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Classification of English Educational Resources Information Based on Mobile Learning Using Cognitive Web Service

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ABSTRACT

English proficiency is increasingly vital in the modern globalized and competitive world, especially for jobs that need cross-cultural communication. Using online educational tools wisely leads to improved English proficiency. Digital learning tools are constantly being improved owing to the emergence of new technologies. An essential problem in academic circles is categorizing and assisting in investigating different forms of digital learning resources. This research proposes an efficient intelligent system for the classification of English educational resources information based on mobile learning (CEERI-ML). The suggested design classifies English educational resources into different categories, applying a Classification based on Marzano and Kendall Taxonomy (CMKT). The system further implements a Classification based on Gagne Learning Categorization Theory (CGLCT) to classify the different levels of complexity in learning.

KEYWORDS

Classification System, Cognitive web service, Digital Resources, Educational Resources, English, machine learning, Mobile Learning

INTRODUCTION

Overview Mobile Learning Methodologies for English Courses

Learning to communicate successfully in English is critical for developing students' abilities and vision (Qureshi et al., 2020). Course designers currently encounter various challenges while creating English language instruction (Ramprasad et al., 2014). Learning via mobile devices, tablets and smart phones, mobile apps, social interactions, and online educational hubs is known as mobile learning (m-learning)(Kumar et al., 2021).Mobile learning is characterized by ubiquity, portability, slenderness, privacy, interactive, collaboration, and near-instantaneous access to information (Chung et al., 2019). Students can be in the right place at the right time, which means they are in a position to experience the genuine delight of learning (Gao et al., 2020).

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College English teaching has received a second chance at life because of mobile teaching, a unique approach that combines education with information technology(Amudha et al., 2019). Exploring phone-based M-learning in today's blended learning environment positively impacts proficiency and growth in professional capabilities of pupils in a field (Zhonggen et al., 2019). Mobile learning is viewed as a model of how education will develop in the future(Saravanan et al., 2021). Mobile learning is not new, as learning may enable students to learn textbooks well in traditional printed textbooks (Yang et al., 2021). As a result, textbooks have long since evolved into supporting tools for mobile learning, and they have been around since the dawn of time (Vu et al., 2020).

Mobile learning utilizes all of the advantages of mobile communication to its fullest extent, such as the ability to transmit data and the portability of devices (Onwubere et al., 2019). Computers or networks receive learning resources and offer them to learners via terminal devices, increasing the amount of interaction between students and the information (Manogaran et al., 2019). Learning is an active process of acquiring new skills and knowledge while working in a cooperative environment (Gao et al., 2020).

Furthermore, it includes the opportunity for sudden, radical conceptual shifts and a continuous process of self-development and enrichment (Gomathi et al., 2021). Education is going through a period of transition, and how students are taught and learned must alter to keep up with the changing needs of society (Zhang et al., 2021). This necessitates active teaching methods and the integration of Information and Communication Technology (ICT) in the classroom (Manogaran et al., 2020). Specialization in a subject of knowledge is another factor to consider when incorporating mobile devices (Zhou et al., 2021). Over time, the user gains knowledge by revisiting previously acquired knowledge in new contexts, and more broadly, through concepts and tactics developed in previous years that serve as a foundation for continued learning throughout life (Yu et al., 2021).

Mobile device integration requires institutional support, and the institution (public or private) has played a role(Yıldız et al., 2020). In today's world, mobile technologies are indispensable because of their ubiquity, flexibility, ease of use, and wide range of capabilities (Nguyen et al., 2016).. Yet, they are underutilized in the educational process (Jin et al., 2017). Mobile technologies presented a challenge to educators and academics as they tried to figure out how to make them work for students. Mobile devices make it possible to learn at any time and from any location, even if one is not at school (Yassine et al., 2016). These options allow adult learners to maximize their productivity while minimizing unproductive time, improving their work-educational harmony. Online education has proven to be a valuable tool for skill development in the no schooling situations. Notably absent universal access to infrastructure and inadequate teacher and student preparation for the unique demands of online teaching and learning, there is still concern that online learning may have been a sub-optimal substitute for traditional classroom instruction. Students can overcome some of the difficulties of online learning by cultivating positive attitudes toward learning.

Students would benefit from frequent mobile technologies in English classes by improving their abilities, and mobile learning applications would benefit from this (Balaanand et al., 2019). The use of English in the classroom promotes the development of individualized learning, engages students' curiosity, and allows for the integration of class time with mobile learning.

Marzano released the new version of taxonomy called the New Taxonomy of Educational Objectives. A two-dimensional system is the New Taxonomy. Levels of mental processing are addressed in one dimension. Mental process information is divided into six degrees of processing knowledge with three different areas of expertise(Irvine et al., 2020). In terms of resource classification, Gagne's learning Category theory offers fresh insights based on the levels of complexity into eight classes and three levels(Rivest et al., 2021).

Modern advances in big data, computing power, the cloud, and algorithms have made AI more accessible and widespread than it was even a decade ago. With AI and Machine Learning, computers are now capable of reasoning, understanding, and interacting in new ways. Knowledge and understanding can be gained through the senses, experience, and thought in cognition. The cognitive learning theory combines cognition and learning to explain the various processes involved in learning effectively Using Cognitive web Services, developers can create AI-enhanced applications without the need for specialised knowledge in AI, machine learning, or data science. Data is not retained by Cognitive Services after processing, making it easier to meet the requirements of data privacy laws and regulations.

The main contributions of the paper are listed below.

- Designing an Intelligent Classification of English Educational Resource Information Based on Mobile Learning (CEERI-ML) to categorize the digital resources of the English language.
- The classification of the resources available digitally into various categories through CMKT and CGLCT.
- A Cognitive Web Service based Machine Learning Algorithm (CWS-ML) is introduced to classify the resources more precisely
- Analysis of the classification model under consideration.

The remaining parts of the paper are structured as follows: Section 2 elaborates existing models of classification of educational resources. In section 3, CEERI-ML has been designed and explained in detail. In section 4, the evaluation results of the proposed technique have been discussed. Finally, section 5 concludes the research article.

LITERATURE REVIEW

Several research studies have designed different intelligent systems that automatically classify digital materials into distinct categories. This section highlights those initiatives. English grew as an important means of communication on the international stage.

