)	71.54%(56.91%)

Original page segmentation U-net results without post-processing in parentheses.

Table 2: Pearson correlation analysis of note taking characteristics and learning behavior data

		Attendance	Getit	NotGetit	Marker	Study time	Quiz	Grade
Text area	Coefficient	0.229*	**0.284****	0.153	0.316**	0.342**	0.367**	0.434**
Formula area	Coefficient	**0.326****	**0.383****	0.292**	**0.351****	**0.510****	0.397**	0.476**
Graph area	Coefficient	0.147	0.187	0.192	0.258*	0.398**	0.324**	0.332**
All area	Coefficient	**0.280***	**0.339****	0.232*	**0.352****	0.454**	0.408**	0.478**
Text character count	Coefficient	**0.268***	**0.339****	0.273*	**0.361****	0.433**	0.412**	0.470**
Formula character count	Coefficient	**0.343****	**0.430****	**0.380****	**0.377****	**0.557****	0.416**	**0.509****
All character count	Coefficient	**0.314****	**0.395****	0.333**	**0.386****	**0.509****	**0.434****	**0.511****
Pages uploaded(Baseline)	Coefficient	0.251*	0.279*	0.339**	0.333**	0.493**	0.428**	0.490**

* p0.05 ** p0.01

Table 3: The average data of 3 grade group

Grade	F (Baseline)	B C D		A	
Text area	0.7079	2.7454	(3.88)	4.8264	(6.82)
Formula area	0.4238	2.0300	(4.79)	4.0905	(9.65)
Graph area	0.1191	0.3996	(3.36)	0.9330	(7.83)
All area	1.2507	5.1750	(4.14)	9.8498	(7.88)
Text character count	3.44	2780.30	(5.04)	25.52	(7.88)
Formula character count	551.78	1694.40	(6.01)	4348.56	(11.44)
All character count	282.11	4474.70	(5.37)	3226.81	(9.08)
Study time	15000.00	81366.00	(5.42)	129626.35	(8.64)
Pages uploaded	833.89	15.10	(4.39)	7575.37	(7.42)

Multiples of the baseline in parentheses

Through correlation analysis, in a course like electronic signal processing, the number of formulas in the notes best reflects students' learning behavior and effects. This should give different results where the content of the course differs, and the page segmentation of the student notes allows for an assessment of the key elements of the course.

3.3 Analysis of the percentage of note content to course grades for different lessons

In order to investigate the effect of different contents of the notes on the learning effect, we counted the percentage of text, formulae, and diagrams in all contents, and it should be noted that in the case of no submitted notes, the percentage data of all three contents were set to 0. We attempted a multiple linear regression of the content percentage data of notes submitted by each student in each class (once a week) on the final course grade, and the results are in Table 4. Most of these lessons passed the F-test and had an R2 value of about 0.4. The coefficients vary depending on the course content and the composition of the notes. Almost no formulas existed in the first lesson's notes, and the conceptual text took up the major part. And in the notes of Lesson 5,6,8, there are almost no graphs, so the coefficient of graph proportion is abnormal. Excluding these lessons, we can see that the coefficients of the graph percentages are generally higher than the other two contents.

4 DISCUSSION AND CONCLUSION

4.1 Limitations

There may be some possible limitations in this study. First, the data set we use is from a single Japanese course and Japanese notes, which may affect the generality of the conclusion. The segmentation model cannot be directly used in other languages. In terms of page segmentation and handwritten text segmentation models, due to the influence of Chinese characters and kana in Japanese, higher precision segmentation requires the combination of characters that are divided into two parts through semantics. This issue may not occur in English notes. If a certain degree of semantic recognition

