Journal of Basics and Applied Sciences Research (JOBASR)
ISSN (print): 3026-9091, ISSN (online): 1597-9962
Volume 3(2) March 2025
DOI: https://dx.doi.org/10.4314/jobasr.v3i2.9

Machine Learning-Based Framework for Predicting User Satisfaction in E-Learning Systems

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ABSTRACT
The usability of eLearning systems is of paramount importance in determining the effectiveness and user satisfaction. This study introduces a machine learning-based framework to predict users satisfaction on eLearning System aiming to create user-centered platforms that cater to diverse learners satisfaction. The study employed machine learning models such as Support Vector Machines, Decision Trees and Neural Networks to predict user satisfaction towards usability of eLearning System. OC2 (Optimal Course Content & Online Collaboration Lab) dataset was subject into the three said models to predict user's satisfaction in eLearning System. The results obtained from these models shows a promising performance and a perfect classification of both satisfied and unsatisfied users in eLearning System. All the three models achieved and accuracy, precision, Recall and FI score of 100% which shows there is no misclassification in the three models. This proves the modes underscore its reliability in predicting users' satisfaction level. The outstanding accuracy of machine learning models in predicting satisfaction levels demonstrates their effectiveness as dependable tools for assessing usability. This study can be extended by employing diverse dataset with different factors in identifying various usability issues and improving the design and functionality of e-Learning Systems. Also other models apart from Support Vector Machine, Decision Tree, and Neural Network can also be applied to this study to know the performance of the models in predicting the usability scores based on the identified factors on the dataset. Future research can extend this study by utilizing a more diverse dataset with additional factors to further refine the identification of usability issues and improve system design. Additionally, alternative machine learning models beyond Support Vector Machines (SVM), Decision Trees (DT), and Neural Networks (NN) can be explored to assess their effectiveness in predicting usability scores based on the identified factors. Also leveraging Deep learning model will enhance the study to know the stage of user satisfaction on the e-learning system.

Keywords:
Usability,
eLearning,
System, OC2,
Prediction.

INTRODUCTION

The increase in Higher Learning Institutions demand for providing effective mechanisms to aid teaching and learning in online adaptive systems has become a focal point in revolutionizing teaching and learning process in almost all the higher learning institutions Mukhtar et al., (2019). The rise of eLearning, encompassing web-based and distance learning systems, has transformed educational landscapes, enabling learning beyond traditional classroom boundaries (Sato et al., 2023). The effectiveness of eLearning platforms hinges significantly on their usability, which is defined by factors such as ease of navigation, interactivity, and user satisfaction (Saqr et al., 2023). Effective usability allows learners to engage seamlessly, enhancing their learning experience and enabling educators to meet diverse learning needs. However, achieving high usability in eLearning systems poses considerable challenges, especially as these platforms are increasingly used by varied populations with different levels of technological proficiency (Dhawan, 2020). Conventional approaches to usability evaluation often rely on heuristic methods, expert reviews, or qualitative assessments, which, although valuable, have limitations in scalability, objectivity, and actionable outcomes (Maqbool and Herold, 2023). Heuristic evaluations provide initial insights but lack the quantitative depth required to pinpoint specific usability factors affecting overall system performance. Moreover, traditional methods may not prioritize usability issues, which is crucial in scenarios where resources for improvement are limited.

There is a rising emphasis on assessing the usability of both web-based and mobile-based systems. As the creation of web applications expands, accompanied by various challenges and limitations, it is crucial to analyze these systems to ensure they meet usability standards Mukhtar et al. (2019). It has revealed that, the absence of proper software quality assurance practices has significantly impacted the usability of web-based systems and applications Mukhtar et al. (2019)

The integration of machine learning in usability evaluation offers a promising solution to the aforementioned challenges. Machine learning enables the development of predictive models that can assess and forecast usability based on specific system features (Almalawi et al., 2024). By leveraging methods such as support vector machines, neural networks, and decision trees, machine learning algorithms can analyze complex relationships within data, identifying patterns and trends that may otherwise go unnoticed (Guido et al., 2024).

