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DEEP LEARNING-BASED MOBILE E-LEARNING MANAGEMENT IN DISTRIBUTED CLOUD COMPUTING

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Abstract:
With the increasing number of schools of higher learning are adopting mobile technologies to improve the quality of service they provide to their student bodies. Even though mobile learning management systems (LMSs) are used all the time in higher education, not much research has been done on the factors that lead to their use and the effects of learning on students' academic performance. In this paper, we develop a cloud-based secured e-learning framework for the various educational system in schools. This framework has three models that includethe client model, networking model and storage model. The study aims at exploring the relationship between the effectiveness of education and the factors associated with mobile LMS, demographics, psychological data, and other external factors. The deep learning-basedregression shows that the employment status and age are significant in classifying the adoption of students over mobile LMSs. Thereby potential links are established between the factors and the mobile LMS. Further, the study is tested in terms of various factors associated with academic performance about mobile LMS.

Keywords
Mobile E-Learning Management, Cloud, Machine Learning, Educational System

1. Introduction

As a direct consequence of the meteoric rise in acceptance of the Internet as a useful tool in pedagogical procedures, the distribution of curricula has moved away from on-site desktops and toward online programmes [1] [2]. As a direct result of recent developments in technology, educational establishments have started implementing new methods of instruction [3]. Because of the development of new technology, educational institutions such as colleges and universities now have access to an abundance of creative resources [4]. The increasing reliance that students have on technology, as well as the requirement that students have access to information at all times, are two of the primary factors that have contributed to the rise in popularity of mobile learning, e-learning, and distance learning. These concepts are gaining more and more attention as a direct result of the proliferation of mobile devices and the use of wireless technology [5].

In educational institutions, the development of so-called Learning Management Systems (LMS) as a shared digital platform that allows students and instructors to connect digitally has been a significant trend [6]. Learning management systems (LMS) not only provide educational institutions with useful learning tools but also make it possible for academic content to be organised and shared effectively.

Cloud computing is one of the more recent technological advancements that, due to its dynamic scalability and resource efficiency, has the potential to have a significant impact on education. When it comes to online education, there is a mechanism for achieving scale efficiency that transfers the responsibility for the infrastructure construction to cloud computing service providers. Customers and service providers can cultivate a relationship that is mutually beneficial by operating in this manner [7]. A plan such as this one can save a significant portion of the money that would otherwise be spent on the introduction of a new educational strategy. Because educational institutions are only responsible for the learning process, content management, and knowledge delivery, cloud-based e-learning continues to benefit from partnerships and cost-effectiveness [8]. This is because the vendor is responsible for the construction, maintenance, development, and management of the educational system, while the educational institution is only responsible for the learning process, content management, and knowledge delivery. Using a cloud-based environment, which is capable of running on any kind of hardware, it is possible to develop e-learning platforms for the next generation. It is no longer necessary to have prior knowledge of cloud computing to connect a personal computer or laptop to a server [9].

The use of cloud computing offers a fantastic opportunity to increase the scope of educational opportunities. The emergence of cloud computing, which is now widely used, has facilitated the development of online learning by

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making it simpler. As a result of the proliferation of the Internet in today world, both students and teachers have access to a plethora of educational programmes and resources that can be accessed online [10]. The implementation of an e-learning system does not require significant amounts of money, time, or human or material resources. This makes it an attractive option for educational institutions. Cloud service providers for e-learning can manage all of these responsibilities. A high level of data security is provided by the cloud-based e-learning architecture because it provides distributed storage, centralised management, and data visualisation [11].

There has been a rise in the implementation of e-learning programmes at a variety of educational establishments. Cloud computing is an option that academic institutions with limited resources for hosting and operating their online learning platforms should consider. This is because cloud computing enables the deliberate use of networked technology in educational processes that would not be possible otherwise. The benefits of cloud computing in education, particularly e-learning, are coming to the attention of a growing number of software developers and service providers [12]. In recent years, educational institutions of all sizes, including colleges, universities, and even K-12 schools, have been increasingly adopting the use of software for online learning that is hosted in the cloud. On the other hand, many people use them in addition to their primary learning management systems (LMS). Researching the technological capabilities of cloud services is now a professional requirement for educators, making it necessary to do so to choose the most effective educational solutions from among those that are comparable [13].

Learning from the convenience of one own home through the use of various forms of digital media is the primary advantage of participating in an e-Learning programme. E-learning typically consists of the following standard components: LMS, courses, and technology. It possible that courseware or other content on the internet could quickly spiral out of control if internet networks aren't properly controlled. The dissemination of information is facilitated even more rapidly than before by the use of instant messaging and social networking. This problem can be made worse by newly developed technologies and applications. E-Learning and other forms of online education are becoming more challenging to disseminate to students as a result of the rising costs associated with the development of learning management systems. At the moment, there is an extremely diverse selection of platforms available for the distribution of web-based services and educational content.