Table 4: Parameter Estimates

	Constant	R^2	F Value	Text area Percentage		Formula area Percentage		Graph area Percentage	
				Coefficients	VIF	Coefficients	VIF	Coefficients	VIF
lessons 1	82.059*** (26.242)	0.082	F=2.331 p=0.081	6.744 (1.731)	1.003	7.292 (0.358)	1.008	16.152* (2.033)	1.006
lessons 2	80.333*** (24.726)	0.126	F=3.743 p=0.014	14.447* (2.015)	1.078	5.078 (0.922)	1.083	32.292* (2.139)	1.005
lessons 3	65.000*** (21.245)	0.483	F=24.310 p=0.000	15.446* (2.337)	1.043	32.652*** (7.450)	1.027	33.825 (1.671)	1.017
lessons 4	71.363*** (21.028)	0.301	F=11.173 p=0.000	13.976** (2.724)	1.026	27.280*** (3.740)	1.031	28.472** (2.742)	1.017
lessons 5	73.000*** (25.881)	0.341	F=13.463 p=0.000	11.557 (1.803)	1.243	26.357*** (4.544)	1.249	14.819 (0.690)	1.016
lessons 6	70.333*** (27.388)	0.454	F=21.605 p=0.000	20.188*** (4.338)	1.141	26.957*** (4.866)	1.187	-164.298 (-0.963)	1.048
lessons 7	68.333*** (29.282)	0.549	F=31.650 p=0.000	24.387*** (6.292)	1.022	23.541*** (5.180)	1.035	36.389** (3.100)	1.026
lessons 8	81.774*** (37.357)	0.180	F=5.704 p=0.001	6.381 (0.949)	1.590	15.472* (2.007)	1.701	15.181 (1.021)	1.282
lessons 9	71.250*** (28.139)	0.434	F=19.910 p=0.000	20.596*** (5.115)	1.012	22.931*** (5.344)	1.002	25.514 (1.121)	1.011
lessons 10	76.923*** (36.984)	0.379	F=15.869 p=0.000	16.828*** (3.482)	1.170	17.954** (3.061)	1.368	17.296 (1.775)	1.184
lessons 11	74.091*** (35.218)	0.462	F=22.365 p=0.000	21.242*** (6.000)	1.216	13.868 (1.425)	1.268	23.402* (2.415)	1.058

* p<0.05 ** p<0.01 *** p<0.001 t statistics in parentheses

can be realized, we could use keywords or compare with the textbook content to extract the note features from the content. This research only conducts quantification on the note through the area of the handwriting area and the number of characters obtained by page segmentation, more accurate and complete note evaluation methods needs to be further studied.

When analyzing the proportion of note content, since the data set is derived from ordinary courses and there is no control group, it is difficult to prove the causality of the handwritten notes and the learning results, and only the correlation can be displayed. Moreover, for different courses, the reasons for the difference in the weights of the different content in the notes on the learning effect remain unclear. This requires a method for reviewing the content of the course and more data.

4.2 Findings and Perspectives

In this paper, a method of segmentation of Japanese handwritten note pages through deep learning is introduced, and the correlation between the area and the number of characters of different content and the learning behavior data and grades of students are analyzed. There is a clear correlation between the amount of note content and the time the students spend textbooks and the course grades, which is consistent with the conclusions of previous research. Students who submitted more notes tended to use textbooks longer and generally could achieve higher grades on the online quiz at the end of the semester. Therefore, it may be a valuable method to know the learning status of students through evaluating their notes. Automatic quantification of notes through page segmentation and character counts can capture data that are difficult to obtain manually, and can give teachers a better view of students' notes without having to read them. It uses more visual and granular data to provide feedback on the amount of note-taking by students. Teachers have the flexibility to use this data according to the content of the course. Although it cannot replace other learning activity data, it will provide a new data source for other educational assistance research such as grade prediction.

In addition, based on the results of page segmentation, a regression analysis is performed on the proportion of text, formulas, and graphs and students' grades, hoping to understand the correlation between the proportion of notes and the learning results and find out what kind of notes will have a better learning effect. It is found that due to different course content, the weight of the impact of each content in the notes on the students' grades will change. However, it is also noticed that, except for some courses that are mainly based on mathematics and formulas, where there are no students drawing graphs on their notes, the weight of the proportion of graph area is generally higher. This may be because drawing graphics (such as schematics or flowcharts) tends to generate a summary of knowledge in comparison with copying texts and formulas. It requires the recorder to express in his own way, and is easier to remember.

The way teachers evaluate the notes will focus more on whether enough key content is recorded or whether it is summarized and organized by the note taker himself, rather than simply copied. In addition, whether knowledge beyond the textbook and the board book was recorded was also one of the ways for the quality of the notes[8]. All these require further recognition of the content of the notes, and page segmentation and text segmentation are also the pre-requirements for character recognition. Even the segmentation-free method, after distinguishing text and formulae can reduce the recognition difficulty.

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