Also the work of Hamid et al. (2020) examined the usability and accessibility of e-commerce websites in Pakistan, identifying significant issues that affect user experiences. The study utilized Nielsen's Heuristics and the System Usability Scale (SUS) to assess usability, while accessibility was evaluated using Web Content Accessibility Guidelines (WCAG 2.0). A total of 20 websites were analyzed through heuristic methods and automated tools. The findings indicated widespread deficiencies in usability and accessibility, with frequent violations of key principles, such as clear navigation and compatibility for users with disabilities. Although the research provided valuable insights, its regional focus limited the applicability of results to other contexts. Furthermore, relying heavily on automated tools without real-world user testing might overlook complex interaction issues. Future studies should broaden the geographic scope and integrate advanced evaluation tools with user-based testing to offer more comprehensive findings.

Kumar et al. (2023) explored challenges related to user navigation and website usability in e-commerce platforms. To address these issues, they employed advanced methods such as machine learning (ML) algorithms and association rule mining (ARM). These techniques analyzed transactional data to uncover user behavior patterns and identify usability problems. The results showed notable improvements in metrics such as navigation efficiency and user engagement. However, the study faced limitations in the transparency and interpretability of its machine learning models, often regarded as "black boxes." This lack of clarity in decision-making processes suggests a need for further research focused on developing interpretable ML frameworks. Incorporating real-time user feedback into usability evaluations could also enhance iterative design processes and improve overall user satisfaction.

Ara and Sik-Lányi (2023) investigated barriers to web accessibility for individuals with disabilities. The study applied decision tree classifiers and Mauve-generated data to evaluate websites against WCAG 2.1 standards. Findings revealed significant accessibility issues, including poor contrast ratios, complex layouts, and limited support for assistive technologies. These issues underscored the urgent need for more inclusive digital design policies. However, the study's reliance on automated tools without validation through real-world testing presented a notable limitation. Future research could address this by combining automated analysis with direct user evaluations to ensure that accessibility improvements meet the needs of diverse user groups. Additionally, exploring innovative machine learning techniques could lead to more effective solutions for accessibility challenges.

Robert et al. (2024) examined the use of machine learning to enhance personalization and user engagement in website development. The study used natural language processing (NLP), sentiment analysis, and recommendation systems to create dynamic content tailored to user preferences. By analyzing user data such as browsing history and interactions, the study demonstrated how adaptive website designs could significantly improve user satisfaction. Despite these promising results, challenges remained in addressing data privacy concerns and simplifying the integration of machine learning into existing systems. Future research should focus on creating secure data-handling practices and user-friendly frameworks for integrating machine learning into website development to overcome these barriers.

Abbas et al. (2022) conducted a review to identify challenges faced by UX designers when incorporating machine learning into their workflows. The study highlighted issues such as communication barriers between designers and data scientists, limited prototyping tools, and insufficient technical expertise in machine learning among UX professionals. These challenges hinder the effective integration of ML into design processes. The authors emphasized the need for collaborative frameworks and advanced prototyping tools to bridge these gaps. While the review offered theoretical insights, it lacked empirical validation, which future research should address by exploring practical methods for improving collaboration and integrating machine learning into UX design.

Abbas et al. (2023) focused on improving usability evaluation methods for e-commerce platforms by integrating machine learning with contextual data analysis. The study proposed a hybrid model that dynamically adapted to user interactions and environmental factors, providing more accurate usability assessments. The results indicated enhanced capabilities in identifying usability issues and tailoring website features to user needs. However, challenges related to the scalability of the model and its integration into existing systems were noted. Future research should address these scalability concerns and explore methods for contextual personalization to further enhance user satisfaction.

Torres-Molina and Seyam (2023) addressed the limitations of traditional usability evaluation techniques, which often rely on subjective methods such as user testing and questionnaires. These methods are not only time-consuming but also susceptible to bias. The authors proposed a machine learning-based approach for evaluating usability, specifically applied to the Moodle e-learning platform. Their method integrated user interaction metrics, such as task duration and click patterns, with subjective responses gathered through standardized tools like the System Usability Scale (SUS) and UseLearn. The findings underscored the potential of machine learning in automating usability assessments, offering a cost-effective and data-driven alternative. While the study provided a robust framework for objective usability evaluation, its scope was limited to a single platform, reducing its generalizability. Furthermore, it lacked exploration of alternative machine learning models or methodologies that could have improved predictive performance. Future research could expand on this by applying the framework to a variety of systems and industries to create a more adaptable usability evaluation mode.

