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Adaptive learning based content management tool for online education platforms

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Abstract: The ways of accessing information are highly developed today. Online education platforms are widely used directly or indirectly in the education of students. Instructors create their course content on these platforms and teach their courses to their students. With the developing internet technologies, the variety of visual, audio and textual course content is also increasing. However, students' learning tendencies differ while studying these course contents. While some of the students can learn more easily from course content consisting only of texts, others can learn more easily from course content supported by audio-visual materials. Identifying these learning differences among students has become important today. In order to enrich learning activities, it would be useful to create content in accordance with the learning tendencies of each student. In this study, we developed an adaptive learning-based help tool for instructors to create course content. This tool analyzes the learning styles of the students and provides recommendations to the instructor for creating the course content. Thus, all the course content prepared by the instructor will be selected and created according to the learning tendencies of the students. It will contribute to the improvement of learning activities.

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Çevrimiçi eğitim platformları için adaptif öğrenme tabanlı içerik yönetim aracı

Anahtar Kelimeler
Adaptif öğrenme
Adaptif hipermedya
e-Öğrenme
Rastgele orman

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Öz: Bilgiye erişim yolları günümüzde oldukça gelişmiş durumdadır. Online eğitim platformları yaygın bir şekilde öğrencilerin eğitimlerinde doğrudan veya dolaylı olarak kullanılmaktadır. Eğitmenler ders içeriklerini bu platformlar içinde oluşturup öğrencilerine derslerini anlatmaktadırlar. Gelişen internet teknolojileri ile görsel, işitsel ve metin olarak ders içeriklerinin çeşitliliği de artmaktadır. Ancak öğrencilerin bu ders içeriklerini çalışırlarken öğrenme eğilimleri farklılaşmaktadır. Öğrencilerin bir kısmı sadece metinlerden oluşan ders içeriklerinden daha rahat öğrenebiliyorken, diğer bir kısmı görsel ve işitsel materyallerle desteklenmiş ders içeriklerinden daha rahat öğrenebilmektedir. Öğrencilerin arasındaki bu öğrenme farklılıklarını tespit edebilmek günümüzde önemli hale gelmiştir. Öğrenme faaliyetlerini zenginleştirmek için her öğrencinin öğrenme eğilimine uygun olarak içerik oluşturulması faydalı olacaktır. Bu çalışmada ders içeriklerini oluşturacak eğitmenler için adaptif öğrenme tabanlı bir yardım aracı geliştirilmiştir. Bu yardımcı araç öğrencilerin öğrenme yöntemlerini analiz ederek eğitmene ders içeriğini oluşturma konusunda tavsiyeler vermektedir. Böylece eğitmenin hazırladığı tüm ders içeriği öğrencilerin öğrenme eğilimlerine göre seçilip oluşturulacaktır. Öğrenme faaliyetlerinin iyileştirilmesinde katkısı olacaktır.

1. Introduction

E-learning is the online platforms used by educational institutions to deliver courses and learning activities. Used as a complement or alternative to traditional education, e-learning has become widespread in recent years, especially due to the Covid-19 pandemic [1]. In the contemporary era, utilizing electronic slides, the internet, emails, electronic learning platforms, and e-course materials has become a norm during course

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presentations. When integrating ICT into lectures, it becomes the responsibility of educators to furnish students with valuable and high-quality information. Numerous instructors who adopt ICT in their teaching methods affirm that its incorporation alongside traditional approaches facilitates smoother lessons and student engagement, rendering classes more dynamic and captivating. Various e-activities also contribute to enhancing the depth of subject matter. E-learning extends an alternative avenue to students, aiding them in achieving equilibrium between personal life, professional pursuits, and education. This modality epitomizes dynamic and enriching learning, lessening dependence on time and physical location. It delivers both personalized learning experiences and opportunities for collaborative engagement among peers [2].

