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# Cloud secured mobile e-learning system solutions using machine learning approach

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***Abstract*---**Specifically designed learning models namely the mobile learning systems are conveniently available at a mobile device. The following are the difficulties that mobile learning systems must overcome: connection speed, processing power, adaptability, and the difficulty of attaining security. In this paper, we design and construct a cloud-based secure mobile e-learning management system (CSMELMS) for educational purposes. The system is made up of three primary modules, which are the client, mobile network, and cloud model. The client model makes the users to access the data via mobile application, which is connected to a mobile network using the client model. The authentication server is responsible for ensuring that each user attempting to access the system is who they claim to be. The CSMELMS system was developed using the Java programming language with the database being provided by MySQL. When the model is tested using a machine learning algorithm, it was found to be effective at enabling it for available to students when and where they need them. The utilisation of machine learning concepts enables better and secured operations for educational purposes. The results of simulation shows that this model is better at providing a better e-learning portal for students and teachers.

***Keywords*---**mobile learning systems, mobile e-learning management, educational purposes, cloud model.

## Introduction

When it comes to e-learning, the cloud is a subset of cloud computing that is used for e-learning. It will have a positive impact on learning technologies and their infrastructure [1]. It is feasible to supplement traditional e-learning


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infrastructure with cloud-based e-learning, which is becoming increasingly popular [2]. Once the instructional resources of e-learning systems have been virtualized on cloud servers, they can be rented out to students and educational organisations through cloud service providers [3].

Because of the relevance of security issues in this sort of technology, the reliability of the system in the minds of users is very important. The usage of cloud-based e-learning technology and the e-learning community is fraught with dangers because the system is dependent on web-based resources for its operational functionality [4]. E-learners obtains a variety of benefits from the cloud, but the cloud security continues to be a source of controversy due to the difficulties and problems associated with maintaining security in a digital environment [5].

The IDC report on cloud security difficulties is an excellent example of how IT professionals and other stakeholder groups are concerned about security vulnerabilities while deploying cloud services for their products or services [6] [7]. There are still concerns regarding cloud security from these organisations, despite the fact that all of them are well-known in the IT sector for providing reliable products and services [8]. As a result, these firms adhere to a diverse set of security principles and regulations in order to safeguard the data of their clients stored in the cloud [9]. While e-learning solution providers implement security standards and protections for their own products, they also ensure that the same standards and safeguards are in place for the resources they supply and the students they serve [10]. Each of the security difficulties and countermeasures associated with cloud computing and e-learning technology is explored individually in order to identify the most important security issues and countermeasures for cloud-based education [11] [12].

As a matter of fact, many governments are making significant expenditures on e-learning today, recognising that the success of a country is directly proportional to the amount of money invested in educational infrastructure [13]. Because of the growing trend in the information technology business and the increasing speed of internet sources, there are several opportunities to give education to a large number of people with relative ease [14]. There is little time or effort required to learn new things and expand your knowledge set. Because issues such as expenditure and hardware prices were relatively straightforward to manage, acquiring information in the field of e-learning was rather straightforward [15]. In line with the growing popularity and demand for e-learning, a slew of new security vulnerabilities has surfaced.

Security problems with e-learning must be addressed, and in order to handle all of these concerns, it is necessary to incorporate a variety of different security functions and technologies into the learning environment. In some situations, such as biometrics, it may be necessary to use a combination of hardware and software in order to carry out these functions. E-learning is used when two or more information and communication systems must work together and other electrically enabled technologies are employed [16] [17]. A wide range of learning approaches, such as web-based learning and computer-based learning, virtual classrooms, and so on, are included in the term e-learning. At the same time, there are a variety of situations in which e-learning is beneficial. In addition to other issues such as speed, dependability, and adaptability, security and privacy should be considered fundamental aspects of e-learning systems [18]-[20].

In this paper, we discuss how a cloud-based, secure mobile e-learning management system (CSMELMS) was conceived and created for educational application development. Among the three fundamental components of the system are three models of clients: client-server, mobile network-based, and cloud-based. Authentication is required for all users before they can have access to any component of the system, and this is accomplished through the use of an authentication server.