Singh et al. (2024) examined the influence of UI and UX design on the effectiveness of e-learning platforms. The study highlighted how poorly designed interfaces can hinder user engagement and satisfaction. Using user surveys, the researchers collected data on the preferences and experiences of users across platforms like Udemy and Coursera. They employed machine learning models, including XGBoost, Random Forest, and Decision Trees, to predict the most effective UI designs. XGBoost stood out as the most accurate model, achieving an 88.13% success rate in identifying user-preferred designs. The study's practical approach to leveraging user feedback for platform optimization was a notable strength. However, the research was constrained by its focus on a limited sample size and specific demographics, which may not represent a broader audience. Moreover, the emphasis on only a few e-learning platforms limited the scope of its conclusions. Future work could address these issues by including a wider range of platforms and a more diverse participant base.

Chaganti et al. (2023) explored usability issues in e-learning tools, especially as the global shift to online education during the COVID-19 pandemic brought these challenges to the forefront. The study sought to identify design deficiencies in platforms like Zoom and Udemy. A two-phase research design was employed: a survey phase to gather user feedback and a machine learning phase where algorithms like Naïve Bayes, Support Vector Machine, and K-Nearest Neighbors were used to evaluate usability. The Naïve Bayes model performed the best, achieving over 80% accuracy in both platforms' evaluations. While the study effectively showcased how ML could improve e-learning usability, its primary limitations included a small and homogenous participant group. Additionally, the use of basic machine learning algorithms left room for improvement, as more advanced techniques could yield better results. Expanding the study to include a broader range of users and platforms would enhance its applicability and robustness. An explainable Deep Learning Model for Illegal Dress Code Detection and Classification was conducted by (Abubakar et al., 2025).

Mukhtar et al. (2019) conducted a usability analysis of MySIKAP portal, applying the ISO 9241-11 standard. The study found that the portal's content, organization, and readability were satisfactory, providing a positive experience for users in these aspects. However, the interface design and navigation links were identified as significant areas for improvement. The paper stressed the importance of integrating usability principles, including effectiveness, efficiency, and satisfaction, to enhance the user experience and improve functionality in web-based systems

Abubakar et al. (2019) examined the role of software quality assurance (SQA) activities in web application development, using the MySIKAP system as a case study. The findings revealed moderate success in aspects such as navigation and efficiency but highlighted shortcomings in the portal's interface design. The research emphasized the need for thorough implementation of SQA processes during development to produce software that meets usability standards. They argued that better adherence to SQA practices could reduce errors and improve user satisfaction during system interactions

Mukhtar et al. (2020) revisited the MySIKAP portal, analyzing its usability from the perspective of user retention and satisfaction. The study identified persistent challenges, particularly in the design and navigation elements, which negatively impacted user experiences. By leveraging the ISO 9241-11 framework, the research reinforced the significance of incorporating usability-focused improvements to meet user expectations and support evolving technological needs. Recommendations included redesigning the interface and optimizing functionality to align with user requirements.

This study, proposes a machine learning-based framework to evaluate the usability of eLearning systems. The framework combines multiple predictive models with a sensitivity analysis to determine the relative importance of various usability factors, thereby providing a prioritized list of improvements. Furthermore, a novel severity index is developed to rank usability issues based on their impact, enabling eLearning system developers to focus on the most critical areas first. The proposed method is validated through case studies, demonstrating its efficacy in identifying usability-related issues and suggesting targeted improvements.

By focusing on a data-driven approach, this research aims to bridge the gap between traditional, qualitative usability evaluations and a more robust, quantitative method. This advancement not only enhances the usability evaluation process but also aligns with the increasing demand for adaptive and user-centered eLearning environments. Consequently, this research provides a valuable tool for developers and educators alike, helping them optimize eLearning platforms to better support learner needs and improve educational outcomes.

MATERIALS AND METHODS

The framework for evaluating and improving the usability of eLearning system was depicted in Figure 1 below. The methodology focuses on evaluating and improving of eLearning usability through a machine learning-based framework. The methodology integrates a data-driven approach to systematically identify, analyze, and address usability issues. The process begins with data collection from eLearning platforms, capturing a diverse range of features related to user demographics, usability metrics, and system performance. Preprocessing techniques, including data cleaning, feature encoding, and normalization, ensuring that dataset is ready for analysis. Feature selection methods, such as statistical analysis and Recursive Feature Elimination (RFE), are applied to identifying the most impactful factors. Machine learning models, including Support Vector Machines (SVM), Decision Trees (DT), and Neural Networks (NN) were trained and evaluated using metrics such as accuracy, precision, recall, and F1-score to predict usability outcomes. Additionally, the methodology incorporates a severity index to rank usability issues and sensitivity analysis to measure the impact of individual features on system performance. The chosen tools and techniques collectively enable a robust, scalable, and user-centered evaluation framework that bridges the gap between technical design and educational needs.