For e-learning to be implemented effectively, potential learning difficulties that learners may face should be taken into account. Instructors' skills should be developed and adequate support should be provided [3]. In existing e-learning systems, the same learning content is presented to different learners. However, an enriched environment for one learner may not always be enriched for another. Learners' preferences, abilities and educational levels are diverse and various types of content are required in learning topics to adapt the learning content to the needs of different learners [4]. A well-designed and sophisticated online learning environment can encourage students to learn, simplify the learning process, facilitate deeper understanding and increase collaboration, which can contribute not only to increasing students' knowledge but also to improving their learning and communication abilities [5]. Adaptive Educational Systems (AES) prove highly valuable in facilitating teaching-learning endeavors. These environments harness intelligent methodologies to tailor educational content in accordance with learners' actual requirements. The objective is to furnish a more customized and tailored learning encounter. These systems should possess the capability to construct educational routes for students, stemming from their previous knowledge, engagements, and inclinations. In simpler terms, an AES should present personalization aligned with the distinctive necessities, expertise, and background of each student. To ensure the efficacy of this personalization, a model capturing the fundamental attributes of learners is imperative [6]. In the realms of intelligent tutoring and Adaptive Hypermedia (AH) systems, there is an ongoing development of personalized e-Learning systems. These systems within AH frameworks customize content according to the user's learning requirements, offering the utmost pertinent material and navigation routes [7].

Adaptive hypermedia systems build a model of each user's goals, preferences and knowledge by collecting and analyzing data about the user's interactions with the system. This data may include the user's browsing history, search queries, feedback and other relevant information. The system then uses this model to tailor the presentation of information and links to the user's needs [8].

This article consists of six sections with an introduction. In the second section, the studies presented in the literature on adaptive learning, learning management systems and research on students' study tendencies are presented. The third section provides information about Moodle learning management system, random forest algorithm and content filtering. In the fourth section, the results of the research are analyzed and interpreted in detail. In the fifth section, conclusions and recommendations are presented.

2. Literature Review

In the literature, systems have been created with different adaptive learning models. Elghouch et al. [9], ALS_CORR[LP], an e-learning system that adapts to learners' needs and learning styles. By analyzing learners' characteristics and learning styles, they customized the learning materials and optimized the learning process. Yasuda et al. [10], studied the implementation of adaptive learning systems using Bayesian networks. With their system, they effectively measured students' understanding and adapted the content according to the students' level of understanding through a field experiment in an elementary school in Japan. Vagale et al. [11], They conducted a study on the implementation of a personalized adaptive e-learning system. In the paper, they proposed an architecture using learner model, content model and alignment model. They used the Moodle platform to develop the system. Chen et al. [12], conducted a review on customized learning systems and recommender systems in order to provide more time for more effective understanding of learning materials. They also proposed a mathematical framework for the evaluation of recommendation strategies. Onah and Sinclair [13], propose a framework that recommends teaching material according to the learner's profile and provides a recommended learning path to meet the learning objectives. The framework aims to replicate the function of a human tutor by providing personalized recommendations. Tseng et al. [14], proposed an innovative adaptive learning approach based on learning behavior and personal learning style. They implemented it using questionnaires for theory and practice. They analyzed each student's interactions and learning outcomes when adjusting the subject materials.

In this study, a random forest algorithm is used to create a tool for adaptive learning-based content creation. Students' learning tendencies on Moodle LMS were measured by creating a course content. Content was added in 5 main categories: Video, Visual, Text, Video+Text and Visual+Text. The tendency of each student was tabulated with the scores they received in these materials. Students' learning tendencies were determined with the random forest algorithm. Then, with the tool created, the course materials in the learning management system were personalized according to their tendencies. Thus, each student was able to access their personalized pages according to their different learning tendencies. The contribution of the study to the literature can be examined in many ways. Adaptive learning integration for Moodle can make the learning experience on educational platforms more effective. In the field of education, it can make significant contributions in areas such as the effectiveness of individualized learning approaches, student performance monitoring, teacher guidance, effectiveness of educational technologies and data analysis. Such integrations can be a powerful tool to enhance the learning experience and make education more effective.

