



M-Learners’ Performance Using Deep Learning Techniques with Intelligent and Adaptive Web Data Extraction

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ABSTRACT

Educational institutions are one of a kind and play a crucial part in the development of every nation. People, communities, nations, and perhaps the planet will be transformed as a result of education's impact. This is the reason why we are so content in our present circumstances. Today's education does not stop at classroom instruction; it also includes things like online education, web-based education, seminars, workshops, and massive open online courses (aka MOOCs). Data recorded in educational databases and learning management databases makes it more difficult to predict student success. There are several methods for assessing student achievement. Educational data mining is the most common method of evaluating student performance and is utilized widely in the educational industry.

Classification, prediction, and feature selection are just a few of the strategies used in this growing field of research. It is used to forecast students' performance and learning behaviour by extracting the hidden information from learning records or educational data. Electronic Data Mining (EDM) may be used to extract relevant information from a large educational database. The student's performance is then projected based on the valuable information and patterns that have been gathered. The primary goal of our research is to identify the categorization strategy that produces the greatest performance outcomes for pupils.

INDEX TERMS: Deep neural networks, Deep learning, Machine learning, Learners’ classification, Adaptive M-learning, Feature weights.

I. INTRODUCTION

Educational data mining tends to focus on developing new tools for discovering patterns in data. These patterns are generally about the micro concepts involved in learning: one digit multiplication, subtraction with carries, and so on [3]. Learning analytics—at least as it is currently contrasted with data mining focuses on applying tools and techniques at larger scales, such as in courses and at schools and postsecondary institutions. But both disciplines work with patterns and prediction: If we can design the pattern in the data and make sense of what

is happening, we can predict what should come next and take the appropriate action. Educational data mining and learning analytics are used to research and build models in several areas that can influence online learning systems [5]. One area is user modelling, which encompasses what a learner knows, what a learner's behaviour and motivation are, what the user experience is like, and how satisfied users are with online learning.

Robust applications of educational data mining and learning analytics techniques come with costs and challenges. Information technology (IT) departments will understand the costs associated with collecting and storing logged data, while algorithm developers will recognize the computational costs these techniques still require [9]. Another technical challenge is that educational data systems are not interoperable, so bringing together administrative data and classroom-level data remains a challenge. Yet combining these data can give algorithms better predictive power. It also requires careful attention to student and teacher privacy and the ethical obligations associated with knowing and acting on student data.

The teacher and the institution have access to the online learning data, which they can use to certify the student's accomplishments. This scenario shows the possibility of leveraging data for improving student performance; another example of data use for "sensing" student learning and engagement is described in the sidebar on the moment of learning and illustrates how using detailed behaviour data can pinpoint cognitive events [6]. The increased ability to use data in these ways is due in part to developments in several fields of computer science and statistics.

II. EXISTING SYSTEM

The current situation is very limited too few resources, students are unable to get knowledge more than that the lecture provides to them [2]. This in the end limits student's performances, because everything a student gets is collected from lectures in class. Here are some of the problems of the current system:

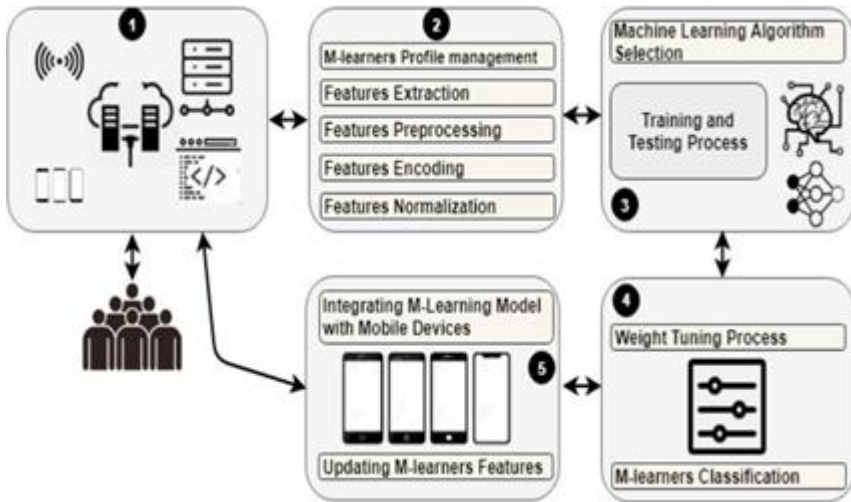
- The current system at Zanzibar University is that lectures download references for students or for lecturing.
- Students submit assignment to lectures through hard copies or personal emails.
- Students only get help from lectures if the lectures are in they're office.
- New lectures to a course have to get materials on their own.
- Student are required to physical be in the classroom in order to gain knowledge thereby sacrificing all other responsibilities.
- Students are unable to share resources effectively and hold group discussions that are monitored or supervised by lectures.