(Elaish et al., 2019) provided a comprehensive review about the research on Mobile English Language Learning (MELL) materials to start a conversation based on evidence on mobile learning in English language education. Findings showed that vocabulary was the most commonly used English language skill, and motivation was the most prevalent problem mentioned in studies. An investigation into how input-based and output-based activities affect productive vocabulary knowledge was conducted. It shows that compared to the control group, students in the input/output activity groups outperformed each other on post-test and delayed post-test assessments

(Kumar et al., 2021)offered a Context-aware mobile learning (CAML) learning experience, which was customized to meet the individual demands of the Learner in every given situation. In the context-awareness process, various methods, such as sensors and user input, are used to identify context entities and refine the information into higher-level knowledge that constitutes the context of the user, which can be used in various applications. In the context-awareness process, various methods, such as sensors and user input, are used to identify context entities and refine the information into higher-level knowledge used in various applications. Smartphones react to ambient light by dimming their screens to improve readability. The device configures a setting to ensure the best possible experience on activation. The count and classify contributions to give an overview of CAML research. A systematic mapping analysis utilized eight main published databases was the strategy used in this case. CAML grew into a thriving research field in the last couple of years.

(Zhai et al., 2021) proposed a mobile technology-based approach to teaching College Mobile learning for college students learning English vocabulary was covered in English vocabulary teaching (EVT). The teaching of college English vocabulary made use of vocabulary technology. To see if mobile technology-based College English vocabulary teaching was effective, researchers conducted experiments that increase memory, vocabulary use, and engagement in English learning among college students.

(Guan et al., 2021) used blended learning theories, mobile learning theories, and instructional design theories (BTMCE-ML). Superstar Learning Link was often cited as an example of a mixed online and offline teaching approach in English language learning apps. Pre-class contact and thought extension were encouraged by this strategy. While students were in class, the input and output-oriented processes were combined; assessment and sublimation occurred after class.

(Rafiq et al., 2021)identified mobile learning trends concerning English for a specific purpose (ESP). Out of 139 publications published between 2012 and 2021, 28 were selected using three databases: Web of Science, Scopus, and the Educational Resources Information Center, with exclusion and inclusion criteria taken into account. In the first step, it was found that mobile apps were the most often utilized mobile learning tool. Second, Mobile learning for ESP places a greater emphasis on vocabulary and linguistic proficiency. Third, in ESP, mobile learning dominated the business field of research the majority of the time.

(Rampeng et al., 2021) focussed on creating the Speaking Materials using Blooms Taxonomy(SPBT). The design included two key steps. The first steps used to develop the Speaking Materials include determining the Materials topics, establishing the learning objectives, and creating activity categories. The Second step was considering the content of Speaking Materials, where each unit's materials in Speaking Materials should be matched to the six thinking levels. Using Bloom's taxonomy as a teacher's tool helps students develop higher-order thinking skills. Behavioral and cognitive learning outcomes. Based on the verbs, the contents are classified.

(Lv et al., 2020), constructed a context-aware data flow cognitive computing model that classification and regression trees in the computation layer of the cognitive model's data processing. Using the clustering method to analyse the user behaviour of a real mobile data service provided by an operator company, the traffic change of users over time can be determined. An operator's job is to provide services that are tailored to the specific needs and preferences of their customers.

According to the survey results, despite various technologies employed to categorize English digital resources, a more practical design is still needed to provide a brilliant automated design to classify English educational resources based on data collected through mobile learning methods.

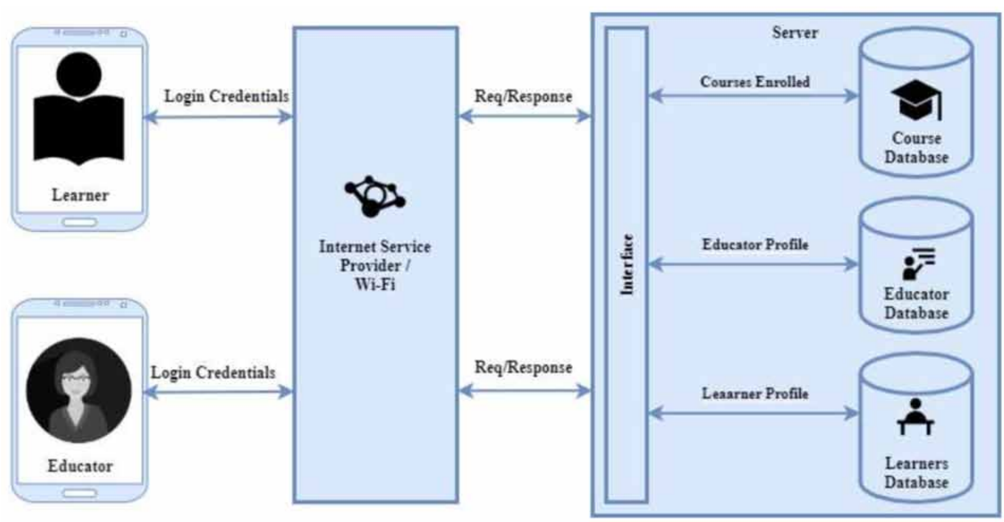
Intelligent Classification of English Educational Resources Information Based on Mobile Learning(CEERI-ML)

The proposed system focused on designing an efficient, intelligent system for the (CEERI-ML) the objective is achieved by implementing two classification methods based on Marzano and Kendall Taxonomy and Gagne Learning Categorization Theory.