However, each one of them suffers from a variety of problems, the most significant of which is the requirement for ongoing investment to maintain one position at the forefront of developments in the fields of education and learning. A wide variety of educators and digital media experts are required, which adds another layer of complexity to the problem. As a result of this, the number of paying customers necessary to justify the costs would be the most troublesome possibility for a company that is spending this much costs.

In this paper, we develop a cloud-based secured e-learning framework for the various educational system in schools. This framework has three models that include the client model, networking model and storage model. The study aims at exploring the relationship between the effectiveness of education and the factors associated with mobile LMS, demographics, psychological data, and other external factors. The deep learning-based regression shows that the employment status and age are significant in classifying the adoption of students over mobile LMSs. Thereby potential links are established between the factors and the mobile LMS. Further, the study is tested in terms of various factors associated with academic performance about mobile LMS.

2. Background

Connecting several different social networks can produce a massive network. Because it is so simple to communicate and establish connections with other users of the network, online socialism is gaining an ever-increasing following. Some individuals achieve efficient administration of e-Learning systems through the utilisation of networking. In the past, academics have used e-learning to investigate the challenges associated with teaching and learning.

E-learning has several advantages over traditional classroom settings, including the capacity to present information in a way that is both more aesthetically pleasing and more engaging [7, 8]. To solve the issue of content and improve the efficiency of learning, every facet of e-Learning needs to address several challenges. The utilisation of a variety of distinct learning management systems is at the heart of the primary challenge that comes with e-Learning. An example of this would be a business-focused programme that was developed by a company like IBM, Oracle, or Blackboard [9] [10]. It is very expensive to create e-learning and learning management systems, as well as to keep these systems up and running [11]. Some academics, such as those using Moodle [12], have resorted to using open-source software to assist in the process of development.

However, to fulfil the requirements of users, free learning management systems require the participation of programmers, developers, and installers. This is the case even though the systems are free. Nevertheless, the costs are of an extremely significant magnitude. The current standard for learning technologies is known as IEEE 1484.11 [13]. There are several essential components, including the profile of the learner, the delivery of the instructional materials, the testing and evaluation, and the recommendation. Because of this, a single learning management system can't cover all of these functions. The examination of learners is yet another topic

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that needs to be investigated regularly. To facilitate the development of the investigation, a model of learners needs to be developed.

For the raw data of both students and teachers to be of any use, it must first be sorted and then stored. Learning profiles, learning habits, types of media, quality of media, learner ability, and test-taking behaviour are some of the things that may be considered [14]. Because of the aforementioned factors, the capacity of e-Learning systems and other forms of educational content to be disseminated over the internet is currently restricted. The use of the most recent and exhaustive information is essential in the field of education [15]. Consequently, a traditional classroom setting or even the unrestricted nature of the internet cannot compete with the advantages offered by the internet for educational purposes. Educators are expected to be proficient in the use of contemporary hardware and software. In addition to the tests and evaluations that have already been mentioned, it is necessary to analyse the results of a large number of other tests and evaluations to keep track of how the course is progressing [16].

The ultimate objective of the vast majority of researchers is to create a model that will be of assistance in the operation of distributed learning systems. It possible that the issue of an expensive e-learning system could be solved by combining the ideas of cloud computing and deep learning [17]. If this were to be done, the system would significantly profit from the web service technology that cloud computing provides [18]. The new infrastructure, which makes use of web service technology, is not only able to disseminate information, but it can also help with learning and teaching registries, in addition to a great number of other things [19]. Through the utilisation of Web services and the incorporation of a cloud computing paradigm, it is possible to cut down on the high costs associated with the development process, enhance the performance of management, and keep an eye on security [20].

3. Proposed Method

In this section, we utilize cloud computing and deep learning to make decisions has resulted in the development of an innovative new model for learning management systems in this field.

