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A Review on Various Developments in Moocs For Prediction of Dropouts To Form A Basis For Prescriptive Framework To Reduce Dropout Rate

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***Abstract*—As the field of Massive Open Online Courses(MOOCs) is a very nascent area, it has lot of potential and challenges. There are not many Indian originated MOOC platforms except NPTEL, SWAYAM which are available, and the major research gap in the literature available on Indian MOOCs is absence of any validated framework which could reduce the dropout rate and improve the completion rate of Indian MOOC platforms. Literature review reveals that most of researchers have discussed about the various MOOC models, their inception, course wise. In India Trends in online learning has been changing since long but with the initiatives of government of India, IIT Madras is promoting the usage of MOOCs through NPTEL but the latest statistics on performance of NPTEL has shown very amazing facts which are really of great concern. Recently in the mid of the month of February 2019 approximately 291 courses were opened for enrollment & registration and out of 1528530 enrolled learner only 40418 registered for various exams which is only 2.6% of the enrollment and this is very poor figure and till date not much of the research is going on in proposing the intelligent framework in MOOCs to find out the ways to attract the learners for registration in MOOCs. This is a challenge for government of India because of the huge financial involvement in NPTEL. So, Research in this direction is very much required because of the plan of MHRD to start Virtual Universities in India in coming years. This research paper reviews the literature related to various developments in MOOCs and proposes a methodology to detect at-risk learners so as to design a framework to reduce the dropout rate from MOOCs. The dataset used in this paper is collected from a SWAYAM course titled Introduction to Learning Analytics in which it was used as a part of a project to predict the dropouts. The dataset contains 4051 tuples and 16 columns and it is a MOOC course based dataset. This paper will form the basis for designing a prescriptive framework to reduce the dropout rate of the MOOCs.**

***Keywords* — MOOCs, NPTEL, SWAYAM**

I. INTRODUCTION

Massive Open Online Courses(MOOCs) follow the theory of disruptive innovation. The MOOCs have high potential of bringing openness in higher education[12]. There is high potential of acceptance of Massive Open Online Courses, and it is considered that MOOCs are an open challenge to all learning methods[2]. The high dropout rate and low completion rate are two big challenges yet to be resolved[7]. MOOC is a paradigm shift in Indian education[28]. The online courses should be affordable, accessible and profitable. The challenges are pedagogy and quality of teaching[12]. The online courses complement the regular

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courses[28]. E-learning is challenging specially in students, the factors responsible for this were curriculum mismatch and a language barrier, the solution exists in terms of bridging courses and curriculum mappings[3]. The cheap, simple and free MOOCs are more acceptable[22]. There are various proposed models for MOOCs e.g. cMOOC, xMOOC, hMOOC, ahMOOC[10]. The user persistence to complete MOOC could be achieved by using parameters like network benefit, user preference and motivation[4]. The network benefit can be predicted by network size and perceived complementarity[4].The user preference showed strong influence on user's persistence in completing one year users than above one year users, while motivation showed stronger influence on user's persistence for above one year users. MOOC usage is also a deciding factor[4]. A conceptual framework is required for continuous teacher education[6]. The factors like video, resources and content, pace of the course, interaction with the instructor and the support, pattern of assignment and assessment were the resulting force to keep the learners engaged in open online courses [17]. The Flipped MOOC concept including gamification and learning analytics features can improvise MOOCs. The MOOCs should not only be content oriented but also personalised interactive and engagement oriented[8]. The pedagogical and teacher training is supposed to be required for improving MOOCs[29]. The factors like purpose or intention to use, frequency and number of interaction, engagement, motivation and satisfaction were important factors for improvement of MOOCs. The author suggested that student academic performance could be influenced by MOOC which could facilitate the learning process[34]. Various researchers discussed the usefulness of data mining in education and latest trends in it[38]. Various Researchers also discussed the potential of MOOCs in providing free, open and online education to massive numbers of students, also discussed the scalability issues[41].The Researchers used EDM and HCI theory to develop usable prediction model[42].