**Related works**

It is vital to examine the quality of LMS-based interactions between users in order to determine the true nature of their behaviour when interacting inside a system. This is done through the use of questionnaires. According to the available evidence, some relevant studies regarding the quality of instruction have looked at LMS data statistics, including learner-teacher debates and exchanges in online forums [21].

The quality of QoI analysis was improved by Dias and Diniz [22], who gave a more complete and quantitative technique. A normalised index of user quality of life (QoI) is quantitatively predicted by transforming the knowledge of subject matter experts into fuzzy constructs, according to their model, which takes into account interactions between users based on LMS use and quantitatively predicts a normalised index of user QoI. As a result, it is feasible to discover trends in LMS engagement and provide users with tailored feedback as a result of this.

A new method of analysing human interaction processes in an LMS-based online learning course has been developed by Dzandu and Tang [23]. They followed a semiotic framework as a guide in order to find gaps or defects in human information interaction in the areas of syntactic, semantic, pragmatic, and social context gaps or issues. They did, however, rely on static questionnaires rather than the more dynamic LMS discussions to accomplish their goals.

Several researchers, including Dias et al. [24], have proposed the Fuzzy Cognitive Map (FCM) as a technique for efficiently characterising how LMS users interact with it and, as a result, measuring their Quality of Interaction (QoI) in the B-learning environment. With the use of their FCM-QoI model, they were able to conduct both static and dynamic analyses of the QoI influential concepts, which revealed the potential to boost flexibility and adaptability in QoI modelling and feedback approaches.

When Cerezo et al. [25] gathered data on student effort, time spent working, and procrastination behaviours, they discovered that they could use this information to better understand the student asynchronous learning processes and match these behaviours with various degrees of academic performance. This study makes an attempt to shed light on the role of LMS interaction in student accomplishments; however, it lacks generalisation power and assesses LMS-based quality of interaction (QoI) primarily based on the grade of student accomplishments rather than the actual quality of interaction itself.

**Proposed Method**

The system is made up of three primary modules, which are the client model, the mobile network model, and the cloud model, respectively.

- The client model enables users to access the content in cloud via mobile or internet application, which is connected to a mobile network using the client model.
- The cloud model is made up of several layers including business layer and authentication server.
- The authentication server is responsible for ensuring that each user attempting to access the system is who they claim to be.
- It also allows for easy interaction between users and the content thanks to different interaction modes such as audio, graphics, and video with feedback features.

Figure 1 shows the architectural model for an enterprise mobile learning management system that is safe.