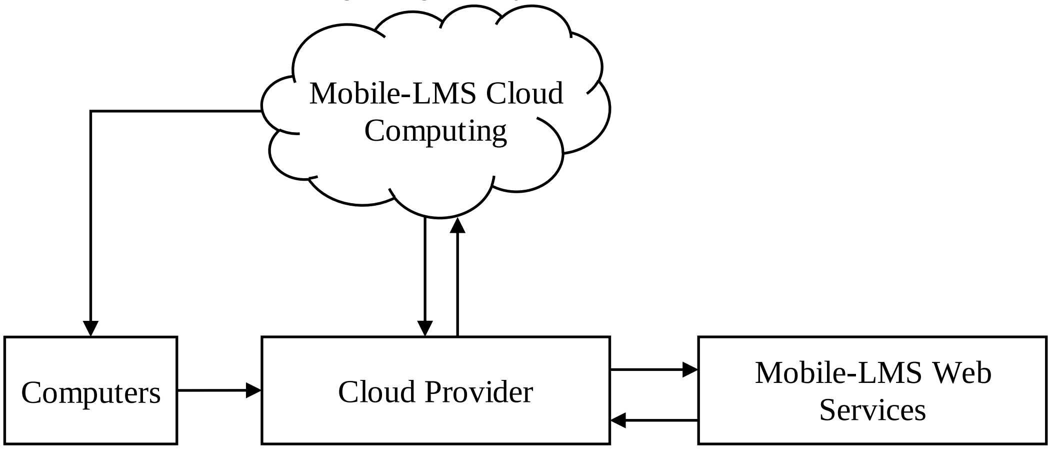

Figure 1: Proposed LMS Web Service

Figure 1 illustrates how distributed e-learning can be accomplished with the help of cloud computing and web services. The user submits a request, which is then received by the provider of cloud services. In the end, the cloud provider will take care of the required resources and services for a particular user, and after that, the e-Learning cloud will be connected to them. In addition, to provide service to the user who requested the cloud, the cloud provider needs to connect to other online services that link together data resources that are located on the internet. By utilising this model of learning management, development costs can be reduced, and the collection of distributed learning materials can be accomplished through the use of the internet. The diagram that can be found below illustrates a fully operational e-Learning cloud.

The procedure starts with users or students submitting a request through the online portal. Before any resources can be assigned, a request has to be processed through the management of the system. Learners who take advantage of this feature will be provided with a copy of the request in addition to the resources that they have requested. The very last thing to do is an evaluation.

Each individual sub-module of the e-Learning services can be used separately from the others. The opening of registration for web services is the responsibility of modules that provide web services. As a consequence of this, the web service registry can collect data and learning materials from dispersed online learners. Consequently, the use of a model allows for the successful implementation of a distributed learning

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management system as well as a cloud computing system. In addition, the costs of both initial investment and ongoing maintenance are significantly reduced.

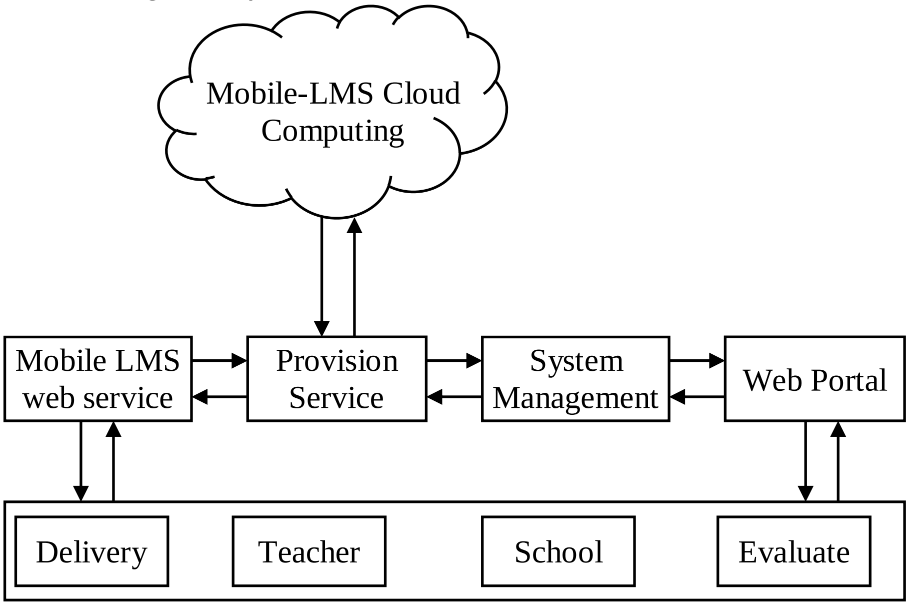

Figure 2: Detailed illustration of Cloud-based Mobile LMS

To develop these models, it is suggested that deep decision learning, which is based on the composition of the teacher, learner, and content, be utilised as in Figure 2. In addition, a model for decentralised learning management systems that make use of web services is presented as a result of the application of web services. The performance of the sample groups is evaluated, and the results are used to help refine subsequent prototypes. The findings revealed a high level of overall satisfaction felt by the company clientele. The model that has been proposed for a distributed learning management system still has a few flaws, the most notable of which are speeds that differ depending on the user internet connection and the lack of content that is available in the language of the user choice.

