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A Machine Learning Based Framework for Education Levelling in Multicultural Countries: UAE as a Case Study

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***Abstract*—**In Abu Dhabi, there are many different education curriculums where sector of private schools and quality assurance is supervising many private schools in Abu Dhabi for many nationalities. As there are many different education curriculums in Abu Dhabi to meet expats' needs, there are different requirements for registration and success. In addition, there are different age groups for starting education in each curriculum. In fact, each curriculum has a different number of years, assessment techniques, reassessment rules, and exam boards. Currently, students that transfer curriculums are not being placed in the right year group due to different start and end dates of each academic year and their date of birth for each year group is different for each curriculum and as a result, we find students that are either younger or older for that year group which therefore creates gaps in their learning and performance. In addition, there is not a way of storing student data throughout their academic journey so that schools can track the student learning process. In this paper, we propose to develop a computational framework applicable in multicultural countries such as UAE in which multi-education systems are implemented. The ultimate goal is to use cloud and fog computing technology integrated with Artificial Intelligence techniques of Machine Learning to aid in a smooth transition when assigning students to their year groups, and provide leveling and differentiation information of students who relocate from a particular education curriculum to another, whilst also having the ability to store and access student data from anywhere throughout their academic journey.

***Keywords*—**Admissions, algorithms, cloud computing, differentiation, fog computing, leveling, machine learning

I. Introduction

In multicultural countries where there are many different nationalities, there are different education curriculums available to satisfy parents and students' needs. Switching from one curriculum to another has become a critical issue as differences among curricula could create gaps in education levels for students. Hence, it is difficult to assign the right level initially for students when moving to a new curriculum. The question is how we can make this transition more precise and smoother with very minimum effect on students' performance. There are many education curricula in Abu Dhabi, and different education curricula have students starting at a different age; for example, some education curricula (e.g., Philippine) start from 2.5 years old, whilst some others start from 4 years old (e.g., India and Pakistan). According to analyses of education curricula outcomes in Abu Dhabi and based on students' results in high school level, most students, who have transferred from one education curriculum to another, have a gap in their education skills and knowledge [1].

Although distributed computing paradigms (e.g. cloud computing) and Machine Learning (ML) have been used a lot "separately" in education for different purposes (e.g. sharing contents and delivering lectures online in the case of cloud, and predicting students' performance using ML), they have never been utilized jointly to perform leveling in multicultural education countries. Therefore, there is an instant need for having a united computerized system for automating the leveling process for students when changing between the most common education curricula. Nevertheless, there is a huge ambiguity in this area, which usually creates conflicts between parents, school, and Ministry of Education. This conflict has obviously a negative impact on the students' performance when making the wrong decision.

This paper aims at proposing and developing a computational framework applicable in multicultural countries, such as UAE, in which multi-education curriculums (i.e., UK and USA curricula) are implemented. The ultimate goal is to aid in a smooth transition during admissions, leveling and differentiation of students who relocate from a particular education curriculum to another; and minimize the impact of switching on the students' educational performance.

II. Cloud and Fog Computing in Education

With the use of cloud, the world will become a classroom, teaching process will be changed by applying e-learning. Students can learn and teachers can teach form any place. With use of cloud computing, students' work can be set, collected and graded online by teachers, while teachers can also put the required resources for students online to use so that students take responsibility of their own learning [2]. The resources could include videos, documents, audio podcasts or interactive images [3]. As long as there is internet connection, students can access these resources via their personal computer, smartphone or tablet. Sharing applications and documents on the cloud, like Google apps provides better opportunity for social lessons, this will enhance the collaborative productivity between students, students can work together if they are in the same room or in different places. These collaborative tools are very helpful for teachers as well. Many schools are following this currently, yet still there is a long way to make sure that all schools are embracing it [4].

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In UAE a smart learning program started in 2012 named Mohammad Bin Rashid smart learning program (MBRSLP). This program will provide a new learning environment in the national schools, with lunching of smart classes. Smart education has become the new trend in educational field globally. Intelligent technologies such as could computing, Internet of things and learning analytics have developed the emergence of smart education. These technologies focus on how to capture learning data, analyse it and use it to improve education [5].