II. REVIEW OF LITERATURE

K. M. Moudgalya et al. (2008) reported the bad state of engineering education and engineering institutions in India. To rectify it IITs should come forward for providing distance education in engineering education. IIT Bombay is providing distance education through satellite, video conferencing, webcast, video on demand and learning management system through Moodle in PGDIIT[20]. M. S. Krishnan (2009) investigated that NPTEL is a repository of various video archives, conducted survey in various science and engineering institutions, also reported that NPTEL is best platform in providing open and free education in higher education[24]. A. Chakraborty and S. Ghosh (2010) proposed Virtual Lecture and Lab Outsourcing teaching model with live webcasting and instant messaging features. Also reported that training based quality lectures can be bought for extending the reach of quality teaching[1]. J. Ravi and H. J. Jani (2011) performed the quantitative analysis based on the survey of eight engineering colleges of Gujrat, and rated NPTEL as high in knowledge enrichment and passing examination, and also treated NPTEL almost at par with OCW of MIT and OLI of Carnegie Mellon University[15]. M. S. Ananth (2011) stated that the objectives of NPTEL include providing curricula to science and engineering students of India. The author proposed the need to train the faculty in the institutions, and to enable the industry to adopt the contents in their training. The challenges in technology and pedagogy were identified[23]. J. S. Ravi and H. J. Jani (2012) performed the cluster analysis of eight engineering institutions of Gujrat, the issues like local language usage and enrichment of knowledge were analysed, proposed the need of features like experiential learning and comprehensive online study program with examination and certification, also proposed to use NPTEL as virtual with on demand online courses[14]. Li Yuan and Stephen Powell (2013) reported in their white paper on the basis of theory of disruptive innovation that Massive Open Online Courses brought trend of greater openness in higher education. A need of new business model was felt to disassociate assessment and accreditation from teaching to generate new revenue structure. The online courses should be affordable, accessible and profitable. The challenges are pedagogy and quality of teaching[12]. S. K. Mohamad and Z. Tasir(2013) discussed the usefulness of data mining in education and