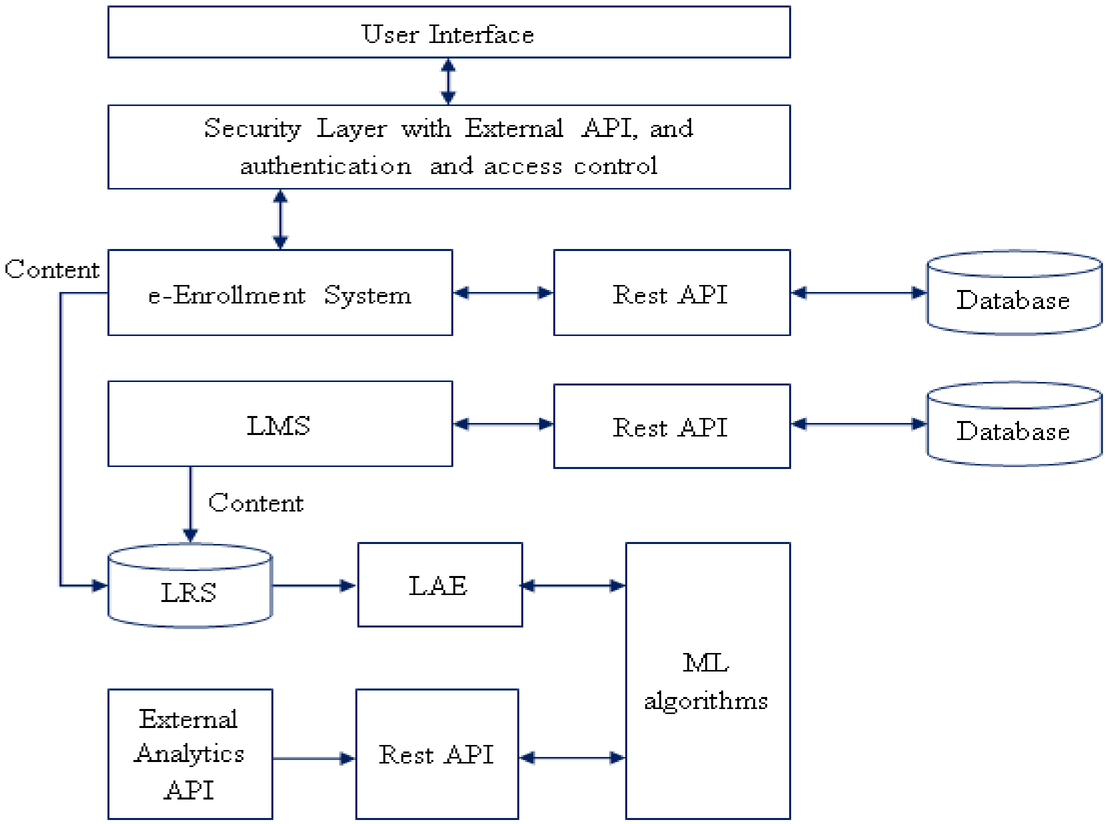


Figure 1: Proposed e-Learning Management System (LRS- Learning Record Store; LAE – Learning Analytics Engine)

In the event that a user requests a cloud resource, the logical layer of the cloud server receives the request and processes it before sending a request to the access layer, which in turn returns the requested resource to the user. In this case, the user is allowed access if he is authorised to utilise the resource he is requesting. Users who are not authorised to access a particular resource are notified by the data access layer, which then sends this information on to the business layer through the use of an error code generated by the data access layer.

**Client model**

It is a two-way communication channel between the user and the software that is represented by the client model. Its role is to handle all user-to-system communication on behalf of the system. In the client model, there are several alternative interfaces for students, educators, and administrators to choose from. There are additional functional components, such as users, mobile devices, and adaptation, that are included in the package. An example of a user model is as follows:

**User model**

In the cloud, there are three types of users who can interact with the system, each with a different set of privileges from the others. These three individuals represent the school principal, an associate professor, and an undergraduate student. In order to gain access to the system, each of them must have a unique user ID and password, as well as varying levels of operational authority and duties within the system.

**User Interface**

All users of the LMS have their own dashboards, which allow them to engage with the system in a variety of ways. Management, instructors, administrators, and students all have their own dashboards. User profiles, chat systems, course navigation, and shared course content are all common components of user interfaces, regardless of the job of the person using the system. For example, based on the job allocated to the administrator, the management interface may include audit logs, teacher performance vs. courses, retention rate, withdrawal rate, new enrollment rate, and so on. Student progress, performance, and work can be examined by external stakeholders, such as funding organisations and awarding bodies, despite the limited capabilities of the LMS.

**Report Dashboard**

The LMS provides a diverse range of reports to fulfil the needs of a diverse range of stakeholders and users. The topics covered include everything from general success rates to individual course patterns, learner employment status, levels of engagement and assessment, among many other things. The overall accomplishment rate, for example, emphasises the achievement rate per cohort for a certain academic year, as an example. The report is used by the administrator to compile the MP annual self-assessment report, which is sent to the MP.

The reports that are required by the teaching staff are separate from the reports that are required by management and other outside stakeholders. They are both quite significant. A report of this nature assists the teacher in categorising students into three groups: those who have not yet begun the course, those who are presently enrolled, and those who have completed the course. These categories give the instructor the opportunity to intervene and provide further assistance to the pupils.