Mobile Learning Architecture:

Figure 1 depicts the general mobile learning architecture. The learner and educator database holds the profile details of the users depending on their enrolment. The Learners and educators must be registered users to get access to resources. The Learner is provided with individual login credentials to get access to the interested courses. The Learner can access the course material allocated and take up the test to check the outcomes. The accessing nature, material type, test performance, and feedback are recorded in the database. The educator details are collected during the registration and provided access to publish the refined materials according to user needs. Considering the learners and educators database records the parameters like id, role, course access, contact details and progressive scores. The learners and educators are connected to the server through internet connectivity. It's important to keep in mind that the database of students and teachers includes information such as their ids and their roles in the courses they take. The user interface in the server collects and validates the login credentials from the user. It identifies the nature of the user and connects to the corresponding server. The resources are stored in the course database with the course details. On Validation of the credentials provided by the user, the course material access is provided. The assignments, assessments, completion status, and feedback are given to the user with the learning management systems that

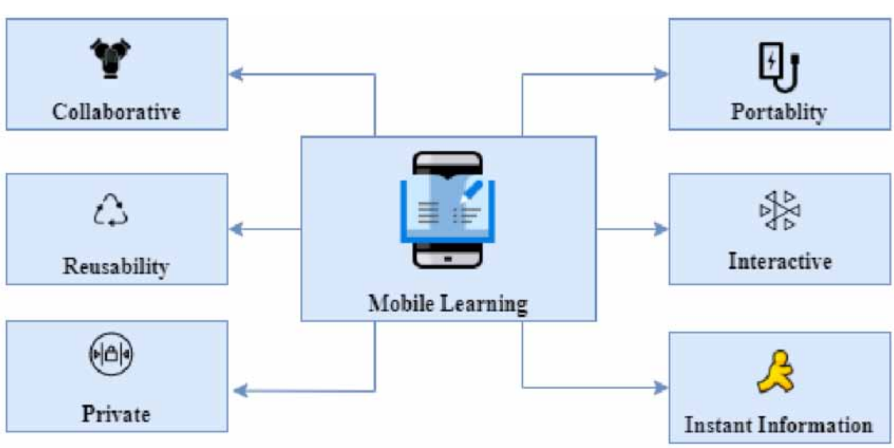
Figure 1.
Mobile learning architecture



govern the outcomes from the Learner. Presentations or performances, written assessments, portfolios, and nonverbal assessments are used to calculate outcomes.

Figure 2 shows the basic characteristics of the mobile learning environment. The portability characteristics of mobile technology ensure learning at any time and from anywhere. It breaks the geographical restriction of getting access to valuable resources, which saves travel time and expenses. The system is highly secured where user privacy is stored privately. Mobile learning provides interaction facilities among educators and learners through different means of communication like video chat, audio calls, messenger, mails, etc. The environment facilitates access to the various educational resources available in the database and opens up the facility to fetch the digital data resources from the internet. With the latest amenities of internet and portable devices, the users can access from remote locations through recorder videos, live video chat, audio call, messages and mails provided the availability of remote accessing features on their portable device and connectivity. The

Figure 2.
Basic characteristics of mobile learning



Learner would be provided with instant information access. The resources can be used collaboratively among the different courses, which enhance the reusability of the materials. The educators' teaching practices can be recorded, and the best practices can be used in the future for better outcomes. The mobile learning methodology is pervasive and induces the easy learning of any subject, language, or technology. The ability to upgrade the resources enriches the course content up to date. Dynamic Presentation Features, Screen Sharing, Multiple Webcam Capabilities, VoIP, robust chat feature, Unlimited Recording are the minimum features that allow educators and students to communicate.

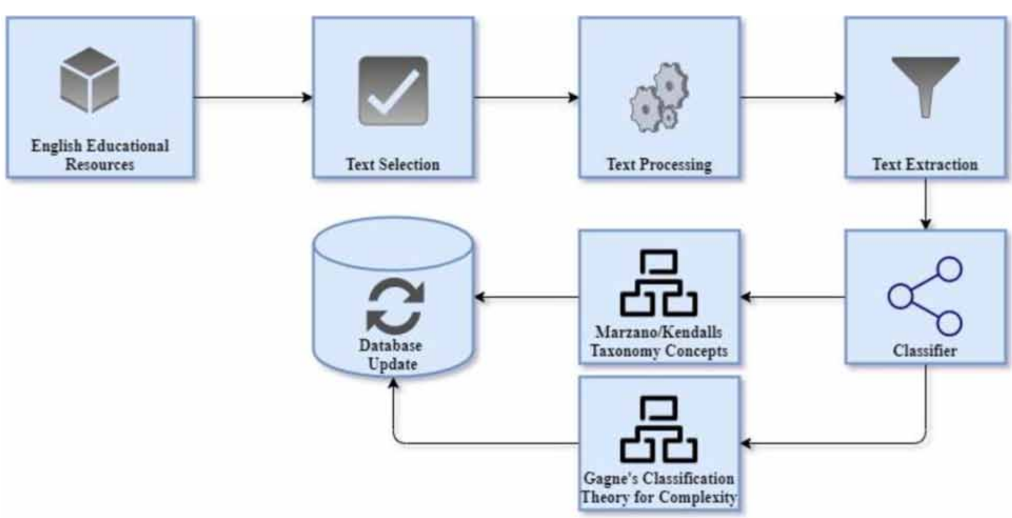
Figure 3 exhibits the proposed model for Classification of English Educational Resources Information Based on Mobile Learning (CEERI-ML). The resources stored in the course database are considered for classification. The text selection is the first step where the materials are converted to small texts and keywords are selected. For example, textbooks are selected as small paragraphs with particular features. The resource contents are broken into paragraphs, and each paragraph is divided into a collection of sentences. The sentences are then divided into noun concepts and verb concepts by deleting punctuation encoded characters and digits. The next step is removing all non-domain terms to minimize the sum of noise in the data. Marazano and Kendall Taxonomy sentences based on the MKT keyword list can efficiently divide a paragraph into two groups depending on the keyword used in each sentence. This entire process is called text processing.

The text extraction step considers the following to select the best feature for tagging the words:

1. The suffixes (ing and ed) for a noun.
2. The action words are related to the nouns.
3. The position of the verb in the paragraph.

The Classifier works on the principle of the Bayes theorem. Naive Bayes assumes conditional independence, P(X|Y,Z)=P(X|Z)P(X|Y,Z)=P(X|Z). In contrast, more general Bayes Nets (sometimes called Bayesian Belief Networks) will allow the user to specify which attributes are, in fact, conditionally independent. The Naive Bayes classification works on the conditional probability of the events. Compared to other methods, naive Bayes classifiers commonly employed in text classification have a greater success rate. It is commonly utilized in sentiment analysis and spam identification.

