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E-Learning Environment Based Intelligent Profiling System for Enhancing User Adaptation

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Abstract: Online learning systems have expanded significantly over the last couple of years. Massive Open Online Courses (MOOCs) have become a major trend on the internet. During the COVID-19 pandemic, the count of learner enrolment has increased in various MOOC platforms like Coursera, Udemy, Swayam, Udacity, FutureLearn, NPTEL, Khan Academy, EdX, SWAYAM, etc. These platforms offer multiple courses, and it is difficult for online learners to choose a suitable course as per their requirements. In order to improve this e-learning education environment and to reduce the drop-out ratio, online learners will need a system in which all the platform's offered courses are compared and recommended, according to the needs of the learner. So, there is a need to create a learner's profile to analyze so many platforms in order to fulfill the educational needs of the learners. To develop a profile of a learner or user, three input parameters are considered: personal details, educational details, and knowledge level. Along with these parameters, learners can also create their user profiles by uploading their CVs or LinkedIn. In this paper, the major innovation is to implement a user interface-based intelligent profiling system for enhancing user adaptation in which feedback will be received from a user and courses will be recommended according to user/learners' preferences.

Keywords: education; e-learning; customization; learner profile; MOOCs; user-profiling

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1. Introduction

To improve the learning experience of a novice learner on the internet, it is essential to propose a recommendation system that can recommend relevant courses from various MOOC platforms as per the preference of the learner [1]. In order to enhance user/learner adaption, an intelligent profiling system for e-learning environments is required to deeply understand the needs of novice learners [2]. The objective of this paper is to build the learners' profiles that will increase the level of understanding of learners' needs [3]. Different kinds of filters are available for websites that divide users into different categories. For example, if a user likes articles on Coursera, EdX, SWAYAM, SkillShare, Lynda, Research Scholar, or any other online platform, it can be predicted that the user is interested in research and could communicate this inference to the user [4]. In the present scenario, learning systems usually do not act according to learners' profiles and preferences. When a learner searches for any course, they get a huge list of available platforms and courses without taking into consideration the learner's learning requirements [5]. Therefore, it becomes a time-consuming process to decide which platform or course is most suitable for a learner. Hence, when they choose any random course, the probability of dropout increases and thus creates a negative impact on the instructor [6]. Moreover, the essential features of the online platforms are in collaboration with various learning tools, brand integration, online course catalogs, responsive design features, and a natural user interface. Machine learning techniques and recommender systems are used to build personalized information filters for online platforms, and these filters are also on trend. The customization of any platform helps the system act as a smart agent for users [7]. There is a growing need to provide people with the opportunity to gain new knowledge by combining the internet with education. This pandemic has forced schools, colleges, universities, business houses, and companies to do work remotely, which, in turn, demands e-learning platforms [8]. It has led to an increase in the availability of e-learning platforms and the nature of the content on these platforms. Researchers are actively doing research in the field of MOOCs to improve the learning experience by analyzing the needs and learning behaviors of learners. Machine learning is a part of artificial intelligence and an approach that provides the ability to learn and improve experiences without being explicitly programmed.

In Figure 1, the process of machine learning is elaborated [9]. A large dataset is required to train the machine, and based on the dataset, the model is trained and gives recommendations as an output. The relevant search option is the biggest challenge for the fast delivery of search results, and there is a lack of advanced filters in the current scenario. The following are some other research gaps that were analyzed during this research:

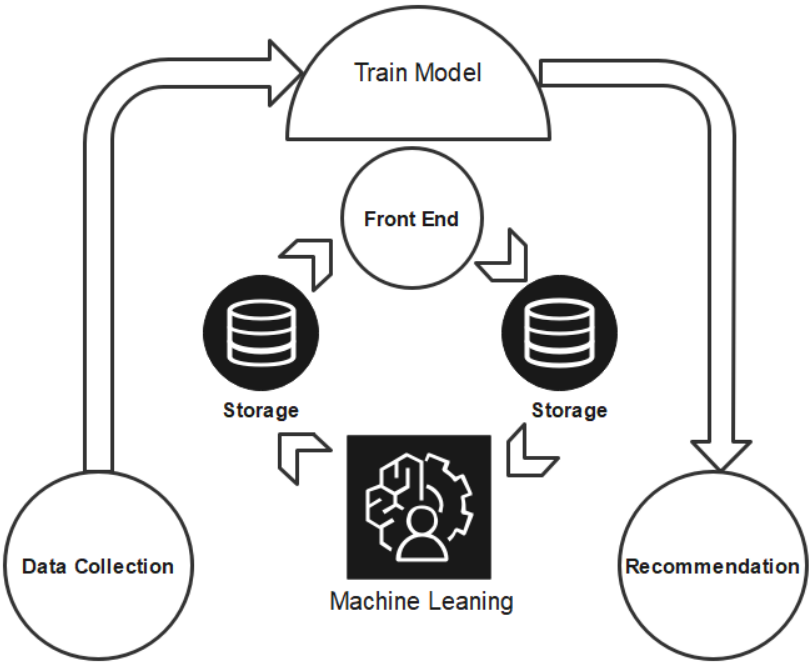

Figure 1. Process of Machine Learning.

1.1. Understanding Learner Behavior

In the present scenario, when a learner searches for any course, they get a huge list of available platforms and courses without taking into consideration the learning needs and competence of the user [10]. The list of available platforms is shown without knowing the requirements of the learner. Therefore, it becomes a time-consuming and random process to decide which platform/course is suitable for that individual learner. Hence, when learners choose any random course, the probability of dropout is increased [11].

1.2. Smart Recommendation System

Currently, recommendation systems are used for many platforms, where recommender systems recommend courses for online learners. But these recommendation systems work for particular platforms [12]. So, there is still a need for customization through which learners can opt for courses based on their needs, income, and levels (beginner, intermediate, or high level). With the help of a smart recommendation system, learners can also identify which topics are useful in their job or industry [13].