Deep Learning-based Regression

As can be seen in Figure 3, the proposed model to predict the overall satisfaction makes use of autoencoder and support vector regression. This is done to do so. The preprocessing method was utilised so that the data could be normalised. In this study, high-dimensionality problems are attacked with the help of a deep autoencoder, which works to reduce the number of dimensions. Deep learning is used to make predictions about future decisions by training a support vector regression model to make use of the reduced features.

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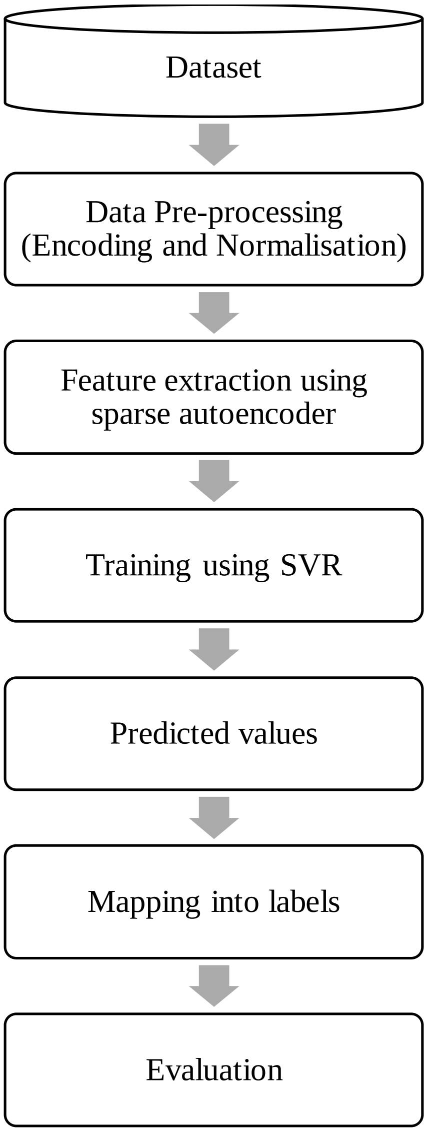

Figure 3: Proposed DL-SVR for finding the overall satisfaction in LMS

The DL-SVR that is being considered makes use of the steps that are detailed below.

Steps:

Step 1: Cleaning of the dataset

Step 2: One-hot encoding is used to encode the cleaned data.

Step 3: Min-Max method was utilised to accomplish the normalisation of the dataset.

Step 4: Train the SVR using a limited feature set.

Step 5: DL makes predictions about the labels based on the testing data.

Training the model

Support vector regression, also known as SVR, is an implementation of support vector machines (SVM) that is used for regression and function approximation. SVR has proven to be superior when dealing with multi-dimensional datasets and small sample sizes. SVR searches for an ideal approximating hyperplane in the high-dimensional feature space to approximate the linear relationship between the n-dimensional input vectors and the 1D output variables. This is done so that the linear relationship can be approximated more accurately.

To implicitly translate the data to higher-dimension feature space and improve the data fit, the radial basis function, abbreviated as RBF, was chosen to serve as the kernel function. During the SVR model training phase, it is necessary to achieve optimal values for the penalty parameter c as well as the kernel function parameter g. The empirical method is the one that is utilised most frequently when searching for the optimal values of the parameters c and g. In this investigation, we used grid search and 5-fold cross-validation to locate a broad range of parameters (c and g) to finish the training of the SVR model.

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This section provides a comprehensive analysis of the SVR training model ability to predict incursions. The support vector machine (SVM) makes use of the function to map the training set onto a feature space with a higher dimension. It is possible to extract a separating hyperplane from the space occupied by the features by making use of the max-margin function. For instance, a data set intended for instructional purposes.

$a_i \subset R^n$, for all $i=1,2,3,\ldots,l$ (1)

where

l- data size for at training phase;

$c_i=\pm 1$ - classlabels.

For instance, the subsequent functions depict examples of +ve and –ve as functions of the direction of the hyperplane w with b standing for the offset scalar. $f(a)=w*\varphi(a)+b\geq 0$and $f(a)=w*\varphi(a)+b\leq 0$are presented in the context of the hyperplane. This indicates that for SVM to determine the direction of the hyperplane, it takes the hyperplane itself as its input and uses the offset as its output. Even though a linear function that is dependent on the input has not been determined to show the category of data, an ideal hyperplane that can differentiate between the two types of data has been determined.