Figure 3.
Classification of English educational resources information based on mobile learning (CEERI-ML)



$$P\left(T / V\right) = \frac{P\left(V / T\right) \times P\left(V\right)}{P\left(T\right)} \tag{1}$$

The general probability of a verb being tagged to a class is given by equation 1, in which $P\left(T / V\right)$ represents posterior probability of occurrence of Tags for the verb in the taxonomy, $P\left(V / T\right)$ is the probability of occurrence of verb extracted in MKT Tags, $P\left(V\right)$ is the probability of occurrence of the verb in the resource, and P(T) is Probability of Tag classified for the verb. .Conditional probability is defined as the likelihood of an event or outcome occurring based on a previous event or outcome. Conditional probability is calculated by multiplying the probability of the preceding event by the updated probability of the succeeding or conditional event.

$$P\left(V / T\right) = \frac{C\left(V,T\right) + \propto}{C\left(T\right) + \propto} \tag{2}$$

Equation 2 gives the probability of occurrence of the MKT tag for the extracted verb. In equation 2, $P\left(V / T\right)$ denotes the probability of occurrence of verb extracted in MKT Tags, $C\left(V,T\right)$ is number of occurrence of verb extracted in MKT Tags, $C\left(T\right)$ represents number of verbs classified as MKT Tags and $\propto$ is proportionality parameter

CMKT uses the probabilities assessed with equation 1 and equation 2 to classify the class of the particular verb, and the number of verbs identified and tagged decides the category of the resource content considered.

Classification Based on Marzano and Kendall Taxonomy (CMKT)

A key component of Marzano's Taxonomy is the knowledge domain, which comprises three categories of systems. The Internal-System, the Metacognitive-System, and the Cognitive System are all parts of the brain. Based on the verbs tagged by the classifier, the framework classifies the resources into one of the six class levels mentioned in figure 4. The mapping can be done based on table 1 that shows the relationship between the identified verbs or nouns or phrases to the MKT tags. The sources under the lower four categories, named retrieval, comprehension, analysis, and knowledge utilization, constitute the cognitive level followed by the next two hierarchical levels as Metacognitive and Self-system.

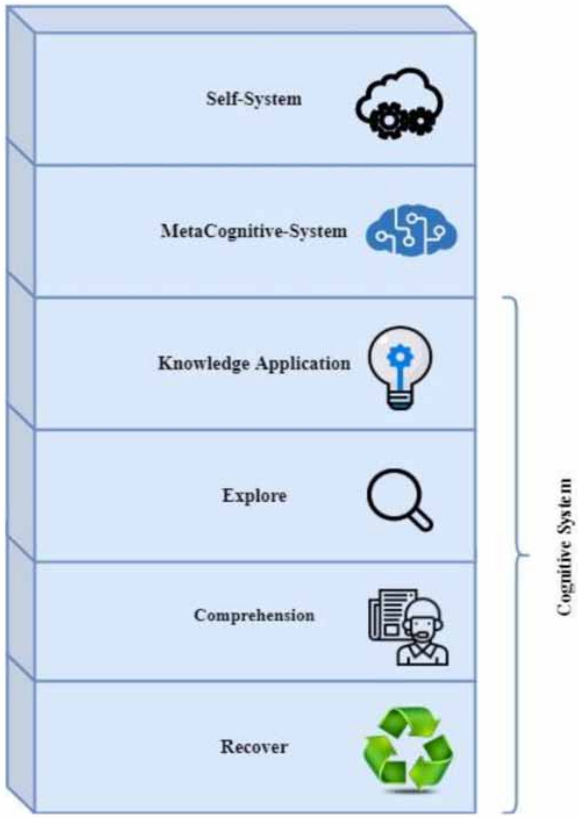
In this proposed system, the verb and noun concepts are extracted. The conditional probability of their occurrence in the resources is calculated according to the tags in table 1. Based on the probability of the verbs extracted from the content, the resource is classified into six categories.

The contents are analyzed for similarities. The verbs identified are tagged and assigned with weights concerning the feature considered. The similarity degree between the two features is calculated by the cosine angle of the weights given.

$$Simi\left(C_i, T_j\right) = \frac{\sum_{k=1}^{n}\left(W_{ik} \times W_{jk}\right)}{\sqrt{\left(\sum_{k=1}^{n} W_{ik}^2\right)\left(\sum_{k=1}^{n} W_{jk}^2\right)}} \tag{3}$$

The similarity degree is determined by equation 3 with $Simi\left(C_i\ , T_j\right)$ as similarity between i^{th} content $\mathrm{C_i}$ and j^{th} tag $\mathrm{T_j}$, W_{ik} is Weight assigned to the content C_i concerning k^{th} feature, W_{jk}

Figure 4.
Marzano and Kendall Taxonomy (MKT)



refers to weight assigned to the tag j concerning k^{th} feature, and i, j, k are numbers given to identify the contents, tags, and features used for selection.

The research mainly concentrates on the verbal classification of the material, and the verbs are compared with tags based on the taxonomy. The weights assigned to the material according to the threshold values are compared to find the similarities. The dynamic threshold value of the similarities is calculated as the average of all similarities calculated. The normal threshold is given by equation (4).

$$\lambda = \frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{Simi}_{\mathrm{i}} \tag{4}$$

Equation 4 is introduced to calculate the normal threshold values in which λ holds the Normal threshold value of similarity degree, $\mathrm{Simi}_{\mathrm{i}}$ gives similarity degree of i^{th} $\mathrm{content}$ and n denote the number of contents. The highest similarity contents are assigned with weights close to a threshold value to reduce the similarity divisions.

$$W_i^{'} = \frac{\mathrm{Simi}_{\mathrm{i}}}{\sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{Simi}_{\mathrm{j}}} \tag{5}$$

Equation 5 provides a formula to calculate the weight ($W_i^{'}$) to be assigned to a resource with $\mathrm{Simi_i}$ and $\mathrm{Simi_j}$ as the similarity degrees of i^th and j^th content, respectively.

$$\lambda' = \sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{Simi_i} W_i^{'} \tag{6}$$

Finally, the dynamic threshold value as per Equation 6. For any content, if, $\mathrm{Simi_i} > \lambda'$, Then it infers that content belongs to $\mathrm{i^{th}\ category}$. With this, similar contents are grouped and allocated for the same type of courses of learners.