1.3. Usability

The measurement of usability of platforms is difficult due to the variation according to the learner's experience, ability in dealing with technology, and understanding [14]. Learning behaviors are learned actions that enable students to access learning and interact with others productively in the community. They complement the curriculum content taught in the elementary grades and are a natural part of the process of learning about oneself while interacting with others [15–17]. Learner behavior, motivation, and engagement patterns are important factors in understanding the success of MOOCs. To understand this, researchers have been using many qualitative, quantitative, or mixed methods. MOOC user behavior is generally studied using the data collected within platform interactions within the learning system or via outside social media platforms [18]. To analyze the learners' behavior, user profiling plays an important role. User profiling is based on two approaches, namely knowledge-based or behavior-based [19]. On the one hand, questionnaires and interviews need a knowledge-based approach, and on the other hand, machine learning techniques are used in the behavior-based approach. Machine learning techniques are used to find patterns in user behavior [20]. The recommendation systems commonly use a behavior-based approach to determine the feedback of the users. After developing a user profile, the next step is to move toward the recommendation system [21]. Recommender systems are software tools that provide a customized environment for users. The recommender system provides revolutionary changes in e-commerce websites [22]. These websites need one click from the user to know their favorites. After that, the recommender system starts filtering similar items and starts recommending them to learners [23]. Nowadays, the recommender system is used by high-rated sites like Amazon, Flipkart, YouTube, LinkedIn, Spotify, and many more. Sometimes, users find it difficult to search for their appropriate choices because there is so much content available online [24]. Choices are good, but more choices does not mean better results, and at this time, the recommendation system helps a lot [25].

The focus of this paper is to create learners' profiles based on learners' preferences to understand their requirements related to online e-learning platforms [26]. The major contributions of this paper are as follows:

- To identify the research gaps that learners face while opting for MOOC courses.
- In order to enhance user adaption of online courses, an intelligent profiling system for e-learning environments is proposed to deeply understand the needs of the learners.
- To develop learners' profiles and datasets extracted from various websites such as LinkedIn, indeed, Google Forms, etc.
- To propose a recommender system that will compare and recommend courses according to learner preferences.
- To design a user-interface that will help to scrutinize learning behavior.

The rest of the paper is organized as follows. A related review of recent studies is carried out in Section 2. Section 3 consists of a proposed methodology in which parameters and survey results are displayed. Section 3 elaborates on the proposed methodology. Section 4 highlights the experimental results, which are followed by the conclusion in Section 5.

2. Related Work

E-learning is a trending topic nowadays, with so many researchers actively working in this area. The main benefit of MOOCs is that learners can learn at their own pace, on their schedule, and in any location in the world. Nowadays, the challenge faced by MOOC platforms is to improve the quality of content, increase the number of enrolments, and keep the learners engaged with the right course as per their preferences. Chen et al. [27] presented the personalized learning path recommender system for proposing the path to meet the preferences of the learners. All the preferences were proposed by the LINE Bot. Further, the LSTM model was used to analyze the video preferences, clusters of students, and learning paths. Chuang et al. [28] proposed a system that recommends personalized exercises for students while analyzing their behavior, knowledge, and level of course. Farnadi et al. [29] proposed a statistical relational learning framework using Hinge-loss Markov random fields to compile the user profile. Boussakssou et al. [30] analyzed that the e-learning system can generate adaptive paths for the learner's profile. Indeed, the authors proposed a dynamically composed approach based on the behavior of learners. This kind of learning is known as reinforcement learning. Kolekar and Pai [31] presented an approach to identify the learning styles for adaptation as per the Felder–Silverman Learning Style Model (FSLSM). The data is used to cluster the learners as per the learning categories of FSLSM. The customization is provided on the portal by generating an adaptive user interface for each learner based on the learning style of FSLSM. Pereira et al. [32] introduced a framework to fetch users' profiles and educational details from Facebook and some educational resources. Information extraction techniques and semantic web technologies were used for the extraction, improvement, and description of users' profiles and interests. The proposed approach was based on learning repositories, linked data, and video repositories. Hagedoorn and Spanakis [33] concluded in the paper that online courses are impressive but the dropout based on learners' profiles raises crucial tasks for MOOC platforms. So, to overcome this problem, dropout learners' behavior was analyzed by extracting the features of their behavior. In this proposed work, three classifiers were compared, namely logistic regression, random forest, and AdaBoost. However, the accuracy of all these three classifiers was the same, but in terms of accuracy, logistic regression was better than the other two classifiers. Liang et al. [34] analyzed the behavior of online learners and built a student profile and also gave countermeasures. This study is based on students' profiles to guide both e-learning and improve learning outcomes. Big data processing technology was used for building the learners' profiles. This kind of profile helps the learner to understand their learning situations and their problems, and also motivates them to improve the completion rate of the online course. Chrysoulas and Fasli [35] proposed two main sources of personalization information, that is, learning behavior and personal learning style based on the adaptive learning approach. Ali et al. [36] contributed to the recommendation of pedagogical resources within a learning ecosystem. Clemente [37] used a biased matrix factorization algorithm to improve the prediction of online latent Dirichlet allocation for building users' and item profiles. In this paper, Yelp data was used, which is limited to the restaurant category. The authors analyzed and compared the applicability of different user modeling strategies in the context of MOOC recommendations. In this study, the author's research was based on five parameters, such as degree below bachelor's, bachelor's degree, master's degree, and Ph.D. degree. A bootstrapped paired t-test was used to test the statistical significance of the results, and the results show that in comparison to skill, job, and education-based profiles, skill-based performance is the best. Li and Kim [38] applied a clustering technique to build a framework for semantic content for user profiles and also suggested some methods to construct user profiles from rating information and attributes to put up user preferences. In another paper, Bradley et al. [39] described and evaluated a two-stage personalized information retrieval system that combines a server-side similarity-based retrieval component with a client-side case-based personalization component. Although recommendation systems recommend courses for many platforms, the issue is that recommendation systems only suggest courses for particular platforms. So, after studying the literature and the research gap, the platform is built with a system that recommends courses after analyzing the user's needs, whether that course is from Coursera, Udemy, or Edx.