The collection of data in which each of the values in the range ($a_i \subset R^n$) corresponds to an input from the sample space and in which $c_i \subset R$ corresponds to the respective output values ($i=1,2,3,\ldots,l$). In this scenario, each of the values in the range ($\{(a_1,c_1),\ldots,(a_l,c_l)\}$) represents input from the sample space. Estimating a function in such a way that it represents long-term values is the fundamental premise behind regression.

The estimation function of the SVR can be described as follows, as a general rule:

$f(a)=w\cdot\varphi(a)+b$ (2)

where,$w \subset R^n$, $b \subset R$

φ - on-linear transformation from R^n to a space with higher dimensions does not follow a linear path in this particular instance. The values of w and b play a significant role in determining the a value, which can then be lowered by minimising the risks associated with regression.

$$R_{reg}(f)=T\sum_{i=0}^{l}\Gamma\left(f(a_i)-c_i\right)+0.5\|w\|^2 \quad (3)$$

Where

$\Gamma(.)$ - cost function,

T - constant and

w - vector is hence stated as below:

$$R_{reg}(f)=T\sum_{i=0}^{l}\left(\alpha_i-\alpha_i^*\right)\varphi(a_i) \quad (4)$$

To make the necessary adjustment to the overall equation, just replace Eq. (2) with Eq. (4).

$$f(a)=\sum_{i=1}^{l}\left(\alpha_i-\alpha_i^*\right)k(a_i,a)+b \quad (5)$$

In this case, the dot product takes the place of the kernel function $k(a_i,a)$. The dot product can be executed in feature space with greater dimensions by using lower dimension space if this function is used. This does not require the input data to be transformed (φ) in any way. To obtain the complete kernel, it is necessary to comply with Mercer condition, which represents a portion of the inner product space. RBF is the kernel function that is used the most frequently, and it is used to solve the regression problem:

$$f(a)=\sum_{i=1}^{l}\left(\alpha_i-\alpha_i^*\right)k(a_i,a)+b \quad (6)$$

The extensively utilised cost function, which is insensitive to loss:

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$$\Gamma\left(f(a)-c\right)=\begin{cases}\left|f(a)-c\right|-\varepsilon & \left|f(a)-c\right|\geq\varepsilon\\ 0 & otherwise\end{cases} \quad (7)$$

By finding a solution to the quadratic optimization problem, it is possible to minimise both the regression risk expressed in Eq. (3) and the ε-insensitive loss function:

$$0.5\sum_{i,j=1}^{l}\left(\alpha_i^*-\alpha_i\right)\left(\alpha_j^*-\alpha_j\right)k\left(a_i,a_j\right)-\sum_{i=1}^{l}\alpha_i^*\left(c_i-\varepsilon\right)-\alpha_i\ \left(c_i+\varepsilon\right) (8)$$

w.r.t $\sum_{i=1}^{l}\alpha_i\ -\alpha_i^*=0;\alpha_i\ ,\alpha_i^*\in\left[0,T\right]$

The Lagrange multipliers $\alpha_i\ ,\alpha_i^*$ point to the solutions to the quadratic formula that was previously indicated. As a consequence of this, the prediction moves closer to the value that is ultimately determined to be ε. The non-zero values in the Lagrange multipliers, which are denoted by the value as in Eq.(8), help locate the regression line. Since the Lagrange multiplier is always equal to zero wherever you are in the tube, the regression function is unaffected by this property. As a consequence of this, Lagrange multipliers might end with non-zero values that, if the requirement ($|f(a)$-$c|\geq\varepsilon$) is satisfied, could be used as support vectors.

The constant T, as stated in Eq.(3), is utilised to penalise estimation errors. When the T is large, regression training needs to be carried out with a reduced degree of generalisation so that errors can be kept to a minimum. A little bit of Tgives more penalties if an error occurs. As a consequence of this, generalisations can become more accurate because the margins of error are reduced to an acceptable level. This is because SVR does not produce an error when T is infinite, which results in the creation of a more complex model than when $T$is zero. When $T$is zero, however, a more straightforward model is produced.

Lagrange multipliers are applied to find a solution for the values of w. Thus, calculating the values b can also be done with the help of KKT.

$\alpha_i(\varepsilon+\zeta_i-c_i+(w,a_i)+b)=0$

$\alpha_i^*\ (\varepsilon+\zeta_i^*\ -\ c_i-(w,a_i)-b)=0$

$(T-\alpha_i^*)\,\zeta_i^*=0$

Calculating the errors requires the use of slack variables known as ζ_i and ζ_i*. These variables can be found in the equation. Because $\alpha_i,\alpha_i*=0$, $\zeta_i*=0$, the solution for B can be expressed as a function of $\alpha_i\in(0,T)$, b.