3. Material and Method

Moodle stands as a 'Learning Management System' (LMS), which is characterized as a web-based application equipped with integrated software, designed to furnish a digital learning milieu. This system is engineered to manage interactive online courses effectively. Through the LMS, an online arena is established to facilitate various facets of student-teacher interaction, both synchronous and asynchronous. This encompasses functions such as assessments, report generation, tracking learning advancements, monitoring student engagements, and furnishing students with feedback [15]. Moodle LMS is one of the popular systems suitable for the application of advanced digital technologies in the educational process [16]. Moodle is an open source system and can be easily programmed. It is modular and widely used. API support is its most important feature. It allows to make different plugins easily with its wide range of APIs. For this reason, Moodle LMS with Web API was used for system design.

3.1. Moodle Web Services

Moodle stands as a free, open-source learning management system scripted in PHP. Operating on a modular and object-oriented framework, Moodle functions as a dynamic learning platform, fostering interaction among educators, administrators, teachers, and students by facilitating the exchange of personalized educational resources. By incorporating a web services API, Moodle provides the means to expose your plugin's capabilities, encompassing functions like user management, registration, event creation, and various core operations. This requires an initial activation of web services by the system administrator, paving the way for REST API endpoints. After this setup, your system's core functionality becomes accessible to external systems through web services, utilizing protocols like XML-RPC, REST (predominantly employed), or SOAP. Secure access to each web service is granted through a token, established by the system administrator [17].

3.2. Random Forest

Random Forest, a machine learning algorithm, predominantly utilizes classification and regression trees to yield mostly substantial outcomes. It demonstrates flexibility, user-friendliness, and efficiency. The RF algorithm falls within the ensemble learning algorithm category, employing the bagging method. A key advantage of the random forest lies in its ability to address both classification and regression issues, forming the foundational principles of other machine learning algorithms. The constituent decision trees of the random forest are constructed concurrently, encompassing both classification and regression trees. Within each decision tree, nodes are partitioned using optimal attributes that derive the finest solution across all features. Notably, the RF algorithm has emerged as a prevalent technique for unearthing concealed insights within extensive datasets. In a random forest, training sets are initially generated through bootstrapping, each leading to the creation of an individual decision tree. The outcome of the algorithm materializes as a collective result of these operations [18]. In Figure 1, there is a recursive partitioning illustrated within a two-dimensional input space, employing boundaries aligned with the axes. At each step, the input space undergoes partitioning, always following a direction parallel to one of the axes. The first partition occurs on $x2 \geq a2$. Then, the two subspaces are split again: The left branch is split on $x1 \geq a4$. The right branch is first split on $x1 \geq a1$ and one of its sub-branches is split on $x2 > a3$ [19].

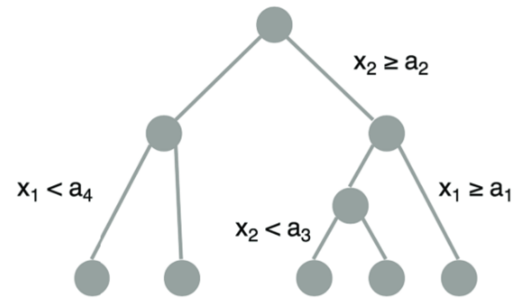

Figure 1. Random forest algorithm [19]

A frequently employed criterion for partitioning in classification scenarios is entropy. This criterion is a tangible application of the source coding theorem, which establishes a minimum length for the bit representation of any arbitrary variable. Equation 1 provides the expression for the entropy at each internal node within the decision tree. In the context of decision trees, where the goal is to make informed splits, the parameter "c" signifies the count of distinct classes present within the dataset, p_i represents the prior probability assigned to each individual class. Maximizing this value holds significance as it enables the extraction of the highest amount of information during the process of decision tree partitioning.

Alternatively, when addressing regression tasks, a prevalent criterion utilized for partitioning is the mean squared error [19], [20].

$$E = -\sum_{i=1}^{c} p_i \times \log(p_i) \quad (1)$$

The pseudo code of the random forest algorithm is given in Algorithm 1.