3. Proposed Methodology

The proposed research work aims to create learners' profiles and build a recommendation model that compares different courses on online platforms and offers courses according to learners' preferences. For developing a learner's profile, three parameters have been considered, including personal details, educational details, and knowledge level, as depicted in Figure 2. In this proposed model, learners can also register with their existing LinkedIn profiles so that they can save time.

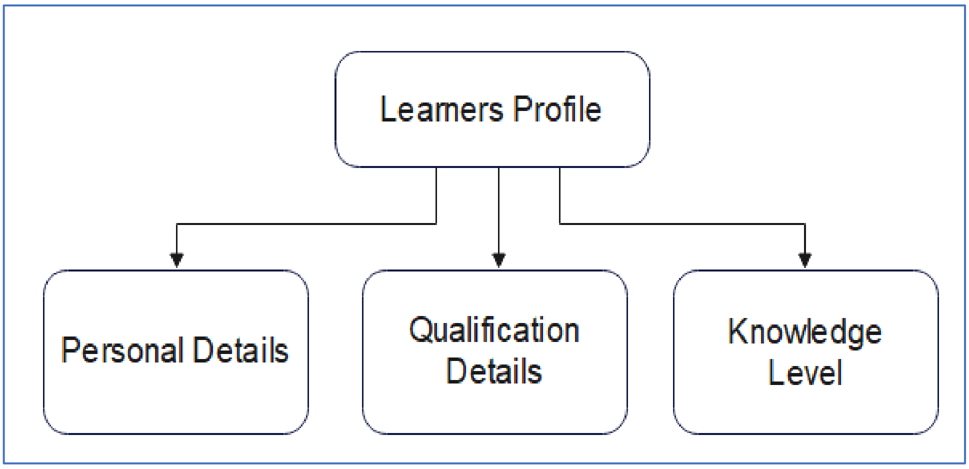

Figure 2. Parameters used for developing the Learners' Profile.

Personal details are further divided into subcategories such as name, date of birth, email address, location, employment status (if any), occupation (student or employee), experience (if any), and earnings (if any), as shown in Figure 3.

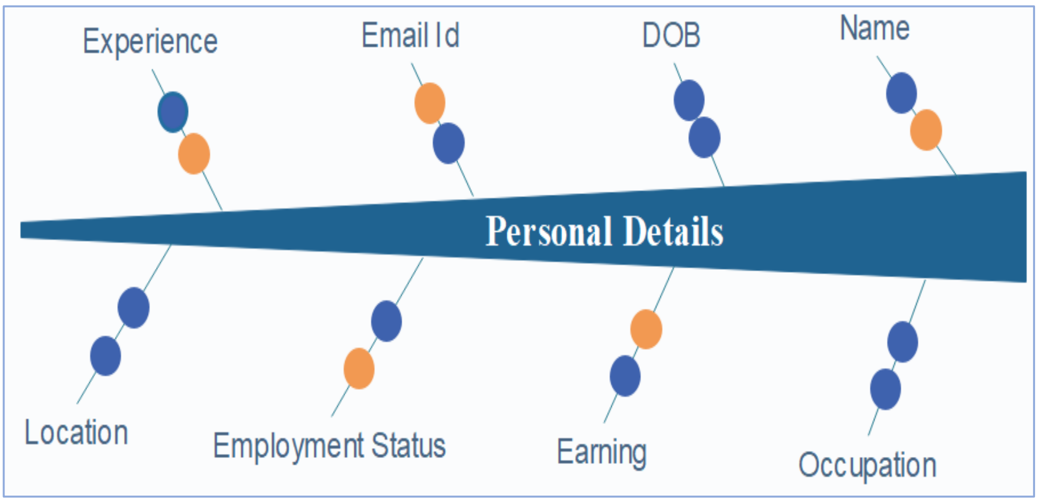

Figure 3. Sub-categories of personal details parameter.

The second parameter is the "education details" of the learner, which is further divided into sub-categories such as "Highest Qualification", "Name of School/University", "Board", and "Grade/Percentage", as shown in Figure 4.

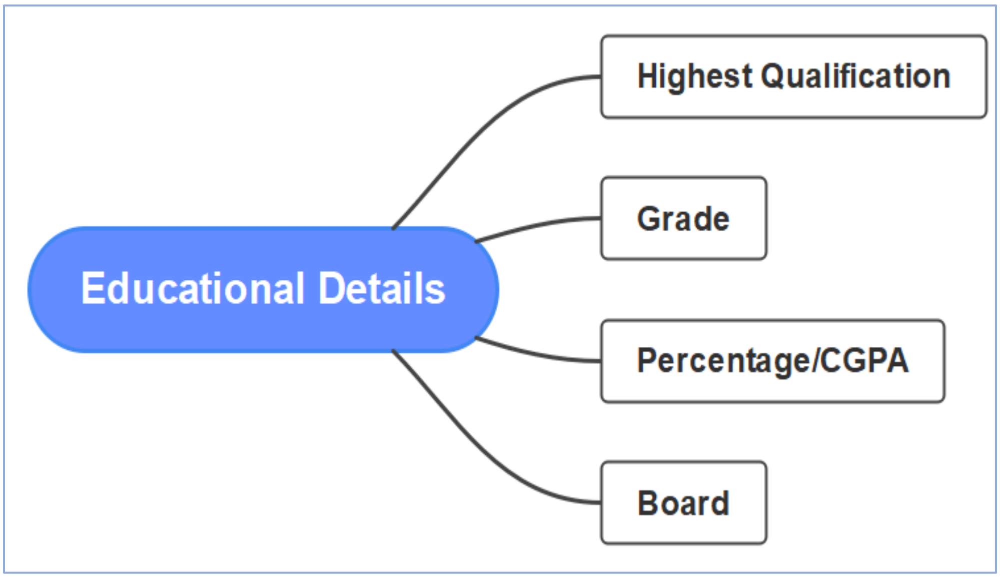

Figure 4. Sub-categories of educational details parameter.