III. PROPOSED SYSTEM

The system will hopefully serve as a centralized database of syllabus for the courses offered at the university allowing students and faculties (current, past and prospective), to view them [10]. The system will end up bringing an effective communication among students, lectures, and the administration, by accessing information and other resources anytime, anywhere. Here are some expected results of the project:

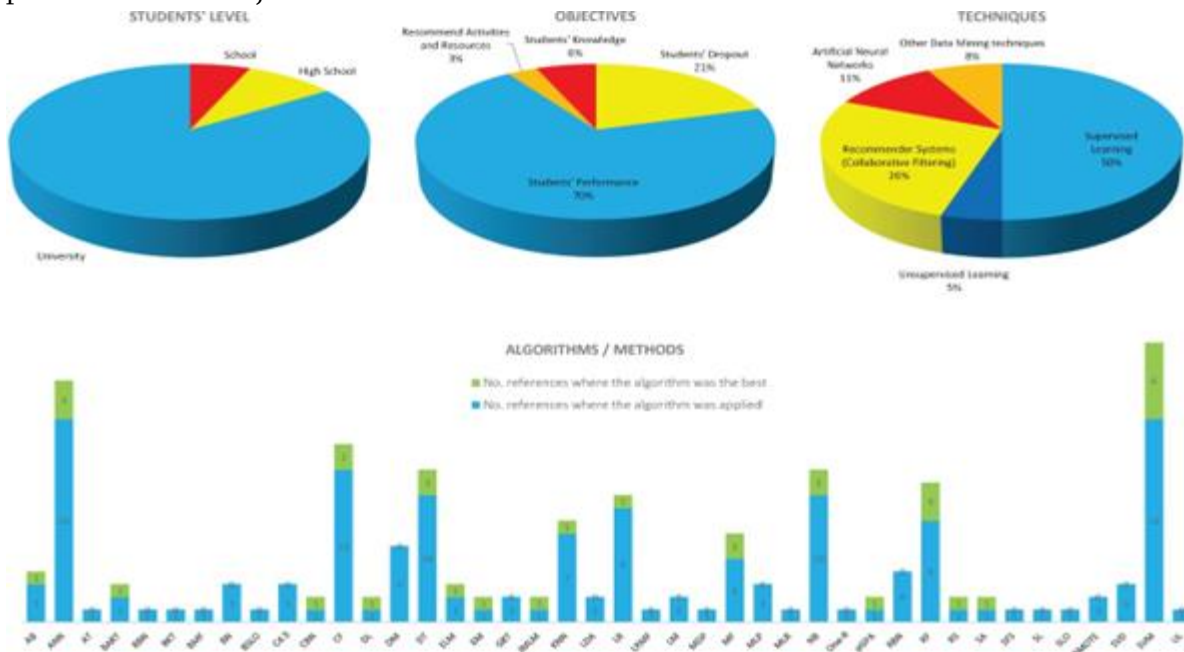
- Lectures to upload assignments and resources for their units.
- Students to download the resources and upload assignments.
- It provides an easy-to-use way to manage course websites that include schedule information, announcements, as well as course discussions.

M-Learning represents an innovative shift in the field of learning, providing rapid access to specific knowledge and information [4]. It offers online instruction that can be delivered anytime and anywhere through a wide range of electronic learning solutions such as Web-based courseware, online discussion groups, live virtual classes, video and audio streaming, Web chat, online simulations, and virtual mentoring.



IV. RESULT

The techniques consider the different algorithms, methods and tools that process the data to analyze and predict the above objectives.



V. CONCLUSION

These results demonstrate the effectiveness of our proposed M-learning system in predicting M-learners' performance and determining significant features with high impact on learning outcomes. Our predictive models are useful for institutions in formulation of a proactive analytics model that supports their decision-making process. In future, we intend to incorporate additional deep learning algorithms such as Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), Self-Organizing Maps (SOMs), etc.

VI. REFERENCES

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