Figure 3. Example Display of Cover Images of Recommended Books

3 Results

This section presents the results of (1) the assignment of NDC categories to Wikipedia articles, (2) the selection and recommendation of books to articles readers, and (3) the evaluation of the recommended books by articles readers.

3.1 Assigning NDC Categories to Wikipedia Articles

The precision of the NDC category assignment to the Wikipedia articles was defined as the ratio of the number of articles to which correct categories were assigned to the total number of articles, expressed as a percentage. The CNN-based NDC category assignment results are presented in Table 3, where *tl*, *cg*, ..., *tl*+*cg*+*bd* respectively represent channel combinations (1)–(7) mentioned in the last paragraph of subsection 2.2.2. It can be seen from the tTable 3 that, for example, when 100 filters and only the titles of the Wikipedia articles (i.e., *tl*) are used, the NDC category assignment precision is 49.0%. The use of article titles, categories, and main texts with 250 filters produces the highest precision of 87.4%.[5] It is also obvious that the use of more filters and channels does not necessarily improve the results, owing to the problem of overfitting.

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[5] As mentioned in Section 1, Tsuji (2017) attempted to assign NDC categories to Wikipedia articles by setting the titles, categories, and main texts in a single channel of the CNN. For performance comparison, the NDC categories were assigned in the same way in the present study. The highest precision achieved in the previous work was 86.6%, which is lower than that of the present study.

Table 3. Precision of NDC Category Assignment Using CNN

	Number of Filters					
	50	100	150	200	250	300
tl	47.4	49.0	47.4	48.6	49.4	49.2
cg	73.4	67.6	67.8	69.2	63.4	68.0
bd	75.2	80.0	80.0	80.8	80.4	80.8
tl+cg	73.6	75.2	73.0	74.0	75.0	77.2
tl+bd	80.2	80.8	82.0	82.4	81.2	82.2
cg+bd	84.8	84.4	84.8	85.8	86.0	86.2
tl+cg+bd	85.8	85.0	86.2	86.0	87.4	85.4

Table 4 presents the SVM-based NDC category assignment results for the LC set of Wikipedia articles. It can be seen from the Table 4 that, for example, the use of the distributed representation of only the titles produces a precision of just 67.2%, corresponding to C and γ (subsection 2.2.5) values of 128 and 0.031250000, respectively. The highest precision of 84.4% is achieved using the distributed representations of the titles, categories, and main texts, with C and γ values of 512 and 0.000122070. This precision is lower than the highest value of 87.4% achieved by the CNN (Table 3).

Table 4. Precision of NDC Category Assignment Using SVM

	Precision	C	γ
tl	67.2	128	0.031250000
cg	79.3	32	0.001953125
bd	79.1	8	0.001953125
tl+cg	80.6	128	0.001953125
tl+bd	80.1	512	0.000488281
cg+bd	84.0	512	0.000003052
tl+cg+bd	84.4	512	0.000122070

Based on the above results, the developed CNN was used to assign NDC categories to all the Wikipedia articles using their titles, categories, and main texts and 250 filters. The number of Wikipedia articles with respect to the NDC category obtained by this means is presented in Table 5. Here, C and N represent the NDC category and number of articles, respectively. It can be seen that, for example, the number of Wikipedia articles assigned NDC category 32 is 9,447.

Table 5. Number of Wikipedia Articles with Respect to Assigned NDC Category

C	N	C	N	C	N	C	N	C	N	C	N	C	N	C	N	C	N	C	N
00	14,434	10	0	20	181	30	3,373	40	963	50	1,522	60	0	70	2,763	80	1,229	90	1,292
01	1,892	11	73	21	68,066	31	12,702	41	7,338	51	2,120	61	23,774	71	0	81	4,614	91	23,539
02	1,735	12	1,945	22	27,584	32	9,447	42	4,308	52	9,379	62	0	72	29,984	82	0	92	1,430
03	0	13	2,594	23	41,070	33	11,263	43	4,570	53	15,671	63	0	73	0	83	1,157	93	4,007
04	98	14	3,599	24	808	34	0	44	8,123	54	13,704	64	4,506	74	2,589	84	0	94	1,988
05	0	15	0	25	902	35	0	45	7,352	55	13,736	65	212	75	1,806	85	0	95	0
06	0	16	3,787	26	0	36	10,642	46	1,841	56	210	66	3	76	95,971	86	0	96	0
07	304	17	4,494	27	0	37	34,331	47	5,493	57	83	67	5,490	77	101,957	87	0	97	0
08	0	18	9,578	28	4,410	38	4,880	48	10,752	58	963	68	49,171	78	127,860	88	0	98	0
09	0	19	7,197	29	92,185	39	32,884	49	19,692	59	5,668	69	22,049	79	22,865	89	0	99	0
T	18,463	T	33,267	T	235,206	T	119,522	T	70,432	T	63,056	T	105,205	T	385,795	T	7,000	T	32,256