**Learning Analytics**

The learning analytics feature of a LMS is one such function. The LMS generates a number of reports to assist in decision-making. The indicators provide users with valuable information on the overall activities and performance of the learners, which they can then use to make decisions. In accordance with the user position, a variety of analytics reports are provided, including an instructor view of group progress, a student performance, and the corresponding activity logs. This allows the instructor to identify those students who require additional instruction and learning support.

Learning Analytics (LA) can be used to track learner progress, personalise learning needs, and a variety of other functions to enhance the learning and teaching experience. Traditional LMS are incapable of analysing the massive volumes of data created by learner interactions with the system. This is especially true for online learning environments. They can be analysed using learning analytics. It is difficult, however, to analyse this data in a meaningful way because it comes from a number of sources and is both structured and unstructured by nature.

Structured data can be properly analysed with the help of machine learning classifiers. The data can be used to train an ML system, which can then be used to uncover rules and patterns for data-driven analytics. The accuracy of a machine learning model is closely tied to the properties of the data on which it is created through exploratory data analysis. In order to identify the most significant LMS system characteristics, a number of factors were taken into consideration. In addition to an online activity log, there are important statistics available, like the number of students in each cohort, their age and gender, and their highest level of education.

With the help of the criteria included in the activity report, the suggested method aspires to provide an accurate and automatic assessment of the participant knowledge level. The user activity model can be utilised as a classifier in a machine learning approach for classification that is both successful and efficient. There is a plethora of different classification algorithms available, each of which has its own set of advantages and disadvantages to consider. For classification models, it is required to examine two possible configurations in terms of domain knowledge dependency before beginning the process of generating them: generic and specialised. Depending on your requirements, you can obtain a classifier for a specific domain or a generic classifier provided you select the appropriate configuration. As a result, the classification models used in this work are based on a single dataset from a single domain, which simplifies the research. Many classification algorithms tested on this dataset, on the other hand, show promise in terms of tackling the issues related to the evaluation of knowledge.

**Descriptive Analytics**

Learning analytics begins with descriptive analytics, which provides a broad picture of current learner status based on data from prior students. Descriptive analytics is the first step in learning analytics. It is important to note that this first step is concerned with minimising the amount of data and performing exploratory data analysis (EDA). This is the initial step in the process of developing a machine learning model, and it serves to create the groundwork for the model. The LMS is responsible for identifying patterns and anomalies during EDA. Because of this, EDA encourages users to use the data set to assist them in selecting the best features, which will result in stronger prediction models in the future.

ML may now learn without having to be explicitly instructed, which represents a significant leap in the field of machine learning. The use of AI and ML has increased dramatically over the past decade, with applications in a wide range of fields. ML algorithms are used to build general hypotheses and predictions about future events based on examples provided by users outside the system.

**SVM Classifier**

Supervised learning is a prominent machine learning technique in the context of constructing an accurate prediction model from pre-labeled data. These comprise characteristics as well as the desired output value for a given combination of attributes. When the training data is analysed, the supervised learning algorithm can predict future examples based on the same feature vector that was used in the training. Supervised regression and classification methods are the two possibilities available to you if you are interested in employing supervised learning. An identified dataset was used in this work to conduct identification on the obtained data. A feature vector consisting of seven features from several wells was used in this study to identify the data.

Specifically, the maximum margin in this scenario is expressed as follows:

$$\text{margin} \equiv \arg\min_{\mathbf{x}\in D} d(\mathbf{x}) = \arg\min_{\mathbf{x}\in D} \frac{|\mathbf{x}\cdot\mathbf{w}+b|}{\sqrt{\sum_{i=1}^{d} w_i^2}}$$

In order to accomplish this, SVM makes use of the kernel method to construct non-linear boundaries between data points that are being compared with each other. SVM calculations are intended to accurately classify all of the data in a set of conditions. It is possible to perform mathematical computations with the help of following expression:

If $Y_i$= +1; $wx_i + b \geq 1$
If $Y_i$= -1; $wx_i + b \leq 1$

Vectors are utilised to express the weight of each component in these two variables, which are vectors in turn. As a result, the value of $wx_i + b \geq 1$ must always be greater than zero in order to correctly separate the information. SVM selects the hyperplane that has the largest distance between it and the user out of all the possible hyperplanes that are available. When you have an extensive training dataset and every test vector falls within an acceptable radius of r from the training dataset, this is known as a good fit. Now we have a winner if the chosen hyperplane is as far away from the data as physically possible. To figure out which hyperplane is best for the margin, you also need to figure out which lines connect the closest points of the datasets in this way.