$b=c_i-(w,a_i)-\varepsilon$,for $\alpha_i\in(0,T)$

$b=c_i-(w,a_i)+\varepsilon$,for $\alpha_i^*\in(0,T)$

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Both SVR and SVM can be used in conjunction with one another without requiring a significant modification. It is necessary to conduct experiments utilising the kernel functions and the penalty *T*. It computes the penalties that are associated with inaccurate estimates.

Testing the model

This section describes the SVR training model that can be used to predicting the instances.

4. Results and Discussions

The use of mobile LMS increased is 12% of self-efficacy, 14% of innovativeness, 13% of perceived ease-of-use, and 8% of perceived usefulness. In addition to this, it was discovered that there is a unit shift in the subjective norm associated with a 6% increase in the likelihood of using a mobile LMS. According to the findings of this research, innovativeness and self-efficacy are more important predictors than psychological qualities and external circumstances. This was found to be the case across the board. Previous studies have found that psychological factors play a significant role in the degree to which people are open to adopting new technologies.

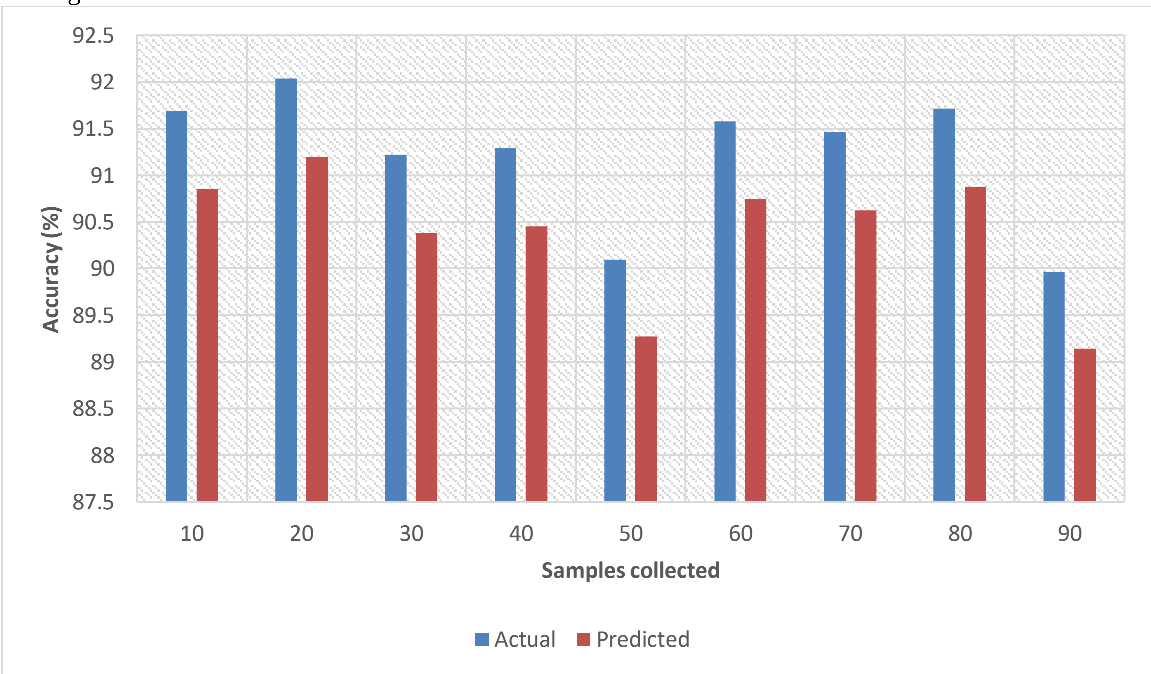

Figure 4: Accuracy of the predicted self-efficacywith actual self-efficacy of the mobile LMS