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latest trends in it[38]. J. Kay et al. (2013) discussed the potential of MOOCs in providing free, open and online education to massive numbers of students, also discussed the scalability issues[41]. A. Nath et al. (2014) reported high potential of acceptance of Massive Open Online Courses(MOOC), considered MOOCs as open challenge to all learning methods[2]. D. F. Onah et al. (2014) discussed the high dropout rate and completion rate as important factors, also related the course factors with dropout rate, likelihood of dropouts, Conducted the same computing MOOC course on two parallel modes traditional and supported using Moodle platform[7]. J. S. Ravi et al. (2014) performed the quantitative analysis on the basis of survey of 5161 respondents across different engineering colleges of India, discussed the use, relevance and quality of NPTEL courses, also collected the opinions regarding whether NPTEL leads to enrichment, established the fact that NPTEL supplements classroom teaching[16]. K. K. Bhattacharjee (2014) studied the survey conducted on NPTEL website by taking inputs from 2323 respondents and conducted the SWOT analysis and used SAP-LAP tools, and reported that reach of quality teachers could be extended. The author considered NPTEL as a medium for knowledge transfer and recommended the status of virtual university to NPTEL[19]. P. K. Singh et al. (2015) studied that online courses act as complement to the regular courses. MOOC is a paradigm shift in Indian education. Also gave the insight of the end user of online courses and recommended best platform for backlog students[28]. R. R. Shah et al. (2015) proposed a TRACE system which uses Wikipedia text to peform the segmentation of videos and also performed the fusion of video clips later on[30]. K. Mohan et al. (2015) developed an open source tool “ExamLink” to further emphasize the effect of NPTEL by linking specific videos with questions so that a particular video can be searched on the basis of a question in the similar manner the way NPTEL is doing in case of preparing students for GATE exam[11]. W. Xing et al. (2015) used EDM and HCI theory to develop usable prediction model[42]. A. M. Shahiri et al. (2015) presented a systematic literature review to predict the student’s performance in Malaysian institution by using various data mining techniques[43]. A. Ravi et al. (2016) reported that E-learning is challenging specially in students, the factors were curriculum mismatch and a language barrier, also proposed the solution in terms of bridge courses and curriculum mappings[3]. L. Aleman and D. E. L. A. Garza (2016) used the quantitative methodology for analysing the quantity of retention, completion, desertion as well as the characteristics of the students who completed the course, the author understood the cause of desertion after positive response of the enrolled participants, identified the problems with structure and guidance in the course, limited availability of time due to family or work, those completed the course were having previous online education experience, economic stability and commitment to course[21]. M. Flavin (2016) discussed the disruptive innovation concept and considered cheap, simple and free MOOCs as more acceptable[22]. K. S. Hone and G. R. El Said (2016) conducted a student survey after the completion of MOOC and concluded that course content was a significant predictor of MOOC retention[49]. C. Alario-Hoyos et al. (2017) discussed self-regulated learning strategies, learner’s motivation, time management as key factors in finding dropout rate[5]. C. Amado and A. Pedro (2017) proposed a conceptual framework which is required for continuous teacher education[6]. D. Riofrío-Luzcando et al. (2017) reported the potential of data mining for predicting students behaviour, collected student model built from previous batch of student logs, student logs were grouped in clusters, extended automation was created for each cluster based on the sequence of events retrieved from cluster logs. The author validated the model by using the student logs in a 3D virtual lab of Biotechnology[9]. K. J. Burle et al. (2017) insisted on project based learning through projects like e-Yantra in IIT Bombay for reducing the gap in engineering education in India[18]. R. Hariharan (2017) suggested that pedagogical and teacher training is required[29]. V. Rao et al. (2017) developed a tool to identify the subject domain from a question[33]. R. Asif et al. (2017) used various EDM methods to study the performance of undergraduate students, and created two groups of low and high achieving undergraduate students, and analysed a few courses giving good or poor results to generate a timely warning and support to low achieving students[36]. C. Angeli et al. (2017) used association rules mining and fuzzy representation for student learning[37]. F. J.

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García-Peñalvo et al. (2018) studied and compared cMOOCs, xMOOCs and proposed ahMOOC model which combined social advanatages and organizational benefits of xMOOCs[10]. J. Madathil Warriem (2018) studied the effects of scalability of NPTEL Online Courses through LC by evaluating it with the dimension of spread, depth , sustainability and shift in reform ownership[13]. K. F. Hew et al. (2018) identified the factors which students found as the resulting force to keep them engaged in open online courses[17]. M. V. Almeda et al. (2018) studied the factors responsible for predicting completion and grades in open and for-credit courses, used different cluster and regression models for open and for-credit course students[25]. O. Zawacki-Richter et al. (2018) developed a text mining tool for knowing the status of research on MOOCs, identified areas like potential and challenges of MOOCs for universities, MOOC platforms, learners and content in MOOCs and the quality of MOOcs and instructional design issues[26]. P. Geetha, W. K. Cherukulath, and R. Sivakumar (2018) discussed technical information resource center of Naval Physical and oceanographic laboratory started the new service by giving access to e-learning through National Knowledge Network[27]. S. J. Nam et al. (2018) proposed a prediction model for funding disengaged behaviour of students, increased prediction accuracy by adding context based features to the prediction models and by introducing pairwise interaction structures into the prediction models[31]. S. Lim, C. S. Tucker et al. (2018) studied that monitoring student engagement is challenging task and measuring its impact on student's performance is important, proposed a semantic network model for measuring the different word association between instructor and students in order to measuring student engagements[32]. W. Al-Rahmi et al. (2018) studied that intention to use, interaction, engagement, motivation and satisfaction were important factors for improvement of MOOCs, students academic performance can be influenced by MOOC which facilitated the learning process[34]. Y. Wang and R. Baker (2018) suggested the relationship between learner's intention to complete a MOOC and the learner's actual or observed completion status[35]. R. Klemke (2018) reported the potential and the drawbacks of Massive Open Online Courses(MOOC), and also highlighted the low completion rates and high dropout rate. The participant engagement and personalization are key factors. The Flipped MOOC concept including gamification and learning analytics features can improvise MOOCs. The MOOCs should not only be content oriented but also personalised interactive and engagement oriented[8]. G. Sedrakyan et al. (2018) proposed a conceptual model and related dashboard design with the learning sciences for providing cognitive and behavioural process oriented feedback to learners and teachers[39]. T. Lerche and E. Kiel(2018) proposed a linear model that included previous knowledge and log-file extracted online activity as predictor of student achievement[40]. C. Burgos et al.(2018) proposed the use of knowledge discovery techniques to analyse historical student course grade data in order to predict drop out status of a student[44]. M. W. Rodrigues et al. (2018) reviewed EDM based research papers and presented perspectives, identified trends and observed potential research dimensions such as behavioural research, collaboration, interaction and performance in the development of teaching –learning activities[45]. A. S. Sunar et al. (2018) analysed learner's social engagement on MOOC platform and the effect of engagement on the course completion. Patterns of learner's social engagement were modelled by using learning analytics technique[47]. E. B. Gregori et al.(2018) used Semi-Supervised Extreme learning Machine to predict completion in MOOC[50]. H. Aldowah et al. (2019) identified the relevant EDM and LA techniques and compared four main dimensions i.e. Computer-supported learning Analytics (CSLA), Computer-Supported Predictive Analytics(CSPA), computer supported visual Analytics(CSVA) and Computer-Supported Behavioural Analytics(CSBA)[46]. M. Cantabella et al. (2019) used statistical and association rule technique by using Big Data framework and obtained results were demonstrated by using visual analytic technique in order to detect recent trends[48].