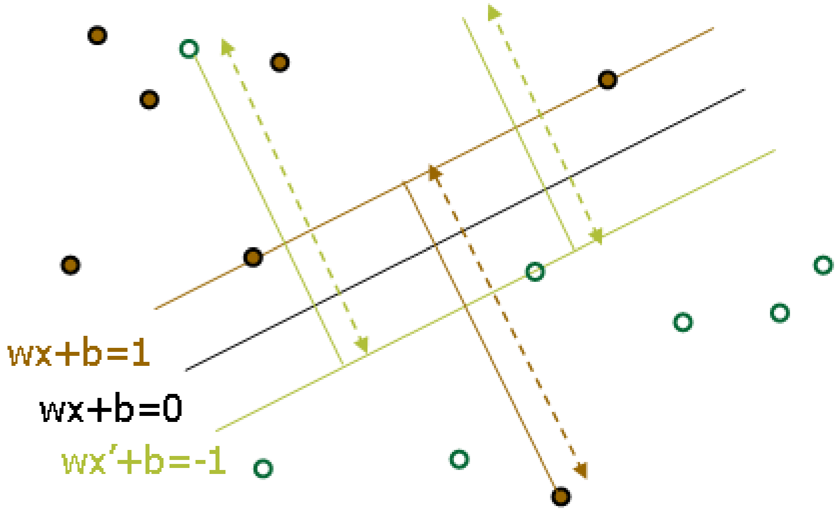


Figure 5: Representation of Hyper planes

The distance between the origin and the nearest point on the hyperplane can be calculated by increasing the value of *x* on the hyperplane. On the other hand, we find ourselves in a similar scenario. The total of the distances between the separating hyperplane and the nearest points is found by solving the two distances and subtracting the two distances from each other.

$$\text{Maximum Margin} = M = 2 / ||w||$$

Margin maximisation has now become synonymous with achieving the bare minimum. The study team was now confronted with a quadratic optimization problem, and they needed to figure out what w and b were. It is necessary to tackle this problem using the optimization of a quadratic function with linear constraints. The answer to the dual question is associated with a multiplier $a_i$, which is defined as the smallest values of $w$ and $b$ necessary to reduce $\Phi(w) = 0.5 |w'||w|$ to the smallest value of (w).

$y_i (w * x_i + b) \geq 1.\ \forall\{(x_i, y_i)\}$

Solving this the following function is obtained

$w = \Sigma a_i * x_i$; $b = y_k - w * x_k$ s.t. $ak \neq 0$

Therefore, the classification takes the form

$f(x) = \Sigma a_i\, y_i\, x_i\ * x + b$

**Personalized Learning Support**

The LMS provides individualised learning assistance as part of prescriptive analytics. The key objectives are to keep students interested and engaged in their learning and teaching. Individualized learning support sessions for individual or group learners are provided in order to boost the user engagement and support for the learning experience. Extra learning resources may be shared with the learner and the instructor, depending on the needs of both parties.

**Results and Discussions**

This system was developed using java framework technology, with MySQL serving as the data storage system. It was decided to employ machine learning algorithms to test the model efficacy in terms of delivering educational information and materials to students when and where they were required. Conclusions. An e-Learning environment is the subject of this work, which builds and tests machine learning classification models using data from the user knowledge modelling data set1. Individual behavioural characteristics, exam performance attributes, and knowledge level as a target attribute are the three key aspects of the data gathering process, and they are all collected separately. One hundred and forty-five instances are used to validate models, with the remaining forty-three occurrences being utilised to build the actual models.