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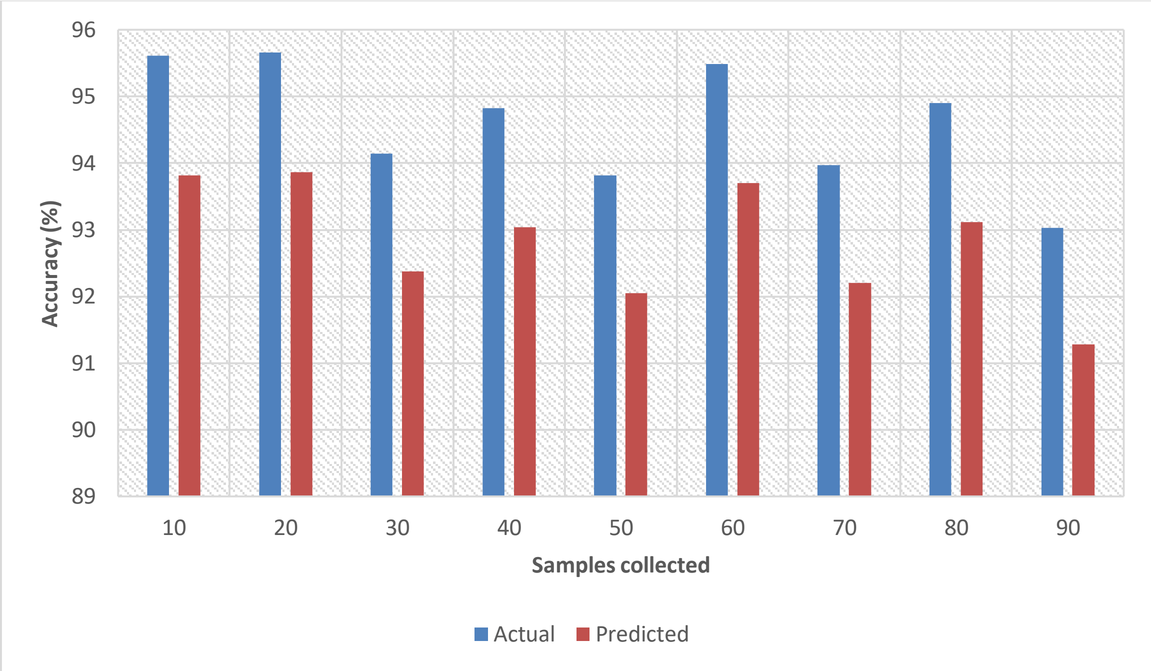

Figure 5: Accuracy of the predicted Innovativenesswith actual Innovativenessof the mobile LMS

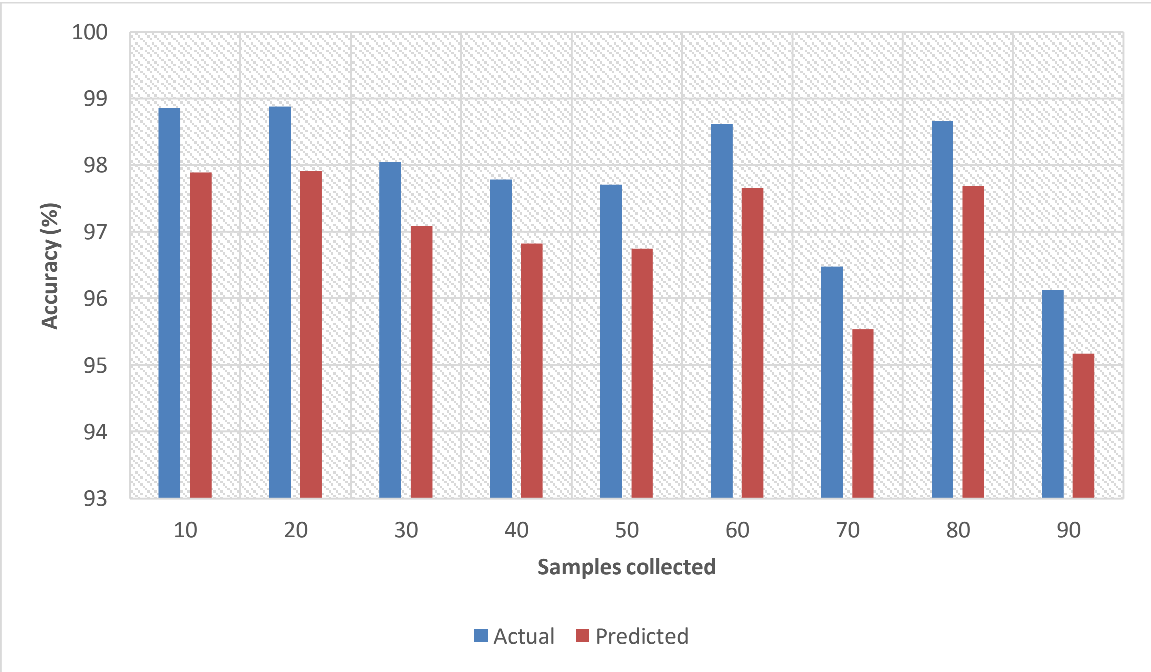

Figure 6: Accuracy of the predicted perceived ease-of-use with actual perceived ease-of-useof the mobile LMS