The knowledge level is further divided into subcategories such as a course of interest, level of skill set (beginner, intermediate, and advanced), preferred language, and interest in theoretical or practical parts, as shown in Figure 5.

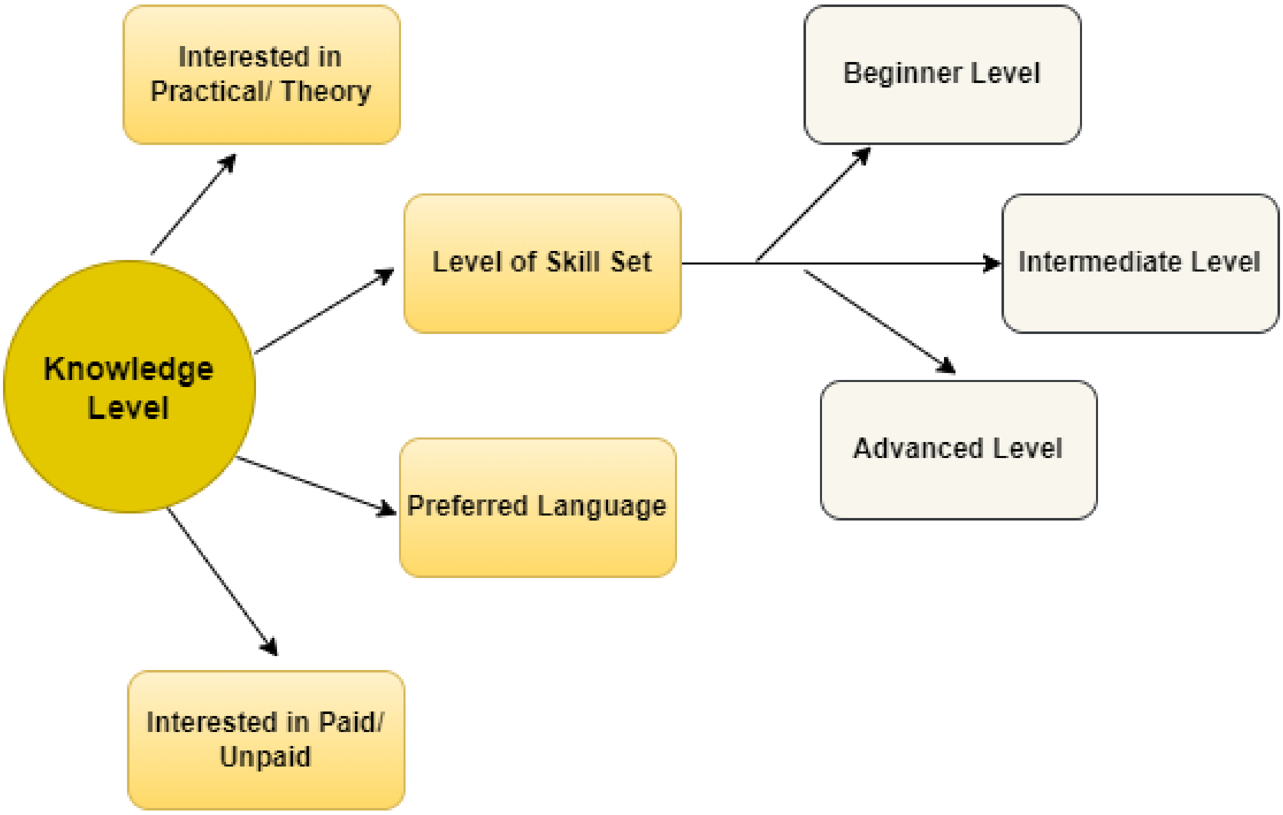

Figure 5. Sub-categories of knowledge level parameters.

The methodology for creating user profiles is depicted using a flowchart in Figure 6. An intelligent profiling system can be produced by creating a user profile.

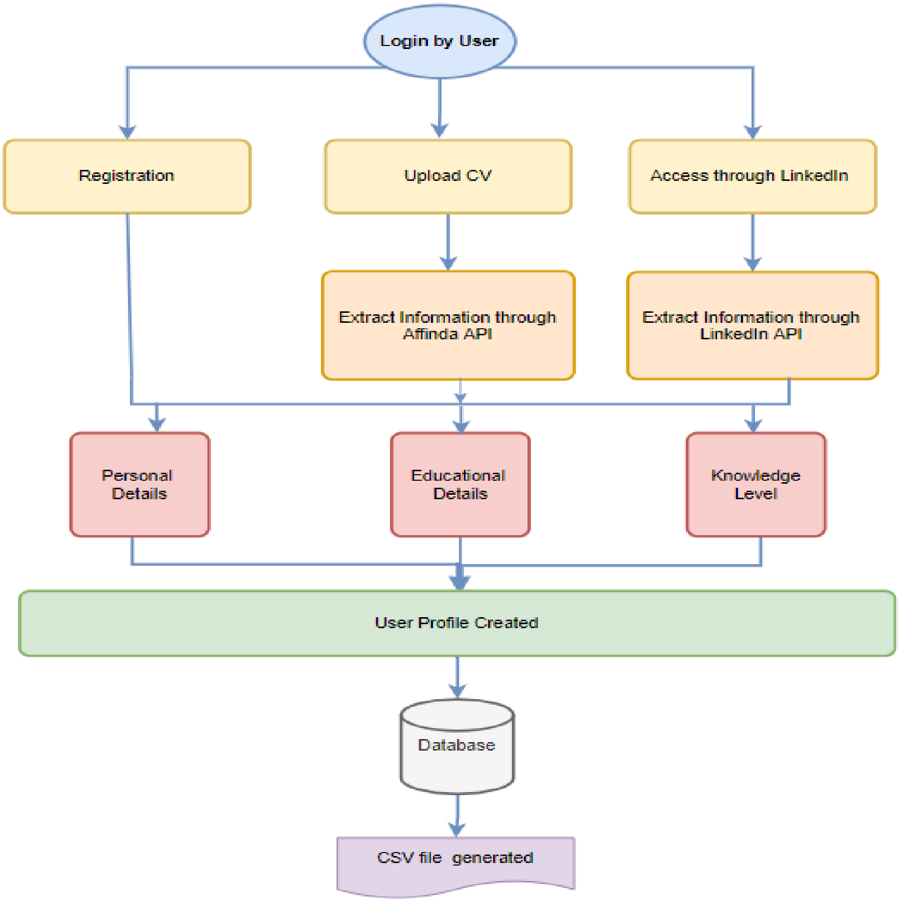

Figure 6. Flowchart of developing the learners' profile.