Table 1 describes the Marzano and Kendall Taxonomy-based categories corresponding to the verbs and Phrases. The pre-processed and feature extracted data are fed as input to the Classifier that tags the identified concepts with the MKT categories. The performance of the method can be calculated by the precision given by equation 7.

$$Precision = \frac{Number\,of\,correctly\,etracted\,MKT\,tags}{Number\,of\,extracted\,tags} \tag{7}$$

The CMKT taxonomy identifies the verbs and noun concepts from the Classifier and effectively classifies the resources into various categories. The system, in addition, categorizes the levels into three domains as cognitive, metacognitive, and self-system. This strategy helps the educator evaluate the Learner, and the resource needs are altered based on the category.

Classification based on Gagne Learning Categorization Theory (CGLCT)

Resource Categorization is re-examined in light of Gagne's learning theory. Gagne postulated eight learning categories based on the degree of complexity.

Figure 5 shows the eight learning categories depicted by Gagne in his theory. Learning basics is the reception layer. The educators would attract attention by raising the volume of voice, gesturing, playing a short video on the topic of instruction, or announcing an event to educate the learners. Stimulus-response learning: Responding to a stimulus. Linking: Complex psychomotor skills are learned through this process. This type of learning connects previously learned concepts. Application of Knowledge: Verbal links connect the items in this type of chaining. Differentiation Learning: Develop the capability to respond appropriately (differently) systematically to a series of similar stimuli. Conceptual Learning: It's all about developing the ability to respond consistently to a wide range of stimuli part of a single category. Generalization, classification, and the like are all built on this foundation. Role-based learning: Cognitively, this is a very high-level process that requires the ability to learn relationships between concepts and apply those relationships in various situations, including ones that have never been encountered before. It's common to link two or more ideas together when learning a rule.

Gagne categorizes the levels starting from simple to complicate, ranging from lower to higher levels of difficulty. This categorization is based on the response of the Learner. The Learner's ability to take assessment and feedback is considered, and the difficulty levels of the resources are assigned in the server. The ability is defined by self-reflection on their perceived level of proficiency technology-based performance portfolios. Peer assessments of the strength of evidence for a skill or capability. This method helps in classifying the resource from beginner to expert level. The timestamps, performance, no of attempts, quality of assignments for allocated course modules students previous record and overall performance are considered.

Table 1.
Taxonomy tags for extracted words

Marzano and Kendall Taxonomy Tags	Verbs, Phrases, Definitions Useful
Self-System	Examine the value of knowledge to one's development.
	Evaluate one's own beliefs to integrate information better.
	Identify the feelings triggered by new information
Metacognitive-System	Delve into why one needs to keep learning and improving
	Establish clear learning objectives and a strategy for achieving them
	Stay updated on your progress toward a goal.
	See how well they comprehended the information
	Test to see if your understanding is correct and then defend your conclusions
Knowledge Application	Take a stance on anything; look into it; find out what it is about; explain what it means, and give an account of your findings. In this activity, the student comes up with hypotheses and then tests them.
	Experiment, develop test, hypothesis, and predict the results. The student comes up with fresh ideas for gathering data.
	Overcoming challenges, recognizing hurdles, adapting, and devising new solutions
	Decide; make a choice from a group of similar options; specify criteria; defend decisions
Explore	Foresee, judge, deduce or argue for the presence of a certain cause or pattern in the data.
	Conclude; go into greater detail on the inferences that can be drawn; give an example of a rule or concept in action; follow the progression of an idea over time and draw new conclusions based on what is already known.
	Correct any mistakes; clarify any ambiguities; clarify faults in information. Assess, criticize, accurately diagnose, appraise, modify, and rework to correct any rational or empirical mistakes.
	Categorize, organize, and arrange the data to decide a more general category; to determine distinct types; to determine higher and lower levels of information
	Sort; establish an analogy or metaphor
Comprehension	The schematic chart illustrates important components of knowledge graphically or symbolically by depicting; representing; drawing; showing; using models
	Explain how or why; list the important features of; describe the results; explain the connection between; summarize; separate important components from those that aren't
Recover	Illustrate how it's done; put to use; finish; conceive. Execute procedures with few mistakes.
	Demonstrate; name; list; label; state; describe; who; what; where; and when create data on demand.
	To recognize; to choose from a list choose (from a set of options); test the following statements to see whether they are correct assess if the information presented is correct, incorrect, or unknown

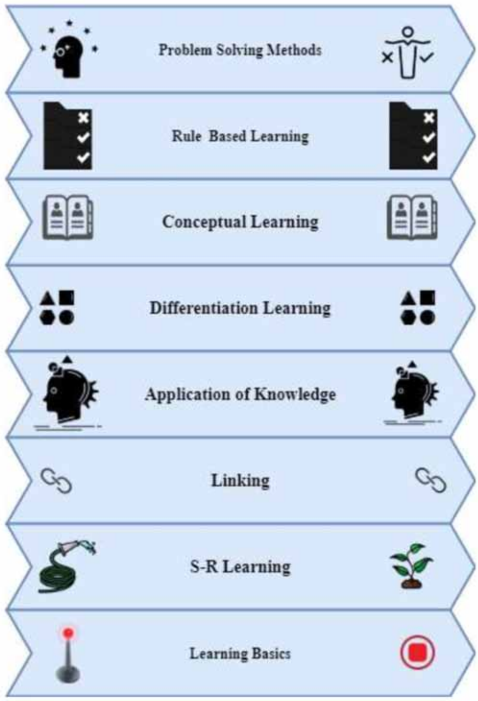
The difficulty levels are assessed from the student's capability to complete the tasks given as assignments as a part of the course.

$$Diffculty = 206.835 - 1.015 \times \left(\text{Avg. SL}\right) - 84.6 \times \left(\text{Avg. SW}\right) \tag{8}$$

The Language course has reading as one of the tasks. As inferred from Equation 8, the difficulty has been calculated. In equation 8, $Diffculty$ gives content reading complexity, Avg. SL denotes Average Sentence Length and Avg. SW denotes Word Syllable Count Average. The levels of difficulty are limited to 1-100.

$$\text{Avg. SL} = \frac{\text{Total Number of Words identified}}{\text{Total Number of Sentences}} \tag{9}$$