Algorithm 1. Random Forest

```
for i ← 1 to B do
  Draw a bootstrap sample of size N from the training data;
  while node size != minimum node size do
      randomly select a subset of m predictor variables from total p;
      for j ← 1 to m do
      if jth predictor optimizes splitting criterion then
          split internal node into two child nodes;
          break;
      end
    end
  end
end
return the ensemble tree of all B subtrees generated in the outer for loop;
```

Random Forest is an ensemble learning algorithm used in machine learning to solve classification and regression problems. It is used to predict a particular category. It is used to identify important features and to predict features. Therefore, it was determined as the appropriate algorithm for the system. With the training of the model used, the train accuary score was calculated as 94%.

3.3. Content-Based Filtering

An adaptive learning system comprises a multitude of models employed to analyze and comprehend user behaviors, culminating in the formulation of tailored learning trajectories for individual users. Two widely embraced methodologies for constructing such adaptive learning models are content-based filtering and collaborative filtering [21]. Content-based filtering (CBF), among the most effective recommendation approaches, hinges on item correlations. It leverages item data, manifesting as attributes, to compute resemblances among items. By assessing item descriptions and user inclinations, CBF algorithms provide users with fitting recommendations. Notably, these algorithms solely rely on the profile details or ratings of the present user. As a result, they can yield precise recommendations even in scenarios where the volume of ratings from other users is relatively limited [22]. Equation 2 shows the model. Where C_i is the rating estimate and is used to estimate the probability that an item belongs to any class.

$$P(C_i|X) = \prod_{k=1}^{n} P(X_k|C_i) \quad (2)$$

Each instance of an item X is described by a combination of 〈x1, x2, ...xk〉 item attribute values. Nonetheless, the Content-Based Filtering (CBF) approach falls short in delivering accurate recommendation outcomes when the content lacks sufficient data for item classification. There are instances where either domain expertise or an ontology becomes essential for pinpointing the crucial attributes that hold significance in the recommendation process. The calculation of the weights is as in Equation 3. Here the weight values obtained from a social network graph are used to predict user preferences. S is the similarity between objects O_i and O_j. ω_n represents the weight assigned to attribute A_n between objects O_i and O_j while the function f varies based on the attribute type. [22].

$$S(O_i, O_j) = \omega_1 f(A_{1i}, A_{1j}) + \omega_2 f(A_{2i}, A_{2j}) + \cdots + \omega_n f(A_{ni}, A_{nj}) \quad (3)$$

4. Results and Discussion

Web API was developed using ASP .Net to establish the system. Additionally, an MS-SQL database was integrated to store user profiles. Within this database, the performance scores of students engaging with Moodle activities are recorded. This data is then extracted and categorized using a random forest algorithm, enabling the identification of students' learning preferences. The adaptive content filter communicates these recommendations to students, indicating which course materials they should focus on. A specialized web API operates in tandem with this data, activating functions within Moodle. This facilitates the grouping of students, ensuring that content relevant to their specific group is presented to them. Figure 2 graphically illustrates the operation of the system.

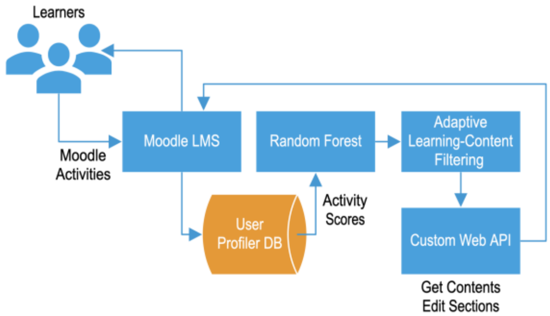

Figure 2. System diagram

The course activities of the students added on Moodle were monitored for a semester. At the end of the semester, their scores on the course content were recorded in the grades field. The data is organized with activities kept in separate fields. The dataset has a dimension of 568 rows and 26 columns. Notably, it appears that each learning tendency category is equally represented in this dataset. Table 1 shows the learning tendencies of 568 students. This table shows the students' total score for each learning tendency. However, all dataset fields were used in the training of the data. Students score between 1-100 points for each learning activity. For example, if the student worked intensively on activities with visual elements, his/her score would be close to 100. Then the scores for each learning activity category are summed up and the scores on Table 1 are obtained. The lowest score on Table 1 is 141 and the highest score is 432.