When a user logs in, there are three ways in which a user's profile can be created via registration, uploading their Curriculum Vitae (CV), and access through LinkedIn. To develop a user profile, the first step is to fill out the registration form. The learner's details will then be entered into the database. This interface was developed in PHP and MySQL and is used as a database. The next step is to click on the Sign In form, and now the user can log in using the username and password that were earlier assigned in the registration step. After filling in the credentials, the user is required to click on the login button. The steps are mentioned in Algorithm 1.

Algorithm 1: Login Details

```
Procedure Login (EID, pwd)
    Enter EID;
    Enter pwd;
        If (EID &pwd in DB)
        Newpage welcome = new NewPage();//Create instance of the new page
        Welcome.setVisible(true);//Create a welcome label and set it to the new page
        JLabel wel_label = new JLabel ("Welcome:" +name);
        Page.get ContentPane(). Add (wel_label);
End If
else
        print ("Please enter the valid credentials");
End else
End Procedure Login
```

To register as a new user, they need to click on the "New User" or "Register Here" table. The steps of registration are also mentioned in the Algorithm: Registration. The registration page, with the help of three parameters that were earlier discussed in the research methodology, is displayed on the screen, and users fill in their name, EID, pwd, DOB, Exp, status, and loc, then click on the submit button. The steps are mentioned in Algorithm 2.

Algorithm 2: Registration

```
Procedure personalDetails (name, EID, pwd, DOB, Exp, Occ, Emp_status, Loc)
        Enter name;
        Enter EID;
        Enter pwd;
        Enter DOB;
        Enter Exp;
        Enter Occ;
        Enter Emp_status;
        Enter Loc;
Save Details to DB
End Procedure personalDetails
Procedure educationalDetails (highest_quali, grade, c gpa, board)
        Enter highest_quali;
        Enter grade;
        Enter cgpa;
        Enter board;
Save Details to DB
End Procedure educationalDetails
Procedure knowledgeSets (Interest, paid_unpaid, prefer_lang, theory_practical, level)
        Enter interest;
        Enter paid_unpaid;
        Enter prefer_lang;
        Enter theory_practical;
        Enter level;
Save Details to DB
End Procedure knowledgeSets
Procedure Registration
    Call personalDetails();
    Call educationalDetails();
    Call knowlwdgeDetails();
End Procedure
```

When a user logs in through authorized credentials then the learners' details are displayed on the screen, as shown in Figure 7.

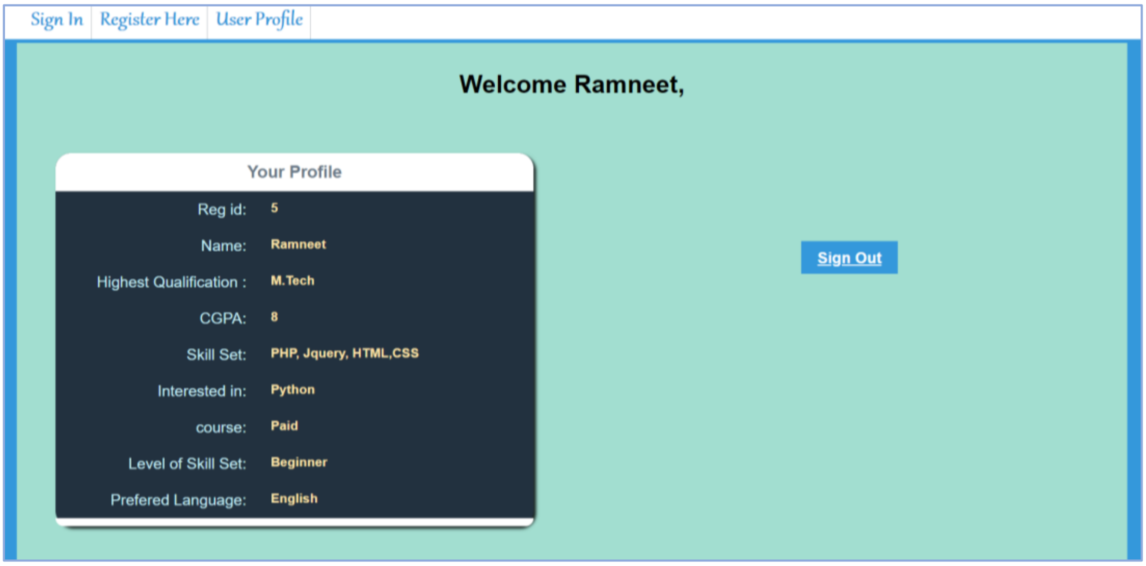

Figure 7. User profile of the registered user.

The second step is to create a profile by uploading a CV. In this step, the CV is uploaded through the "Affinda API" option. In this step, PDF files are uploaded by a user on a website and, with the help of the Affinda API, parsing will be done and, further, the information will be saved into the database, as shown in Figure 8. The data will be received in text format and then it will be easy to manipulate that data using Regular Expressions and save them into the database. The steps are explained in Algorithm 3.