When classifying test circumstances simply on the basis of data from the developed model, more than one strategy was tried in this study, and the results were mixed. In Figure 5, a visual depiction of the categorised (predicted) circumstances that the actual examples are confronted with is depicted as a confusion or contingency matrix (actual instances). A lot of different ways are used to figure out how well the algorithms that have been used work together.

The disparity between the rows carrying actual classes and the columns containing predicted classes draws attention to the tangle known as classification mistake. The number of successfully identified cases in a row is represented by the True Positive (TP) and True Negative (TN) indicators, respectively. Consequently, true and false are both true and false in this situation, and vice versa. Better algorithms will have the greatest amount of TP and TN, indicating that they are more efficient than their counterparts. Incorrect classification will result in false positives (FP) and false negatives (FN) being misclassified as true and false, respectively, when they should have been classified as correct and actual incorrect.

Experiments were carried out in order to assess the effectiveness of the specified categorization algorithms in determining a user degree of knowledge. In this case, some algorithms that can be used include J48, Random Forest (RF), Multi-Layer

Perceptron (MLP), Logistic Regression (LR), and Naive Bayes (NB), to name a few. The algorithms that have been applied use the training data to build a model, and then the test data is used to check the accuracy of the model. In the test data set, SVM, MLP, and SL beat all other classification methods in terms of overall accuracy, whereas MLP and SL are the most accurate classification methods. Correct classifications account for 1.39% of total prediction results in the top models, according to the study. The total accuracy of all models is shown in Figure 2. Naive-based algorithms fall short of 98% accuracy, while tree-based algorithms are slightly better than Naive-based algorithms.

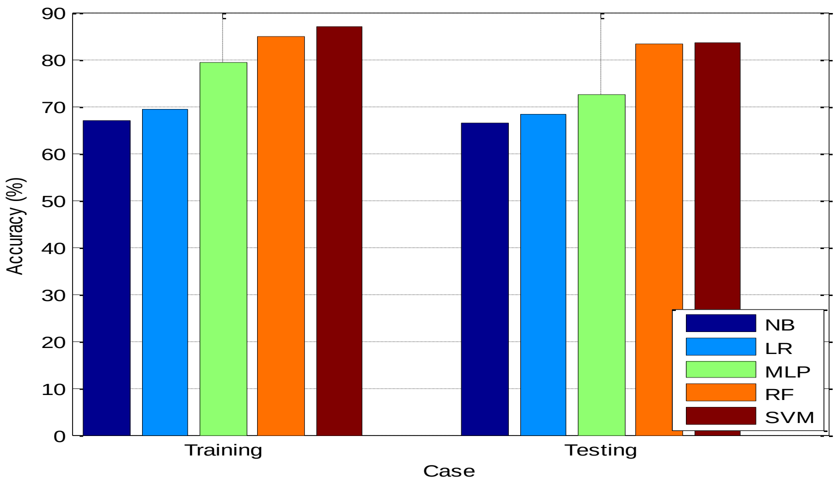


Figure 2: Accuracy of SVM with other models over test dataset

Figure 3 shows a study of the error rate using the SVM model, which demonstrates that the SVM model has the lowest error margin for all measurements. In Figure 4, it is demonstrated that a weighted average of all the measures for all the classes results in overall algorithm performance, which is summarised and displayed. The results of classification with various other metrics are depicted in Figures 4-6. In this case, the variations in performance across algorithms for specific classes are immediately noticeable. This demonstrates that MLP, SL, and SVM are less forgiving of socioeconomic differences.