Figure 5.
Gagne learning categorization theory



$$\text{Avg. SW} = \frac{\text{Number of Syllables}}{\text{Total Number of Words identified}} \tag{10}$$

Avg. SL and Avg. SW is calculated as per equations 9 and 10.

$$Difficulty' = Difficulty \times \left(\frac{-6}{100}\right) + 3 \tag{11}$$

Normalized difficulty levels can calculate the average difficulty of content according to equation 11 where $Difficulty'$ refers to normalized $Difficulty$ value.

$$TD = w \times Difficulty' + \left(1 - w\right) \times LID \tag{12}$$

Equation 12 describes the procedure to calculate Total Difficulty (TD). The Total Difficulty of the resource is calculated with the above mentioned normalized difficulty ($Difficulty'$), Learner inferred difficulty (LID) and the weights (w) assigned to the content. This value decides the complexity of the content considered for evaluation, and the database is updated. The evaluation process considers the learners' performance and completeness of the tasks, whereas the feedback of the evaluation process is considered to modify the course modules and the level of Difficulty may be reallocated to the learners to participate again in the evaluation process.

The system further considers the Learner's ability to perform the tasks given in the assessment part of the course.

$$a_{j+1} = \begin{cases} a_j + \left(a_w - a_j\right) & when\, 0 \le u \le 0.45 \\ a_j & when\, 0.45 \le u \le 0.55 \\ a_j + \left(a_c - a_j\right) & when\, 0.55 \le u \le 1 \end{cases} \tag{13}$$

The Learner's ability to complete a task in the course allocation is evaluated as equation 13. The parameters mentioned in equation 13 are explained below.

a_j = Predicted value of Learner's ability to complete the task based on the previous task completion.
a_{j+1} = Predicted value of Learner's ability to complete the new task j+1.
a_w = Predicted value of Learner's ability assuming the completion probability is zero for task j+1.
a_c = Predicted value of Learner's ability assuming the completion probability is 1 for task j+1
$u =$ Inferred Level of understanding of the Learner.

The Learner's ability to complete the task is correlated to the maximum knowledge gained by the Learner in completing the task by calculating the maximum information obtained from the task. The Maximum Knowledge gained is calculated as follows.

$$K_j\left(a\right) = \frac{1.7^2}{\left[e^{1.7\left(a-d_j\right)}\right]\left[1+e^{-1.7\left(a-d_j\right)}\right]^2} \tag{14}$$

Equation 14 defines the formula for maximum knowledge gain calculation.where,

$K_j\left(a\right)$ = Knowledge value of the task
a = ability of the Learner
d_j = Difficulty parameter of the jth task

Equation 14 shows that if, maximum the value of $K_j\left(a\right)$, the Learner completely understands the concept, and the next level of resources can be suggested to the user.

With Gagne's Classification theory, it is possible to prescribe the difficulty level for the course and activities to learners with a reading ability of 0, depending on the ranking order of knowledge worth. The classification theory of Gagne makes it possible to prescribe the difficulty level for a course and activities to learners with a reading ability of 0, based on the ranking order of knowledge worth having. When a task has the highest knowledge value under the Learner's reading ability, it suggests that the recommended system has the highest priority. The timestamps, performance, no of attempts, quality of assignments for allocated course modules, students' previous record and overall performance are considered

Cognitive Web Service Based Machine Learning Algorithm

The Cognitive web Services analyses the courses based on Vision, Speech, Language, Knowledge,Search. CWS helps to search through images and videos for relevant information, provide tools for better speech recognition and speaker identification, comprehends more than just the meaning of words, tracks down scientific journal articles for you, and Gives web searches are analysed using machine learning. The CWS-ML analyses the content of the resources based on the contents and groups it. The intervention of human can be reduced and the process of classification can be automated for any amount of resources.

Figure 6 Shows CWS-ML method, in which the filtered data are fed to cognitive web service to classify the data. The system is provided with training for classification based on the features of the content. There are various models developed to take advantage of context, which the researchers recognise is important in dialogue processing. Applications like learning environments, search engines, and social network analysis all generate a great deal of contextual data as they are used by their users. Data is being transmitted at a rapid rate, and the degree of correlation is chaotic. The data collection layer is where the system gathers data generated by users in the course of performing tasks. Data classification-based storage systems are what they are at the data storage layer. data computing layer is responsible for classification with decision tree algorithm. For classification of resource regression analysis is used. To find the similarities between the resource k-means algorithm is used.

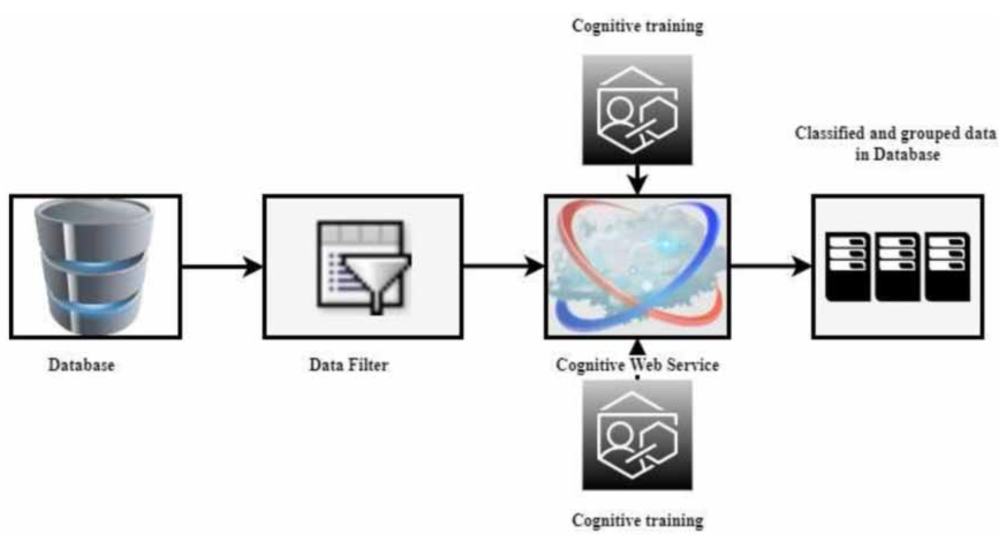
$$J = \sum_{j=1}^{k}\sum_{i=1}^{n} d_i^j - g_j^{\,2} \tag{15}$$

where J = function to to fed to the decision tree, I,j, are variables, d is the resource data, g is the cluster centroid,n is the number of resources, k is the number of clusters.