It shows the scores that each of the students received from different categories of activities during the semester. According to this, students score high in the activity in which they are most engaged. The data of the table was classified with the random forest algorithm and the learning tendencies of the student was determined in the result section.

Table 1. Students' learning tendencies

ID	Video +Text	Video	Visual	Visual +Text	Text	Result
1	255	159	326	187	158	Visual
2	271	353	281	308	274	Video
3	260	152	320	309	189	Visual
4	252	278	354	202	204	Visual
5	374	236	193	224	181	Video+ Text
6	216	185	278	194	225	Visual
7	123	189	322	331	277	Visual +Text
8	256	271	359	167	354	Visual
9	172	166	287	313	350	Text
10	171	263	272	204	206	Visual
11	238	83	232	148	240	Text
12	231	251	297	189	307	Text
13	310	263	211	221	168	Video+ Text
14	207	264	287	289	270	Visual +Text
15	260	220	261	278	309	Text
...						
567	258	299	298	193	307	Text
568	242	130	155	296	171	Visual +Text

After the learning tendency of the student is determined, the web service required for the content of the course pages to be placed in the learning management system is running. Figure 2 shows the diagram of the running system.

Once users' learning tendencies have been identified An adaptive learning engine runs for content filtering and sends the data to the Web service. The web service runs two methods in Moodle. The first method is to identify all the content in the course. Here the instructor has to have created all the content of the course. The second method is to display the relevant content. Figure 3 shows the course content. Within the content, each topic is shown in separate areas. The instructor adds content from each topic and organizes the activities under 5 topics (Visual, Text, Video, Visual+Text, Video+Text) according to different learning conditions. The content of each learning tendency is different.

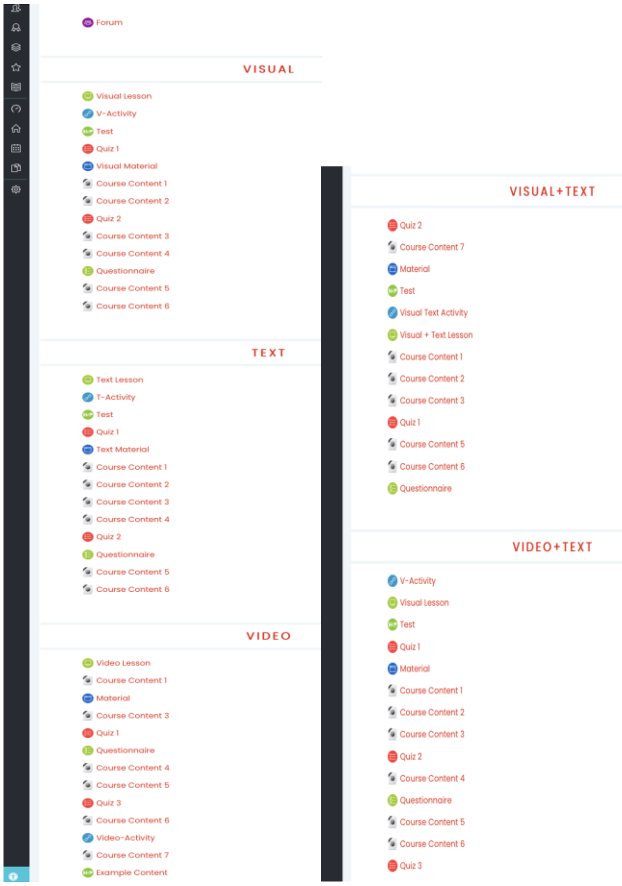

Figure 3. Example course contents

Whichever the student's learning tendency is (Visual, Text, Video, Visual+Text, Visual+Text, Video+Text), these contents will be seen intensively in the student's lesson. Different activities can be used to separate the lesson activities here. However, in order to diversify the course content, this service will work and the appearance of the course content will change. Thus, the page structure for the learner will be reconstructed according to his/her interest.