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III. PROPOSED METHODOLOGY

Step 1
Analysis of Framework of Various MOOCs Providers which includes NPTEL, Coursera.org, edx in this step, a detailed working and process of MOOCs will be studied and different provision for Learner and Mentor will be examined.

Step 2

Log details of various Courses in Session wise and Year wise which include following attributes like Log Times/Video Watching Time/Number of Question Ask/Visit on Discussion Forum/ Number of Time Portal visits/Number of Assignment Completed/Time to attempt assignments etc. equation number in parentheses.

Step 3.
Applying Preprocessing Techniques to different dataset containing different Log files using appropriate Tool.

Step 4
Building Model using different techniques to identify different class labels as desired like slow learner/eager learner/late responder/early responder/less video watch time/less material access time etc.

Step 5

This phase includes deploying and Testing of models using Rapid Miner or Weka.

Step 6

Using Cross Validation with different iterations and comparing the results.

Step 7
Proposing a prescriptive framework as per the results and incorporate the feedback and others findings related to assignment submissions etc to promote registration for the MOOCs.

A. Dataset Collection

This paper uses the sample dataset of a MOOC course provided as a part of the SWAYAM course project. The name of the course for which this project was conducted is Introduction to Learning Analytics and it was floated in the session July-Dec 2019 on SWAYAM platform. The dataset contains 4051 records of the learners and 16 attributes.

B. Dataset Pre-Processing

Once the raw log data is collected, it is pre-processed by handling missing values and outliers. The data wrangling techniques are applied to bring the dataset in an organized form. The TABLE I explains the structure of the sample pre-processed anonymized dataset.