Algorithm 3: Upload CV

1. Procedure upload_cv()
2. Browse file from local device
3. Upload CV
4. OCR will convert CV into text
5. Details saved in DB
6. End Procedure upload_CV

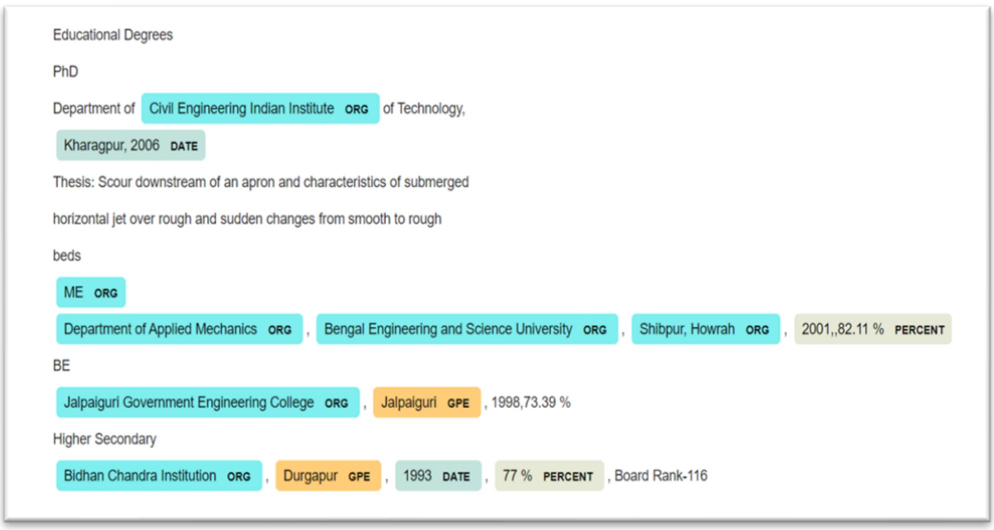

Figure 8. User/learners' profile via uploading the CV.

The third step is to login through a LinkedIn account. With the help of an authorized email ID, a user will jump from a LinkedIn account to the “welcome.php” page, where the details of the user will be displayed. For this step, the LinkedIn API service will be used. With the help of the LinkedIn developer, a client id and secret key will be generated. By using this client id and secret key, the data will be displayed via a LinkedIn account. The steps are explained in Algorithm 4.

Algorithm 4: Login Via LinkedIn

```
Procedure viaLinkedln ()
Generate Request by clicking on LinkedIn icon
Display Consent_page//from user side
Redirects Web application => secret token//from LinkedIn Account Authorization
Requests access with token from web application
Respond with requested data
If (EID(abc@gmail.com)&&pwd (“********”))
Newpage welcome = new NewPage();//Create instance of the new page
Welcome.setVisible(true);//Create a welcome label and set it to the new page
JLabel wel_label=new JLabel(“Welcome:” +name);
Page.get ContentPane(). Add(wel_label);
End if
else
print (“Please Choose the valid credentials”);
End else
```

Once the user profile is created, it is saved in the database, which is used as an input by the recommender system to make recommendations for online courses. Every e-learning platform has a recommendation system, and these platforms create profiles of the learners as well. However, the challenge is to understand the learner’s needs. Every learner is different from others. Every day, online platforms offer so many courses that understanding which course is relevant for novice learners is a difficult task. When novice learners are not able to find a suitable course, they switch platforms, but every time filling out the registration details is cumbersome, and it may also happen that the learner has lost interest in that particular course. The recommender system facilitates both the instructors and the learners. A user profile is created so that the user’s correct information can be fetched and, as per the needs of the learner, courses can be offered to them. If a learner is enrolled in a course as per their preference, then the chances of dropout will automatically be reduced, thereby also helping the instructors. The novelty of this work is to build a platform where all the online courses are available on a single platform. This single platform only offers e-learning courses, not the platforms. The motive of this research is to create competition between the platforms and maintain the quality of the courses.

4. Result & Discussion

After analyzing the literature of MOOC courses, it is stated that among all the MOOC platforms, learners mostly enrolled in Coursera courses. To study the dropout rate of Coursera courses, a dataset is fetched from Kaggle.com that contains information on 891 courses. The dataset contains details of the total number of students enrolled in a particular course. Course_difficulty contains information regarding the level of the course: beginner, intermediate, and advanced. Certification_type contains information regarding the certification, including whether that course counts as a professional degree or not. Course_rating contains the rating of the course, and the course_dropout field contains the number of learners who left the courses after enrolment. In Figure 9, from 891 Coursera courses, 487 courses are offered to beginners, 385 courses are offered for intermediate learners, and 19 courses are for advanced learners. In Figure 10, out of 891 courses, 297 courses hold specialization, 12 courses offer professional certificates, and 582 courses help to enhance your skills.

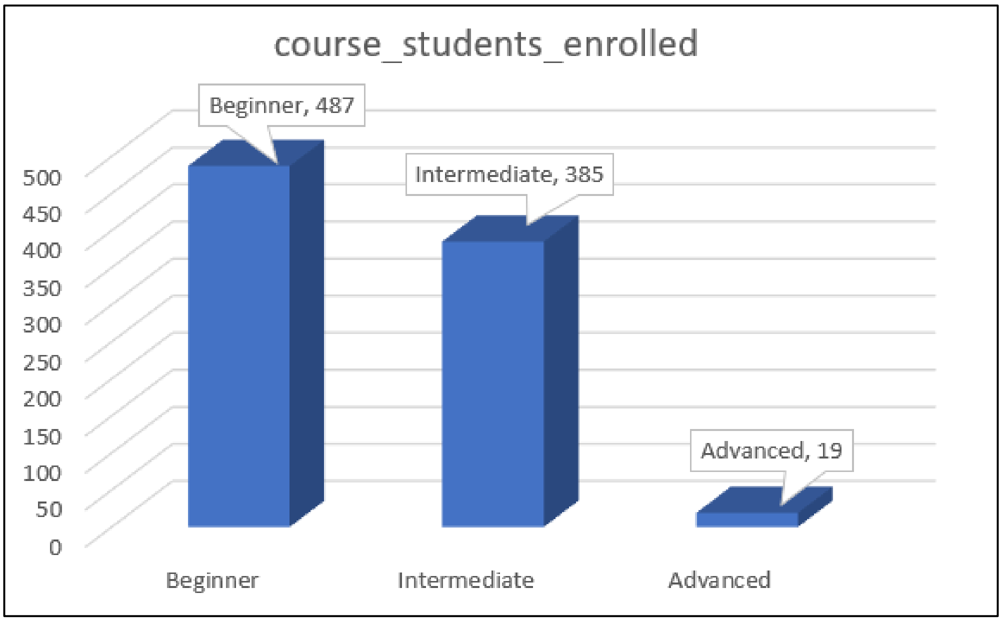

Figure 9. Number of students enrolled in each level.