A. Related Work

Chandra and Bora [6] did a research on the role of Cloud Computing in education. The researcher came to a conclusion that Cloud Computing will introduce a change in the way teaching is provided to students by allowing teachers to focus on teaching and research activities rather than on intricate IT implementation. Chandra and Borah also stated that Learning as a Service (LaaS) is likely to be a new way of cloud computing education platform.

Khan et al. [7] presented a research on Education Cloud Model and ways the cloud can be implemented in higher education. The research shows that users (students, teachers, parents, etc.) would be able to access different education cloud services with use of IoT devices (laptops, smart phones, etc.). Education Cloud Models can provide an extensive linked structure between universities.

Rao [8] presented a new model for education as a service (EaaS), which enables stakeholders (students, teachers, parents, etc.) to overcome current challenges faced in education in terms of communication and learning in general. The suggested model demonstrates different services by the cloud in the form of an Education Management System (EMS).

III. Data Mining and ML in Education

Data mining or Knowledge Discovery in Databases (KDD) is the concept of finding the novel and useful information from a huge amount of data [9]. Recently there is an increased interest in using data mining in educational research, Educational data mining (EDM) is focusing on developing methods for finding the unique and important data which come from educational setting and using them to enhance the level of understanding about students and the setting [10].

There are many applications of EDM; one of the key areas of applications which got an attention within the field is in improving student models which provides information about students' level of knowledge, motivation, attitudes and other characteristics [11]. The most essential theme in educational software research is modeling students' individual differences for enabling software to react and deal with these differences [12].

Most practical ML uses supervised learning. Supervised learning is where we have an input variable known is (x) and an output variable (y), and then we use an algorithm to learn the mapping function from the input to the output [13].

$$Y=f(X)$$

The purpose of supervised learning is to make an approximate of the mapping function close to accurate so that when we introduce a new input data (x), we are able to predict the output variable (Y) for that new data inserted. Supervised learning is anticipated in find the patterns in the data which can then be applied to an analytics process. [13]

There are many ways in which ML can enhance education process in the coming future, which are:

1) Customisable learning experience
2) Student path prediction
3) Unbiased grading system
4) Overall feedback on both students' and teachers' performance