All content components are grouped under the same topic so that learners do not get lost in differentiated content. In this way, the learner will be able to easily find a different content on the page within the relevant topic without searching for it. It will save time and resources by helping them avoid repeating content they do not need or have already learned. This will allow students to focus more on new topics and will positively affect their learning performance while studying. Figure 4 shows a regular course content followed by a personalized course content from the same course. Since the learners are divided into different groups, they see the course content as limited. Each learner accesses a different area outside of their own course content.

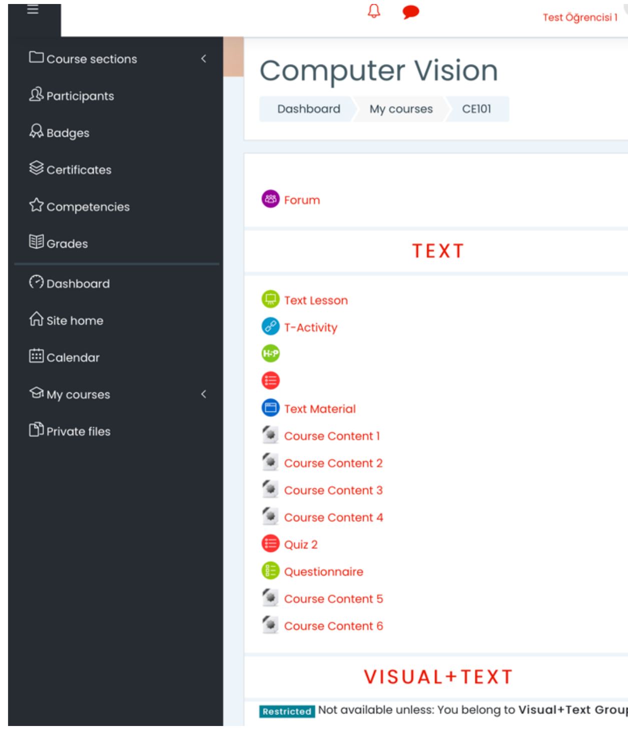

Figure 4. Example course contents (Student's page)

The restrictions are grouped and made accessible to the student in the relevant category. Students cannot see different versions of the same course content.

The approach used in this study differs from the methods typically found in the literature. Instead of employing generalized models that apply to all students, this study implements a student-centered system. It recognizes that each student possesses unique learning tendencies and comprehension levels. While previous studies measured students' study tendencies using questionnaires, this study introduces a personalized learning system. This means that individualized pages can be tailored to each student, ensuring that they receive relevant content without any classroom-wide confusion.

5. Conclusion

Adaptive learning is an approach to learning that aims to provide an individualized and flexible learning experience. This approach aims to create a customized learning plan that takes into account the student's learning needs, pace, interests and learning style. Today, institutions that carry out educational activities in many fields benefit from online education activities. With the developing technology and opportunities, these opportunities can be used in almost every field. However, every person's learning tendency is different. Personalized methods need to be created on educational platforms.

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With the proposed system, learning processes can be optimized by providing students with fast and effective learning experiences. Students can achieve better learning results by spending more time on the subjects they are interested in or deficient in. Adaptive systems can reduce students' information overload. It prevents information clutter by providing students with only the content they need and are interested in.

However, the system has some limitations. In order to create the course content, separate content from each category should be created and added to the system. This is a long process for the instructor. For the learner, content that is constantly created according to his/her own tendencies may become self-limiting. For future studies, systems that can be further enriched can be created by taking different contents from different platforms and comparing the contents and adding them to the system.

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