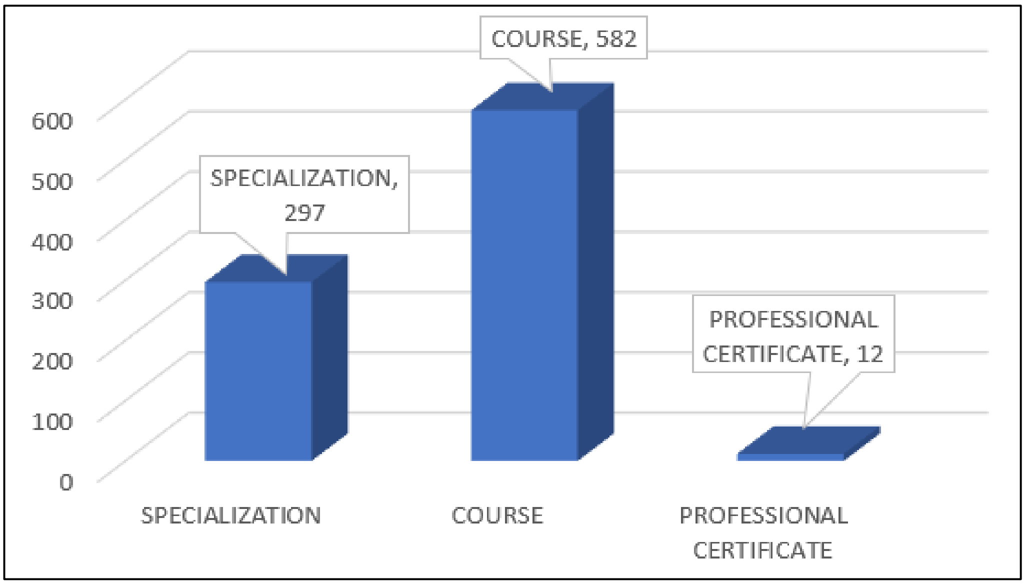

Figure 10. Number of certification courses in each level.

In this paper, the authors have applied regression analysis to the Coursera dropout dataset that was fetched from Kaggle.com to predict student dropouts from the Coursera platform. The regression analysis is performed using the IBM Watson studio service for predicting student dropout cases. The relationship map of coursera_data is depicted in Figure 11, which highlights the pipelines, top algorithms used, and feature transformers. The training set consists of 90% data, and for cross-validation, 3 folds were performed for computation.

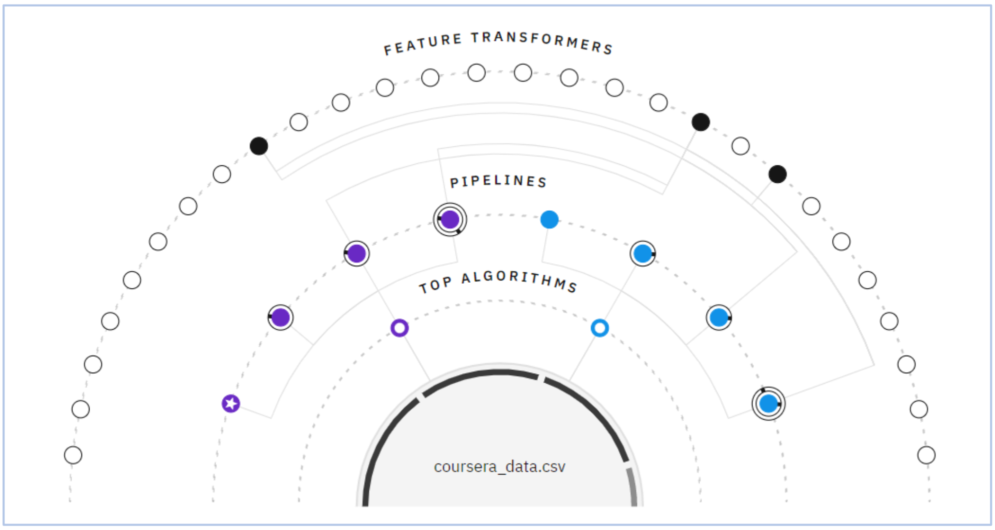

Figure 11. Relationship Map.

In the progress map shown in Figure 12, eight pipelines are generated from algorithms. Each pipeline contains unique steps that generate each model candidate. The top algorithms or estimators are selected in order to train and test the pipelines. The top two algorithms are selected and trained based on the selected dataset. Feature transformers are applied to features (columns) in the dataset during the feature engineering phase. These transformers are applied to two pipelines per algorithm.

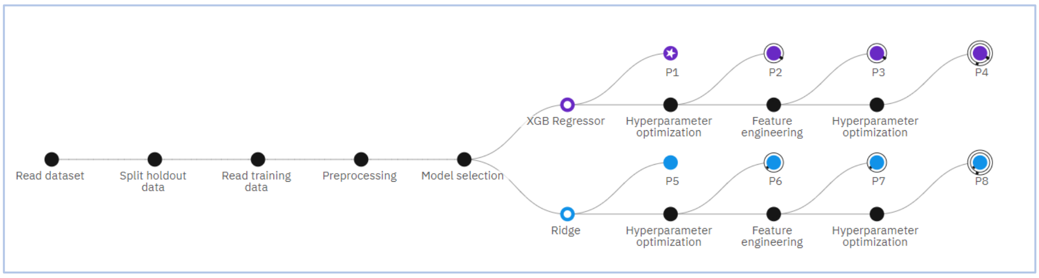

Figure 12. Progress Map.