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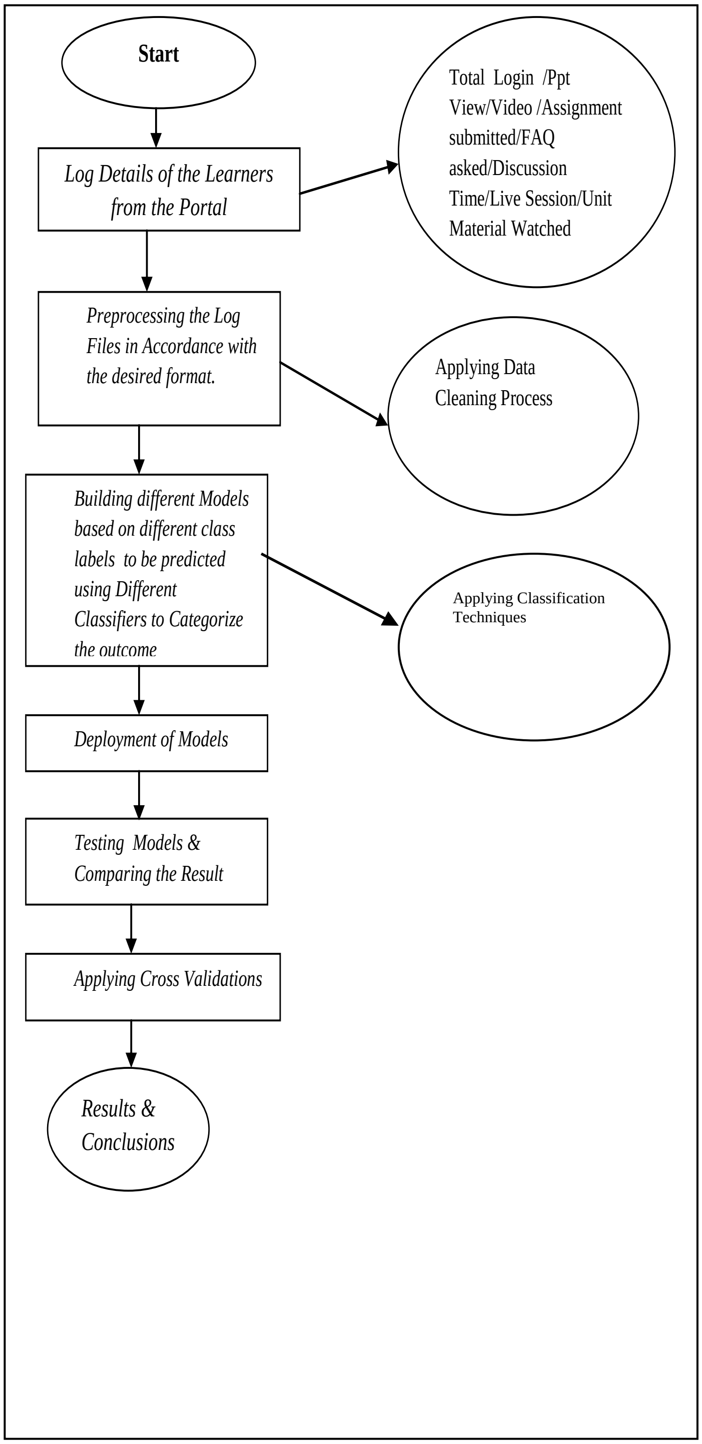

fig 1. Proposed Methodology

TABLE I
SAMPLE DATASET STRUCTURE

Feature	Description
lmsUserId	User ID anonymised
Week_no	Week Number. This course ran for 5 weeks.
Time spent on video in Mins	Time spent on watching video lectures in minutes
onSlideSeek	Seek in videos. Number of Seeks in a week.
Forum	Number of times the forum page is accessed
Discussion forum	Number of times interacted with discussion forum
Grade	Performance in the quiz. Maximum marks is 10.
Attempts	Number of quiz attempts.
Vote	Number of time upvoted any post in the forum
Thread	Number of threads interacted in a week
Forumsearch	Number of searches in forum
Play_video	Number of time videos are played
showanswer	Request for the answer
Transcript_download	Number of times transcripts downloaded
UserFollowed	Number of users followed
Dropout	Label to predict

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C. *Feature extraction*

The dataset contains 16 attributes and all the attributes are not significant predictors. To find the significant predictors, techniques like forward regression, backward regression and incremental regression were conducted using SPSS and out of 14 leaving the lms_UserID and the output variable only 6 attributes out of 14 were found to be significant predictors. The list of the significant predictors along with their significance value is listed in the TABLE II. The criteria to select and reject the attributes is decided by assuming the probability value. If the significance value comes out to be less than 0.05 then the feature or the attribute is selected as significant predictor else it is rejected as insignificant predictor. The list of insignificant predictors is shown in the TABLE III along with their significance values.