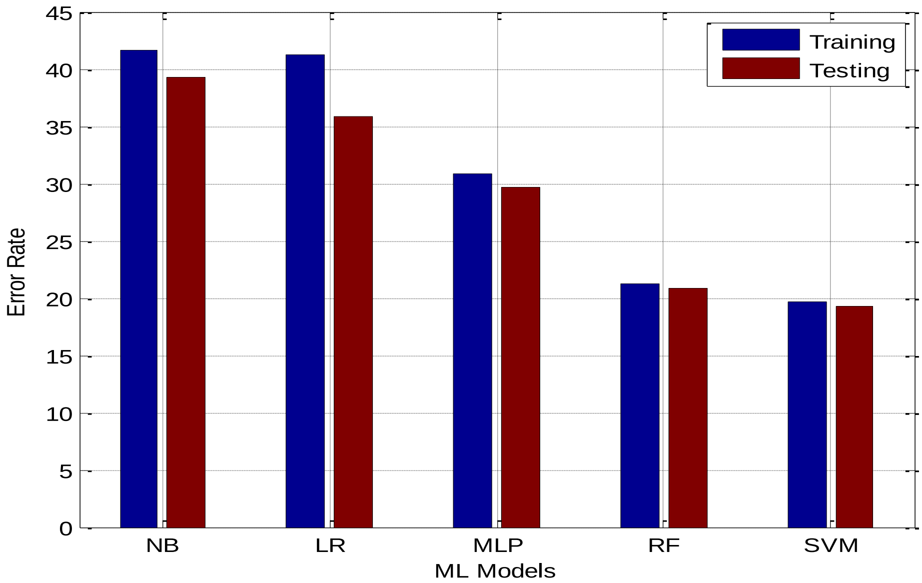


Figure 3: Error Rate

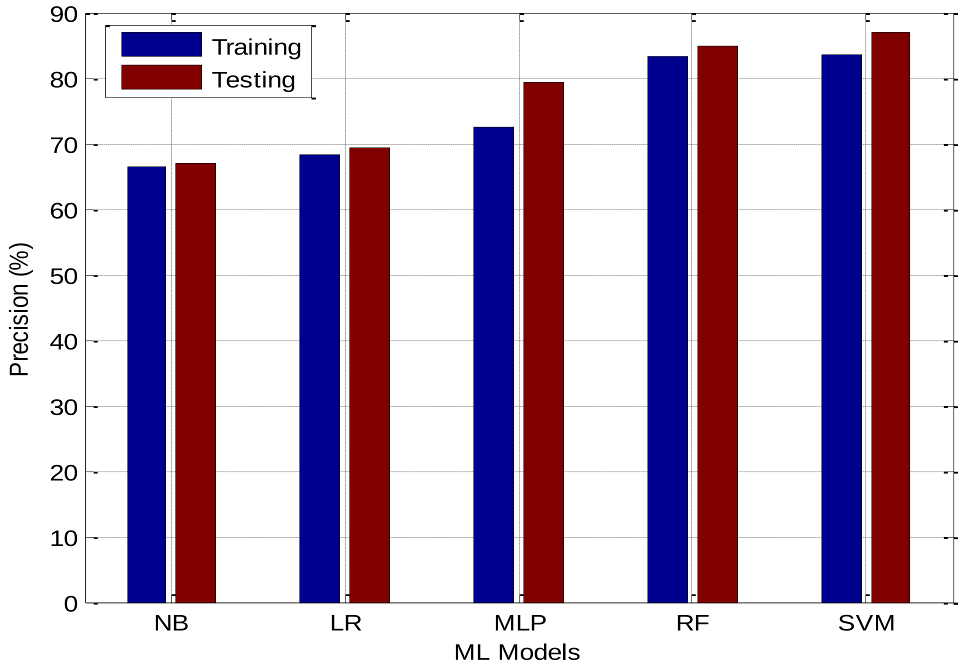


Figure 4: Precision

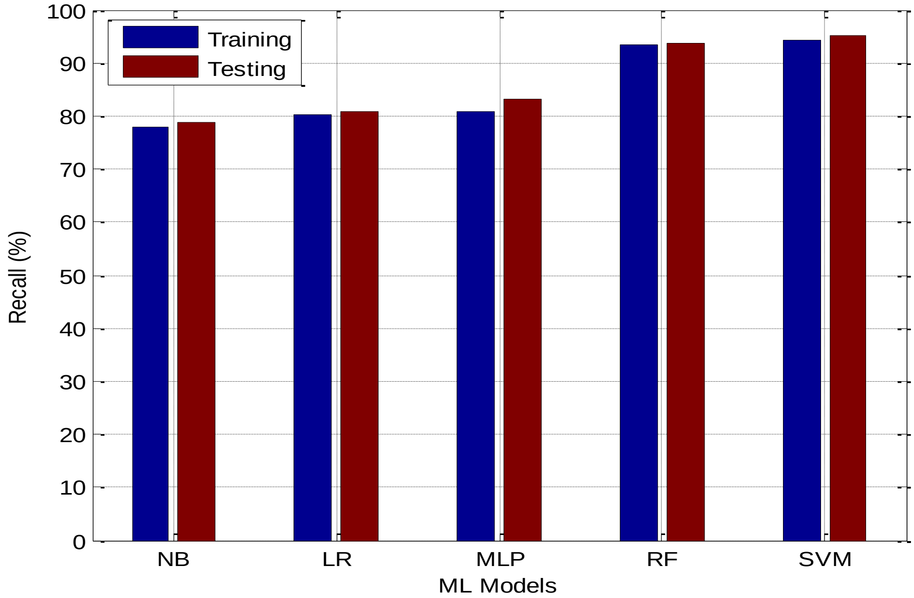


Figure 5: Recall

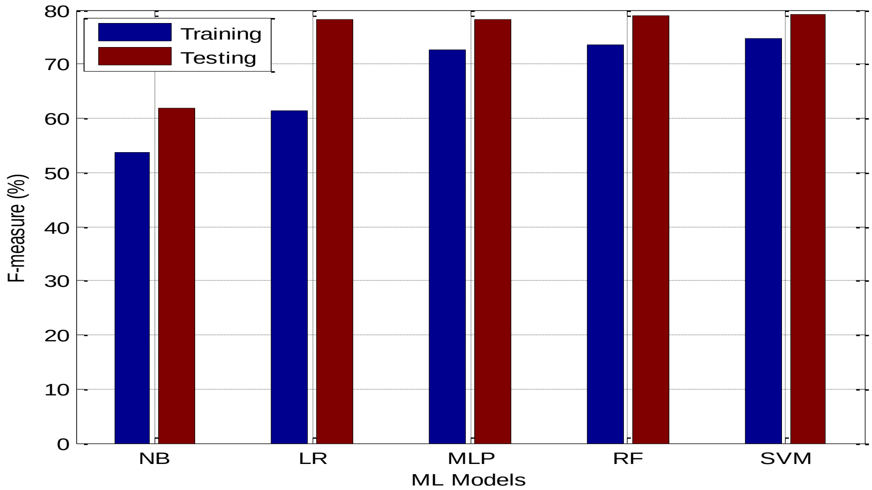


Figure 6: F-measure

As demonstrated by the performance assessments in this work, SVM-based classification models outperform other machine learning approaches in terms of classification accuracy. Therefore, SVM-based models are more stable and have the lowest error margins when compared to other classification models of the same type.

Based on the predictions of the SVM-based model, it appears that algorithms can be divided into three basic categories. SVM and MLP are included in one group;

random trees and naive-based algorithms are included in another; and naive-based algorithms are included in the third. To put it another way, the generality of a classification method is correlated with its performance. As a result, SVMs perform better in terms of stability and error rates than other classification models, and as a result, they can be used to evaluate the effectiveness of learning interventions.

## Conclusions

This study, which makes use of CSMELMS for educational purposes, explains how to address security concerns. Increasingly popular for teaching and learning aids, LMS rely on learning analytics to achieve general adoption. Learning analytics within LMSs are critical to their widespread acceptance. Through the use of a learning management system, the organisation can enrol and teach new employees, and the reports provided by the system can be utilised to improve the overall quality of education and training. It was decided to employ machine learning algorithms to test the model efficacy in terms of delivering educational information and materials to students when and where they were required. Users will find it easier to interact with the material if they have access to many forms of interaction, such as voice, pictures, and video, as well as feedback elements. Because SVM models outperform other classification models in terms of stability and error rates, they can be beneficial in determining student knowledge levels in certain fields.

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