In the progress map, various steps have been discussed that help in building a model. Firstly, the AI tool reads the dataset and then further divides it into two parts: training and testing. Then a preprocessing step is done in which various filters are applied to clean the dataset. According to the dataset, IBM Watson studio suggests a model that helps train the machine. Furthermore, according to the model, eight pipelines are created for this model. In this model, the dropout_students column is used as a prediction column. As a comparison to other algorithms, the XGB Regressor algorithm gives better results. The XGB Regressor algorithm used four features: course_student_enrolled, course_difficulty, certification_type, and course_rating.

- XGB Regressor stands for Extreme Gradient Boosting Regressor. It is an open-source library which renders an efficient and effective implementation of the gradient boosting algorithm.
- The Hyperparameter optimization is all the parameters that can be arbitrarily set by the user before starting training.
- Feature Engineering is the art of articulating the useful features (characteristics, properties, and attributes) from datasets and targets to be learned by the machine.

- Ridge: Regression is a way to create a frugal model when the number of predictor variables in a set overpass the number of observations or when a data set shows correlations between predictor variables.

The model is evaluated using eight pipelines which are explained as follows:

4.1. Root Mean Squared Error (RMSE)

This is a standard deviation of the error that is predicted according to the dataset. The errors are squared before they are averaged, as mentioned in Equation (1). It means *RMSE* is useful when a large number of errors are present and they affect the performance of the model. This metric avoids taking absolute value and this metric also lowers the value and improves the model preference.

$$RMSE = \sqrt{\frac{\sum_{i-1}^{x}(predicted\ value_i - actual\ value_i)}{X}} \tag{1}$$

4.2. R Squared (R^2)

This metric indicates how the model is fitted to a given dataset. R Squared values lie between 0 and 1, where 0 indicates that the model is not fit and 1 indicates that the model is perfectly fit to the dataset. R Squared is also known as the coefficient of determination.

4.3. Mean Squared Error (MSE)

These metrics are commonly used in machine learning. This metric is useful when the dataset contains outliers. The values calculated by *MSE* will never be negative. The formally defined equation is mentioned in Equation (2):

$$MSE = \frac{1}{T}\ \sum_{i=1}^{T}\left(A_i - \overline{A_i}\ \right) \tag{2}$$

where T is the number of samples that are used for testing.

4.4. Mean Squared Log Error (MSLE)

The MSLE metric is used to measure the percentual difference between true and predicted values as mentioned in Equation (3):

$$L\left(\mathrm{A}, \hat{A}\right) = \frac{1}{T}\sum_{k=0}^{T}\left(\log(\ A_k + 1) - \log\left(\hat{A} + 1\right)\right) \tag{3}$$

where, $\hat{A}$ demotes the predicted value.

4.5. Mean Absolute Error (MAE)

The *MAE* is similar to the MSE, the result of these metrics will never be negative, and they always use absolute values for error. In comparison with MSE, the *MAE* metric is not sensitive to outliers. This metric is used when the performance of continuous variable data is measured. The *MAE* has a slightly different definition from the MSE but provides almost exactly the opposite properties, as mentioned in Equation (4).

$$MAE = \frac{1}{m}\sum_{k=1}^{m}|x_k - \overline{x}_k| \tag{4}$$

4.6. Median Absolute Error (MedAE)

MedAE is a non-negative floating-point metric. The best value of MedAE is 0.0. To evaluate the regression models, unlike classification, regression models allow the gradation of true or false. However, it is always challenging to choose the right metrics and to determine the realistic range of prediction errors. Knowledge regarding different error metrics is a must.

After the analysis of all the eight pipelines, model evaluation is done in which various measures are Root Mean Squared Error (RMSE), R Squared (R2), Explained Variance (EV), Mean Squared Error (MSE), Mean Squared Log Error (MSLE), Mean Absolute Error (MAE), Median Absolute Error (MedAE), and Root Mean Squared Log Error (RMSLE), as shown in Figure 13. In a nutshell, it is observed that although every MOOC platform has their own recommender system, these systems work for their particular platform only. So, in order to provide an e-learning environment, online learners require a system in which all the courses will be compared and recommended according to learners' preferences. In this paper, a recommender system is proposed that compares all the courses at one interface after analyzing the user profile of a learner so that relevant courses can be recommended to a learner according to their preferences.

Figure 13. Performance parameters evaluation for pipeline 1.

5. Conclusions

Today's world is facing the COVID-19 pandemic, and this pandemic has forced schools and universities to work remotely. Nowadays, schools and universities are opting for e-learning platforms to survive, but the problem here is that every user is different, and their learning patterns are also different. So, to improve the results and reduce the drop-out ratio, customization is a must. One of the solutions is to create a user profile for each learner. In this paper, the user profile is created through PHP. For developing a user profile, three parameters are used: personal details, education details, and knowledge level. The data is collected through three different modes: by registration on the website, uploading a CV and through a Google account. The main goal of this user's profile is to recommend courses to learners by understanding their needs. The courses that will be recommended to the user will not be based on one platform. The courses that the recommender system recommends are from Udemy, Udacity, Coursera, SWAYAM, and many more. Thus, a user profile is created that is based on various platforms and will recommend courses from all these platforms according to the learner's preferences. So, in order to improve the learning experience of novice online learners, a recommendation system is needed. In this paper, a recommender system is proposed that compares all the courses on one interface after analyzing the user profile of a learner, so that relevant courses can be recommended to a learner according to their preferences.

In the future, results will be generated with the help of implementing the hybrid recommender system, which is a combination of content-based and collaborative filtering techniques. With the help of content-based and collaborative-based recommendation filters, a top-popular course list will be generated. The recommendation system will make recommendations based on three parameters, namely keyword-based, paid or unpaid courses, and skillset level. To validate the proposed model, a multi-model will be used to get the values of the performance metrics such as RMSE, precision, and recall, and on the basis of the results, the best-recommended system is obtained that will help to find the suitable courses based on user profiling. Thus, an e-learning environment based intelligent profiling system is proposed for enhancing user adaptation.

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