To group the data to the same cluster decision tree is used. Using machine learning in cognitive computing, a solution is sought to the problem of analysing and processing massive amounts of data.

The proposed design incorporates the procedures of Marzano and Kendall Taxonomy with Gagne's Learning Categorization Theory to automate the resource classification process in the mobile learning environment. The model designed has enhanced the overall performance, categorization ratio, precision ratio, knowledge gain ratio of the learners and analyses the complexity levels of the resource contents to classify them according to the expertise levels of learners enrolled. Students' learning outcomes, instructional strategies, and assessment are all guided by a teacher's daily implementation of materials.

Figure 6.
Cognitive web service based classification



Teachers benefit from course outlines because they provide a detailed outline for each class that they can follow. Thus the mobile architecture can be relayed to provide a consistent improvement over the standards of the materials and courses along with the students' knowledge level. With online collaboration, team members can work from any location, even while traveling or working from home. There is less "downtime" and more time for people to be productive with this. Team members can quickly access the information they need by logging in to a secure online platform. Searching through long emails is no longer necessary, which leads to more effective communication. With the ability to work from anywhere, collaborating online can reduce the cost of office overheads like equipment, electricity, and space.

EVALUATION AND RESULT ANALYSIS

An experiment was conducted to analyze the proposed Classification of English Educational Resources Information Based on Mobile Learning (CEERI-ML) performance and efficiency along with CWS-ML. 100 digital educational resources of various categories related to the English language were used. 10 learners and 5 educators of mixed categories were enrolled as users of the proposed system for evaluation. The learners are selected such that they are with various levels of understanding. The educators range from beginner level to expert level teachers. This selection is done, to analyze the efficiency system in handling different kinds of learners, educators, and the course modules. This experiment aimed at classifying English Educational Resources, and hence, Courses were designed into three levels based on the complexity like a beginner, intermediate, and Pro Level. To obtain feedback, tasks were given to the learners related to each resource content.

Resource Categorization Analysis (CMKT)

Figure 7 shows the resource classification based on CMKT. The role of the Classifier is to tag the verbs and noun concepts identified from the resource content. The Marzano and Kendall tags list is mapped, and resources are classified accordingly. It is inferred from the graph that the prescribed method efficiently classifies the resources into six levels according to MK taxonomy.

Precision Analysis

Precision is the percentage of relevant results among all of the results. Precision % is calculated by comparing the classification results of CMKT with the manual categorization. The graph in figure 8 shows that the precision levels are high in the lower categories and less with increasing levels of complexity.

Figure 7.
Categorization of resources based on CMKT

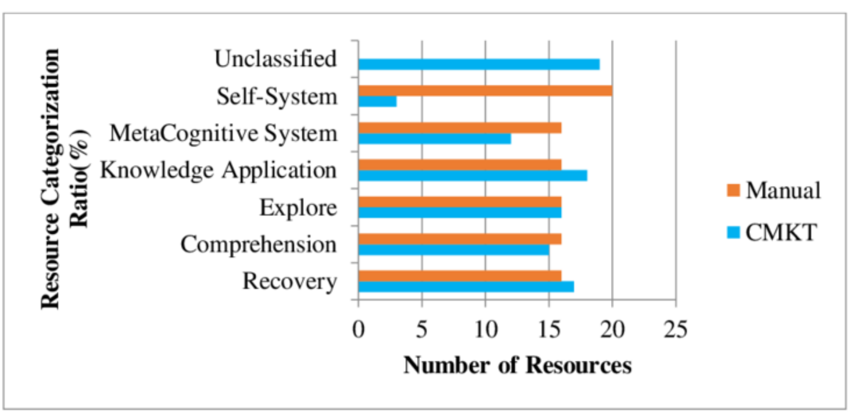
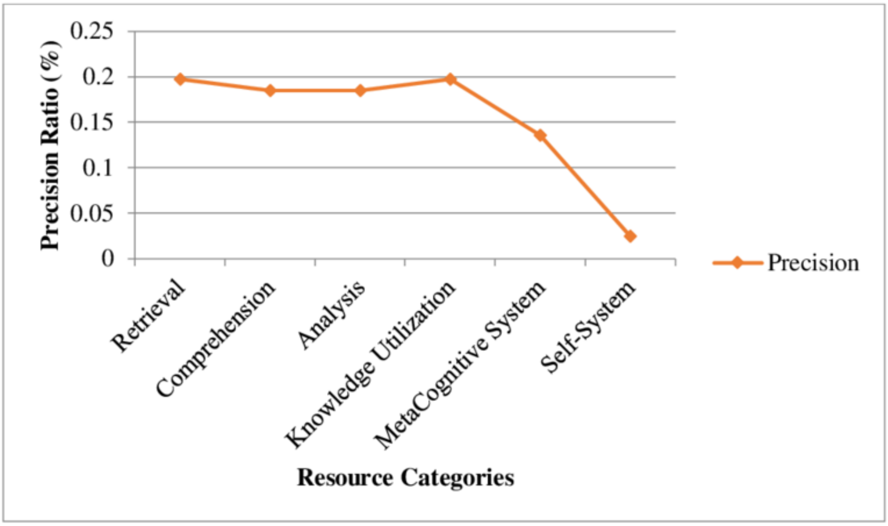


Figure 8.
Precision analysis



Learner's Total Difficulty Analysis

Figure 9 represents the graph of the total difficulty level faced by the individual learners per task. This parameter analyses the complexity of the task by comparing the performance of the Learner in the current task with the previously completed task. It can help improve the task quality as per the learner's needs and provide space for enhancement in the assessment content.