3.2 Selecting Books for Recommendation

The precisions of the CNN and SVM for classifying books to recommend or not recommend are presented in Table 6 and Table 7. A comparison of the tables reveals that the SVM produces better results, with its precision reaching 99.8%. The SVM was thus used to select books for recommendation to the Wikipedia articles readers. The three books with the highest probabilities of belonging to the group of books to be recommended for each Wikipedia article were selected and recommended to the subjects of the test implementation of the propose system.[6] [7]

Table 6. Precision of Book Classification Using CNN

	Number of Filters			
M	50	100	200	400
10	98.3	98.4	98.3	98.4
20	98.4	98.7	98.6	98.5
30	98.6	98.6	98.6	98.5

Table 7. Precision of Book Classification Using SVM

M	Precision	C	γ
10	99.8	512	0.03125
20	99.8	32	0.12500
30	99.7	32	0.12500

3.3 Obtaining User Evaluation of Recommended Books

The results of the student subjects' evaluation of the recommended books are presented in Tables Table 8 and Table 9, which correspond to when the loan frequencies of the books were shown and not shown, respectively. In the tables, "evaluation," N, and "ratio" respectively represent the evaluation response, the number of books to which that response was given, and the ratio of that number to the total number of book (150 = 10 students × 5 Wikipedia articles × 3 books), respectively. It can be seen from the tables that the ratios of books that the subjects evaluated as "I want to read this book very much" and "I want to read this book if possible" are 47.3% (= 15.3% + 32.0%) and 45.3% (= 18.0% + 27.3%), respectively. Although not shown in the tables, the subjects found at least one book that "I want to read" among the three recommended books for 41 out of 50 (= 10 students × 5 articles) Wikipedia articles when the loan frequencies were shown. In other words, the proposed system provided a useful book with a rate of 82.0%.[8]

[6] When the probabilities were higher than 50%, the books were judged by the CNN and SVM as books that should be recommended. When the probabilities were lower than 50%, the books were judged by the CNN and SVM as books that should not be recommended. The above-mentioned precision was calculated based on the respective numbers of these books.

[7] The option -b was used to show the above-mentioned probabilities in LIBSVM.

[8] When the loan frequencies were not shown, the ratio was 40 out of 50 articles (i.e., 80%).

Table 8. Evaluation of Recommended Books When Loan Frequency is Shown

Evaluation	N	Ratio
(1) I want to read this book very much	23	15.3
(2) I want to read this book if possible	48	32.0
(3) I do not want to read this book if possible	41	27.3
(4) I do not want to read this book at all	38	25.3
Total	150	100.0

Table 9. Evaluation of Recommended Books When Loan Frequency is Not Shown

Evaluation	N	Ratio
(1) I want to read this book very much	27	18.0
(2) I want to read this book if possible	41	27.3
(3) I do not want to read this book if possible	39	26.0
(4) I do not want to read this book at all	43	28.7
Total	150	100.0

Although there are slight differences between the results when the loan frequencies are shown and not shown, they are not statistically significant. However, it should not be concluded that the display of the loan frequencies does not affect the evaluation. It was examined whether extremely low or high loan frequencies affected the evaluation. The results are shown in Table 10, where "up" and "down" indicate that the student increased and decreased the evaluation of the same book, respectively (e.g., changed from "I do not want to read this book if possible" to "I want to read this book if possible") after seeing the loan frequency. It can be seen from the Table 10 that, for example, while only one student increased their book evaluations after seeing the loan frequencies, the same caused four students to decrease their evaluations. Conversely, more students (four vs. one) increased their evaluations after seeing that the loan frequencies of the books were ≥40. Students may be attracted to popular books (in the sense that they are frequently borrowed books). This is consistent with the so-called Matthew effect ("the rich get richer and the poor get poorer") proposed by Merton [44]. Showing loan frequencies that are up to 40 would thus be effective for increasing the interest of students in the books. The display of low loan frequencies should be avoided so that they do not discourage interest in such books.

Table 10. Change in Book Evaluation with Display of Loan Frequency

		Loan Frequencies					
		1	2	3	20–29	30–39	40+
Evaluation	Up	1	0	1	5	8	4
	Down	4	3	1	4	4	1

The evaluations of the students when the book cover images were displayed and not displayed are presented in Table 11 and Table 12, respectively. It can be seen from these tables that the ratio of evaluation (1) significantly decreases when the book cover images are not displayed (from 22.7% to 4.8%), while the ratio of evaluation (4) increases (from 21.6% to 30.6%). It can thus be said that the book cover images increase the interest of the students, at least the ratio of evaluation (1). It would, however, be useful to further investigate the effects of particular images in this regard.