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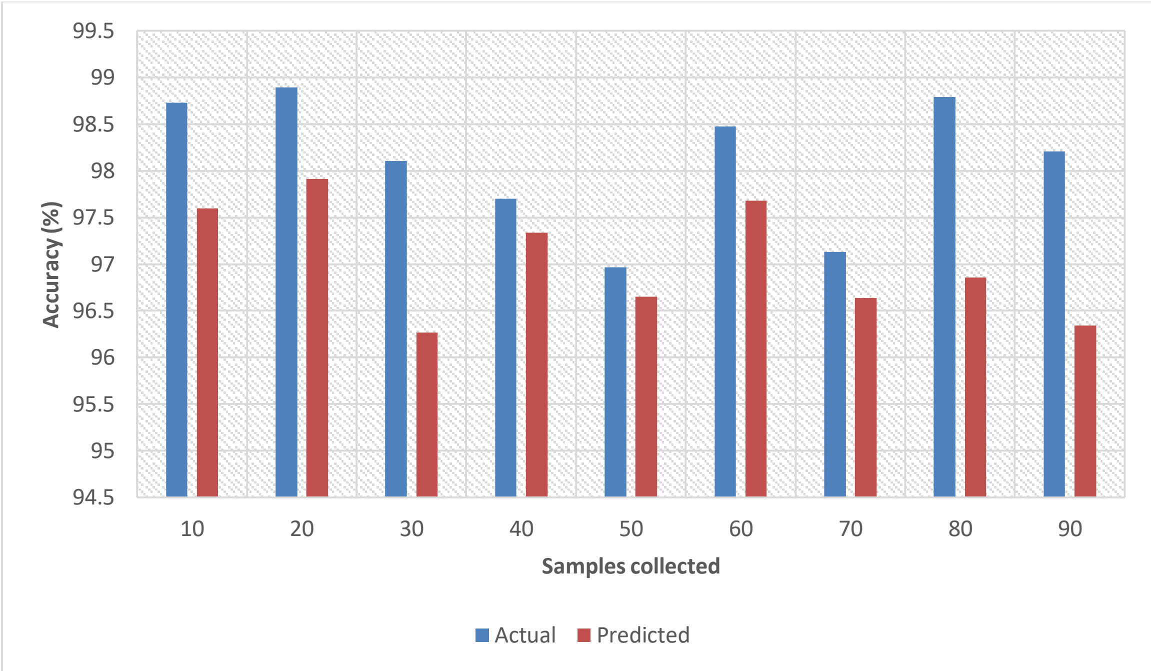

Figure 7: Accuracy of the predicted usefulness with actual usefulness of the mobile LMS

It was found that individual factors, such as age and employment status, had a significant bearing on whether or not mobile learning management systems were adopted. Because online college students are typically adult learners who fall within a wide range of age and are likely to be working in full-time mode, it is reasonable to anticipate that their mobile usage patterns will differ from one another. Even after controlling for other factors, the findings of this study indicate that students at the age of 15s and older make use of mobile LMS a great deal less frequently than students in their 20s do. Previous research has pointed to the relatively small screen sizes of mobile devices as a potential disadvantage.

This disparity might have a rational explanation, such as the gradual blurring of one vision that comes with advancing age. Mobile learning management systems were utilised on a more regular basis by students who worked full-time jobs in comparison to those who did not work full-time jobs. Full-time employees who use mobile LMS have the advantage of being able to access with learning activities and lectures whenever they want and from wherever they are.

We looked into the correlations between variables based on the findings of the initial analysis by comparing with logistic regression, including additional sets of variables, and comparing these results to one another. By comparing the outcomes of the following models to those of the earlier models, we were able to establish that certain predictors that had been previously significant had lost their statistical significance as a result of controlling for other factors that had been incorporated into the following models. To put it another way, there may be a connection between the components that have experienced a shift in their relevance and the new model. In the first logistic regression model that we constructed, we found that age and gender differences between the students are statistically significant. This was the case for both groups. However, when psychological characteristics were taken into account in the second model, neither of these remained statistically significant after the correction. It was found that both males and females used mobile LMSs at the same level when three psychological characteristics were controlled for. These characteristics were innovation, self-efficacy, and perceived ease of use. According to the findings of this study, gender does appear to play a role in these psychological aspects.

5. Conclusions

In this paper, we develop a cloud-based secured e-learning framework for the various educational system in schools. This framework includes the client model, the networking model, and the storage model. When it comes to mobile LMSs, the study takes into account demographic data, psychological information, as well as other external factors. According to the findings of the in-depth learning-based regression, the use of mobile LMSs by students can be categorised in several different ways. As a result, it is possible to establish a connection between the factors and the mobile LMS. In addition, the research is analysed in terms of several different aspects of academic performance that are associated with the use of mobile LMS.

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