Knowledge Gain Analysis

Knowledge Gain means a method of sharing ideas in which participants actively interact with one another. The system's main aim is to design a mobile learning architecture that enhances the learning capability of the learners with continuous refinement in the resources. The graph in figure 10 explores

Figure 9.
Learner's total difficulty analysis

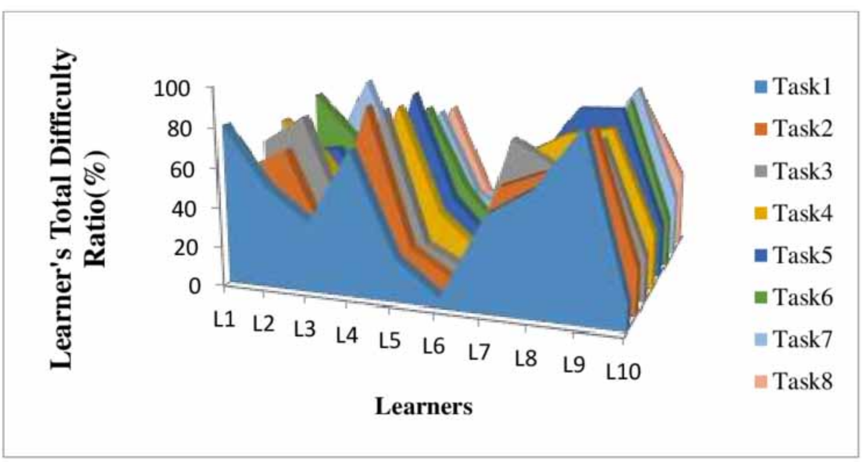
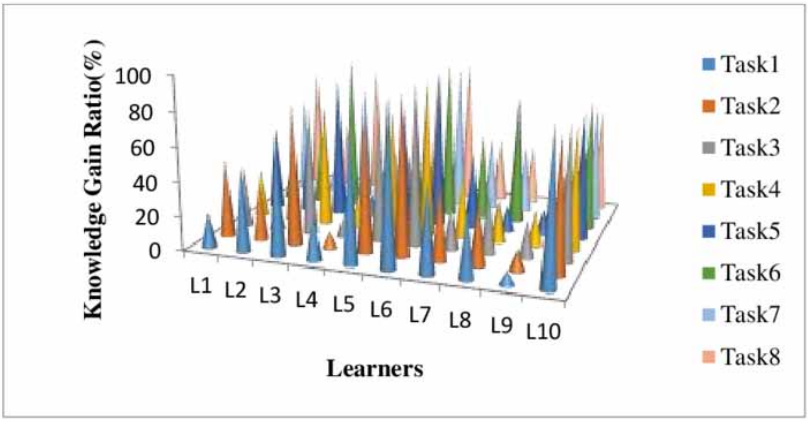


Figure 10.
Knowledge gain analysis



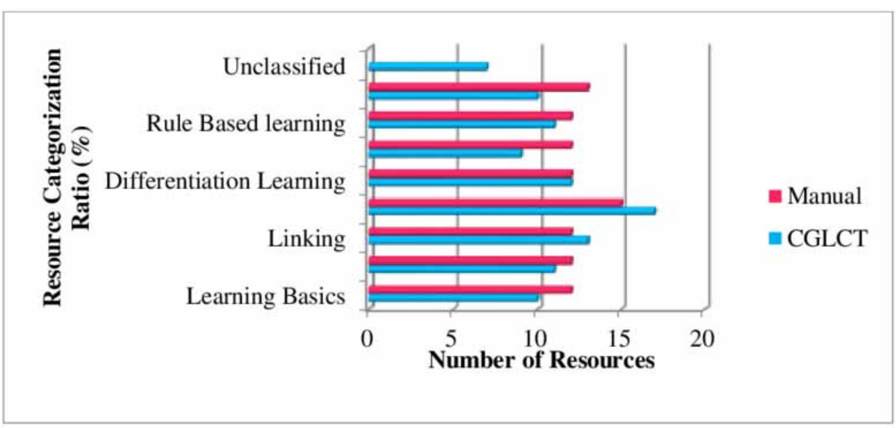
knowledge gained by each individual after completion of each task. This analysis helps the educator to modify the resource content or arrange the resource to the categorized levels. Students' learning outcomes, instructional strategies, and assessments are all guided by a teacher's daily implementation of materials. Teachers benefit from course outlines because they provide a detailed outline for each class that they can follow. Thus, the mobile architecture can be relied on to provide a consistent improvement over the standards of the materials and courses and the student's knowledge level.

Resource Categorization Analysis (CGLCT)

Figure 11 shows the classification of a resource based on Gagne's Learning Categorization Theory. This analysis helps in identifying the complexity of the resource according to Gagne's classification. The first four levels are considered simple, and the next four levels are increasing in complexity. Some of the resources remain unclassified. The complexity identification helps in allocating the resource from beginner to Pro level learners.

To summarize, the efficiency of the proposed design CEERI-ML is calculated as 84%. The CWS-ML classifies the resources based on the content to an extend of 91% accuracy. The system

Figure 11.
Resource categorization analysis (CGLCT)



efficiently classifies the resources into the same category done manually in the lower levels. With the increasing levels of complexity, the categorization decreases create the need for training the system with pre-classified datasets.

CONCLUSION

Educators must keep up with the expansion of online language materials due to the rapid growth of the internet in our modern-day. The proposed system has specified a new efficient, intelligent method for the Classification of English Educational Resources Information Based on Mobile Learning (CEERI-ML). Classification of resources was done by applying Marzano and Kendall Taxonomy (CMKT) integrated with specific features of Gagne's Classification Theory (CGLCT). The system categorizes the resources into recovery, comprehension, explore, knowledge application, metacognitive, and self-system based on MKT classification. The experiments suggest that an efficient method for automatically classifying English-educational resources into multiple categories can be developed. Further, based on the complexity, the resources are classified into eight levels: learning basics, S-R learning, linking, application of knowledge, differentiation learning, conceptual learning, rule-based learning, and problem-solving methods. The overall performance of the proposed CEERI-ML is observed to be 84%. The cognitive web Service based Machine learning (CWS-ML) algorithms are used to classify the resources more efficiently up to 91%, The scalability, reuse and retrieval of relevant resources would be the barrier of the proposed study that has to be concentrated on in future work. When educational resources are categorized, the language instructor can use them as a guide to choose and use the best ones for their teaching needs. The reuse of resources will be the focus of future development. In the reuse phase, a method for searching for and retrieving the most relevant material must be developed and implemented.

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