Table 11. Change in Book Evaluation with Display of Book Cover

Evaluation	N	Ratio
(1) I want to read this book very much	20	22.7
(2) I want to read this book if possible	22	25.0
(3) I do not want to read this book if possible	27	30.7
(4) I do not want to read this book at all	19	21.6
Total	88	100.0

Table 12. Change in Book Evaluation with Display of Book Cover

Evaluation	N	Ratio
(1) I want to read this book very much	3	4.8
(2) I want to read this book if possible	26	41.9
(3) I do not want to read this book if possible	14	22.6
(4) I do not want to read this book at all	19	30.6
Total	62	100.0

The student evaluation with respect to NDC category is presented in Table 13. It is noteworthy that the ratio of evaluations (1) or (2) for NDC categories 40–49 is relatively low. This may be due to the fact that only one such article was among those used for the study.

Table 13. Book Evaluation with Respect to NDC Category

NDC	Evaluation	N	Ratio
00–09	(1) or (2)	34	49.3
10–19	(1) or (2)	4	44.4
20–29	(1) or (2)	6	66.7
30–39	(1) or (2)	5	41.7
40–49	(1) or (2)	1	16.7
50–59	(1) or (2)	6	40.0
60–69	(1) or (2)	4	66.7
70–79	(1) or (2)	11	45.8
80–89	(1) or (2)	0	—
90–99	(1) or (2)	0	—

4 Discussion

This section considers some potential error sources in the present work and how such may be addressed for further study. Among the 500 test data that were used for NDC category assignment, 63 Wikipedia articles were wrongly assigned NDC categories by the CNN. Among these 63, articles with proper nouns in their titles were predominant, with 12 containing the names of persons and six the names of organizations. Three articles with the names of historic Japanese personalities in their titles were assigned NDC category 21 (*History of Japan*), although the “correct” category was 28 (*Biography*). In this study, the correct NDC category was determined based on the books cited in the Wikipedia articles. These persons were mentioned in articles that cited their biographies. However, considering that the personalities are actually of historic significance, the above-mentioned assignment of *History of Japan* to the relevant articles is not entirely a failure. Other “incorrect” categorizations were observed for articles that belonged to multiple categories. For example, while the “correct” NDC category of an article on a historic Chinese calligrapher and philosopher is 72 (*Painting and Calligraphy*), the proposed system assigned category 12 (*Oriental Philosophy*) to it. This apparent failure may be difficult to correct, and it may not even be necessary to attempt a correction for the purpose of book recommendation because recommending a book for a specific aspect of the article may be acceptable.

The book selection precision of the SVM reached 99.8% and few errors were observed here. Regarding user evaluation, the 79 (= 41 + 38 in Table 8) books were evaluated as “I do not want to read this book if possible" and "I do not want to read this book at all." One means of reducing such negative evaluations is to recommend a book only when the probability mentioned in subsection 3.2 is sufficiently high. Table 14 gives the evaluation ratios for recommended books when the probability exceeded 99.99%. It can be seen from the table that the number of books evaluated as "I do not want to read this book if possible" or "I do not want to read this book at all" decreased to 35 (= 17 + 18), while those evaluated as "I want to read this book very much" and "I want to read this book if possible" increased from 47.3% (= 15.3% + 32.0% in Table 8) to 56.3% (= 22.5% + 33.8%).

Table 14. Evaluation of Recommended Books when Probability > 99.99%

Evaluation	N	Ratio
(1) I want to read this book very much	18	22.5
(2) I want to read this book if possible	27	33.8
(3) I do not want to read this book if possible	17	21.3
(4) I do not want to read this book at all	18	22.5
Total	80	100.0

It is also noteworthy that the developed CNN achieved a precision of 87.4% in assigning the two-digit (main class and division) NDC categories. There are actually 100 main class and division categories with notations ranging from 00 to 99. Considering that the probability that the correct category would be randomly chosen is 1%, the precision of 87.4% is very high. Further, although the proposed system uses the NDC categories assigned to Wikipedia articles to recommend books to the article readers, the data can also be inversely utilized, namely, to recommend Wikipedia articles to book readers. In addition, the procedure can be modified to assign NDC categories to Web pages generally and recommend books to readers of the Web pages. Hence, in a broader sense, the proposed system can be regarded as a tool for linking Web content with printed books. This promises to be beneficial in various fields.

5 Conclusions

To encourage students to read library books as a more reliable source of information, a system was developed for recommending library books to Wikipedia article readers in university libraries. The system assigns NDC categories to Wikipedia articles and recommends library books in the same categories as the respective articles. The CNN-based NDC category assignment precision of the system for Wikipedia articles was determined to be as high as 87.4%, while the SVM-based book selection precision reached 99.8%. In 82.0% of the test cases, the student subjects found at least one book that they evaluated as "I want to read this book" among three recommended books. Although the precision of selecting books for recommendation to the article readers was high, the subjects' evaluations of the books were relatively lower. This implies that the system training data obtained from the books cited in the articles were not ideal for book recommendation. Although it would be labor-intensive, training data could be manually generated by requesting many students to evaluate many books. The results could be used to achieve better book recommendation performance of the proposed system. In the present study, the system was implemented as a Google Chrome extension. It would be interesting to further implement the system as an extension of other Web browsers such as Microsoft Edge and Mozilla Firefox, and investigate whether the books recommended to the Wikipedia article readers are actually borrowed from the library.

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