TABLE II
SIGNIFICANT PREDICTOR ATTRIBUTES

Feature	**Significance Value**
onSlideSeek	.000
Forum	.026
Discussion forum	.000
Grade	.015
Play_video	.004
Attempts	.000

TABLE III
INSIGNIFICANT PREDICTOR ATTRIBUTES

Feature	**Significance Value**
Thread	0.789
UserFollowed	0.187
Vote	0.710
Transcript_download	0.653
showanswer	0.425
Forumsearch	0.369
Time spent on video in Mins	0.937
Week_no	0.129

D. *Applying classifiers and building model for cross validation .*

Once the feature extraction is done, various classifiers are applied like Naïve Bayes, Decision Tree and Binary Logistic. Out of all these classifiers logistic classifier is chosen for this sample dataset because the outcome is binary or categorical for the dropout feature. The logistic classifier model is applied and cross-validated with 10-folds cross-validation. The accuracy of the classifier comes out to be 86.9%.

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IV. RESULTS

The Results of the cross-validation of the logistic regression model is shown in the fig. 2. Which shows Precision, Recall, F-Measure, Kappa, percentage of correctly classified instances.

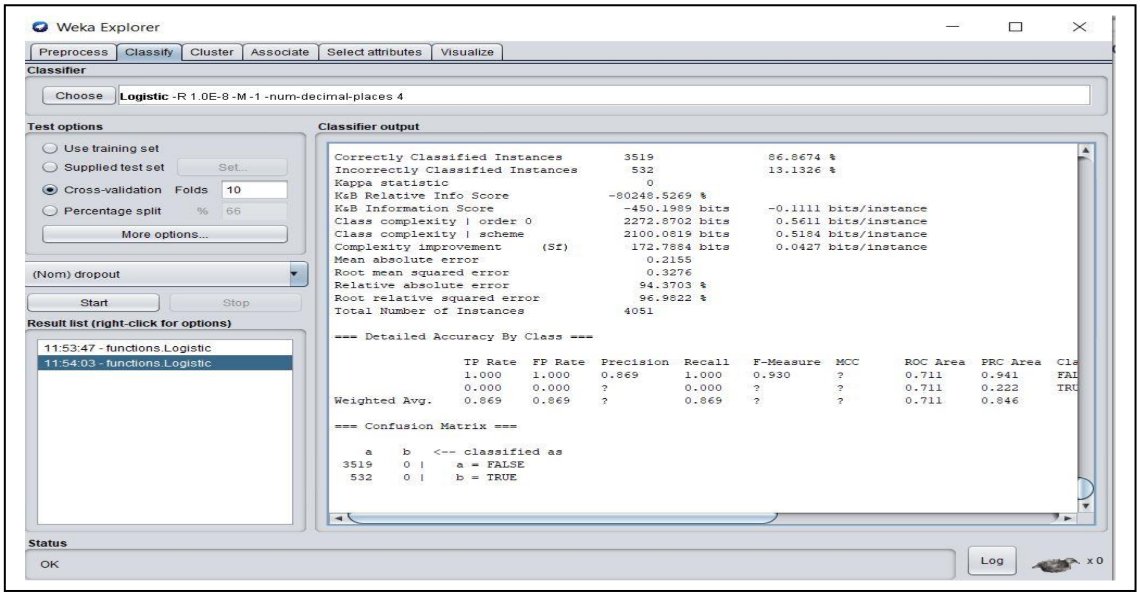

fig. 2 Logistic Classifier output in Weka

V. CONCLUSION

The results thus obtained can be used for prescriptive analytics for prescribing the required framework to reduce the dropout of at the risk learners. For this decision making is required to be performed for all the predicted dropouts.

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