IV. Identified Gaps in Current Systems

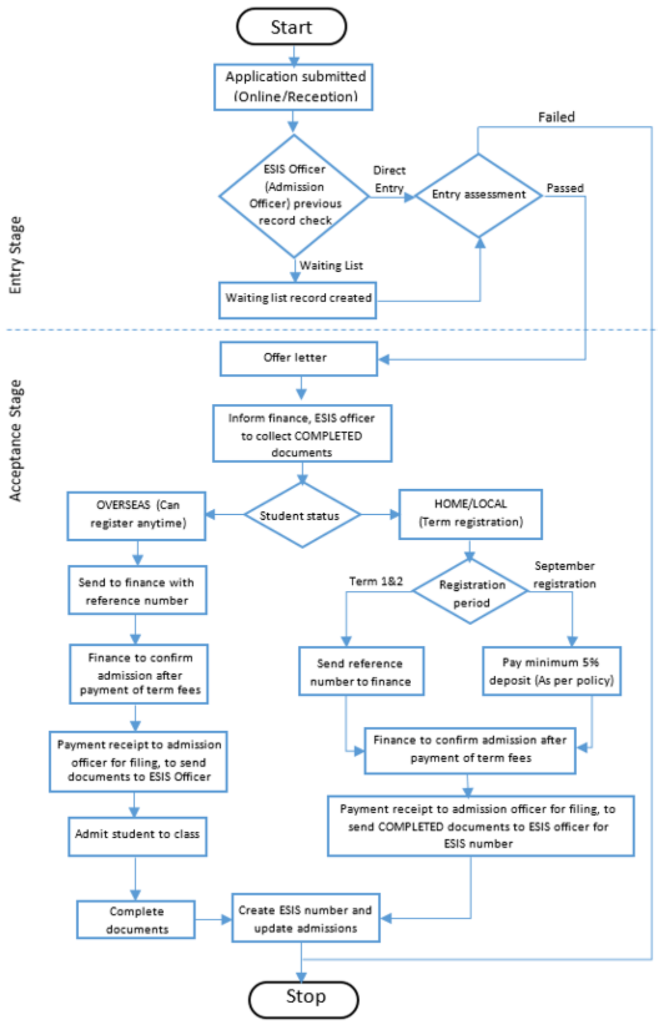

Fig. 1 Standard admission process followed by a school in Abu Dhabi

It has been seen that the education sector in general underutilizes the advanced technologies and is not able to proficiently increase its operational efficiency. Likewise most of the students' records are on papers inhibiting information sharing. The admissions procedures as shown in Fig. 1 that are currently used in schools across Abu Dhabi are not that efficient in terms of time consumed and errors caused.

Previously, schools in Abu Dhabi have considered that the year system is equal to the grade system, and therefore students were assigned to the wrong year/grade groups. Overall student admission, levelling, and differentiation is not consistent throughout schools as some use their own levelling criteria while some use external agencies.

V. Proposed Distributed ML Based Framework

The framework consists of three layers, intelligent decisions layer (Stakeholders), fog layer and cloud layer, as shown in Fig. 2, schools make intelligent decisions with the use of different IoT devices (PC, Laptop, Smartphone, and Tablet) to send a variety of student data and request easily through cloud computing to obtain different decisions and levelling reports. Each network has several application hosts = (H_1, H_2, H_n) providing the SaaS, and can be allocated to execute the cloud stakeholders that make the intelligent decisions. Each application host has a set of resources = (R_1, R_2 and R_n) that can be allocated for the coming school requests. Each network has a network administrator that is responsible for the coordination of the communication between the hosts inside the networks and other networks in the cloud. Network administrator is responsible for running of the algorithm based on the foundation shown in Fig. 2.

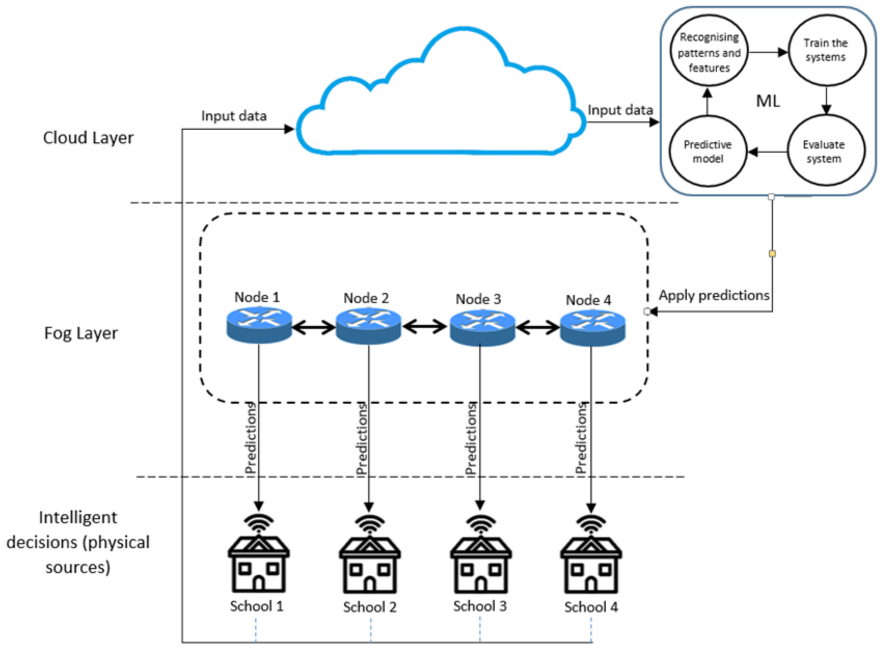

Fig. 2 Proposed system framework overview

A. Initial Suggested Dataflow on the Cloud and ML Process

Different algorithms have different outcome on the outcome of the model and its performance. In order to select the algorithm that performs the best from the start will be difficult because the caret package in R has 237 models, and out of those, 189 can possibly be used for classification problems, [10], [12]-[14].

As shown in Fig. 2, each of the school will be having access to the system and data moved to and from the cloud will be stored there. The cloud is a virtual machine itself and then further split into small virtual machines separated by each port. Apache server being the first server to interact with the user, it will act as the fog layer and then it is connected to the database and finally the collected dataset will be passed onto the ML tools. The data flow among the servers will be done on a controlled basis through the web application to the apache server and thereby to the database. The data in whole are processed with ML algorithm which is supervised decision making. The data are processed and analysed depending on the results patterns and analysis. The logics were embedded and pushed to the web application for each node which does the task of filtering and predicting data.

We will process new datasets of students with parameters to look for ML algorithm to give out results and hereby checking for the results. Once the results have a satisfactory outcome as per expectations, the data will be processed via TIBCO tools to be presented back to the nodes which are authorized to visualize the data. Keeping the ideology of student data, the possibilities of results could be individual algorithms for the levelling, prediction of performance, analysis of student's migration and many more data sets and patterns can be visualized and studied. One perspective of levelling done by the brain.js will be subjected to update depending on the ML results. TIBCO tolls also further extend to the process of reporting and analytical dashboard which shall be embedded to the view of the nodes depending on the permission level provided by the routes and controller.

B. System Data Modelling

There are many factors that have an influence on student admissions, levelling and differentiation, as shown in Table I.

TABLE I
PRELIMINARY FACTORS THAT HAVE AN INFLUENCE ON STUDENT ADMISSION, LEVELLING AND DIFFERENTIATION

No	Quantity	Quantity	Description
1	Student ID	Numerical	0001 +
2	First Name	Nominal	Given Names
3	Last Name	Nominal	Family Name
4	Gender	Nominal	Male / Female
5	Nationality	Nominal	British, American, UAE, etc.
6	Previous School Name	Nominal	Belvedere British School, GEMS American school, etc.
7	Previous Curriculum	Nominal	American, British, MOE, etc.
8	New School Name	Nominal	Belvedere British School, GEMS American school, etc.
9	New Curriculum	Nominal	American, British, MOE, etc.
10	Previous year/grade	Numerical	FS1/PRE-K, FS2/KG1, Year1/KG2, etc.
11	Proposed Year/grade	Numerical	FS1/PRE-K, FS2/KG1, Year1/KG2, etc.
12	Interview Status	Nominal	Passed / Failed
13	Math Entry Exam Mark	Numerical	0% - 100%
14	Science Entry Exam Mark	Numerical	0% - 100%
15	English Entry Exam Mark	Numerical	0% - 100%
16	End of Term 1 Math Mark	Numerical	0% - 100%
17	End of Term 1 Math Mark	Numerical	0% - 100%
18	End of Term 1 Math Mark	Numerical	0% - 100%
19	End of Term 2 Science Mark	Numerical	0% - 100%
20	End of Term 2 Science Mark	Numerical	0% - 100%
21	End of Term 2 Science Mark	Numerical	0% - 100%
22	End of Term 3 English Mark	Numerical	0% - 100%
23	End of Term 3 English Mark	Numerical	0% - 100%
24	End of Term 3 English Mark	Numerical	0% - 100%

VI. CONCLUSION AND FUTURE WORK

Schools in multicultural countries are constantly levelling students without the use of automation. Therefore there is a need to implement the suggested framework in order to assist schools in student transition between schools while also have access to a unbiased grading system that can predict student level based on previous data.

For the future work, there are additional researches to be conducted in order to be updated about the current development of our area of interest. We will continue on developing the computational framework and implementing the framework with the use of different tools to be able to facilitate student admissions on other curricula. Further we will design and develop the sophisticated ML software that will generate the level of the student and provide differentiation information for the teachers. To test the system we will use data that we have already collected. Training of the algorithm will be commenced once the system is tested to be functioning as per expectations. As we have schools that contributed to this research by providing us with valuable data, we aim at implementing the system on those schools and gather results and findings to compare them with the simulation results to discover the reliability of the system.

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