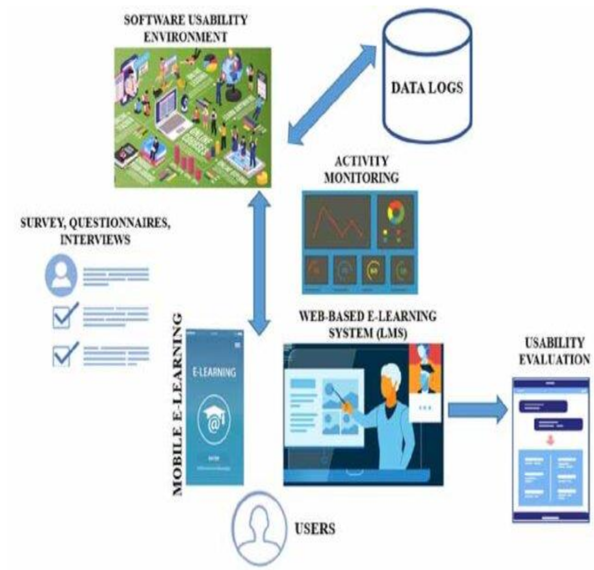

Figure 1: Framework for evaluating and improving the usability of elearning systems

Figure 1 above presents a framework illustrating a comprehensive methodology for evaluating the usability of eLearning systems, utilizing data from the OC2 Labs platform. It begins with users interacting with both mobile and web-based eLearning systems (LMS), generating a diverse datasets of activity logs. These logs capture critical interaction data, such as navigation patterns, response times, and error occurrences. Simultaneously, user feedback was collected through surveys, questionnaires, and interviews to provide qualitative insights into usability challenges and user satisfaction. The data is then processed through activity monitoring systems, which analyze real-time user behavior and performance metrics, offering detailed insights into system functionality and user engagement. The framework emphasizes the role of a software usability environment, which acts as the central hub for integrating and analyzing data logs, activity monitoring results, and user feedback. This environment facilitates the identification of usability issues, ensuring that both objective metrics and subjective experiences are accounted for in the evaluation process. The outputs are then utilized in a structured usability evaluation, enabling the development of actionable recommendations to enhance system design and improve user satisfaction.

Data Collection and Preprocessing

The dataset for this study was collected from OC2 Labs, a leading eLearning platform that integrates web-based Learning Management Systems (LMS) and mobile applications. The data captures a diverse range of user interactions, including navigation behavior, task completion times, error occurrences, and feedback through surveys, questionnaires, and interviews. The dataset encompasses both quantitative metrics, such as system logs and performance data, and qualitative information, such as user satisfaction ratings and open-ended feedback. These data points represent a comprehensive perspective on eLearning usability, incorporating demographic attributes such as age, gender, educational background, and system usage patterns. By collecting data across multiple dimensions, this study ensures a robust foundation for analyzing the key usability factors impacting user satisfaction and system performance.

To ensure the dataset's readiness for machine learning analysis, a series of preprocessing steps were implemented. Data cleaning was performed to address missing values using imputation techniques, such as replacing missing entries with the mean or mode for numerical and categorical features, respectively. Outliers were identified and handled using statistical methods, such as z-scores. Feature encoding was applied to convert categorical variables into numerical forms through one-hot encoding, enabling the machine learning models to process them effectively. For numerical features, normalization was conducted using min-max scaling to bring all feature values into a uniform range, ensuring model stability and preventing biases due to scale differences.

Model Development

The model was developed by splitting the OC2 dataset into 80% training and 20% testing to ensure robust model development and evaluation. The dataset was subjected to three Machine Learning models (Support Vector Machine, Decision Tree and Neural Network) for the training and testing of the models. Each model was trained, tested and evaluated independently to predict usability factors impacting eLearning system performance and user satisfaction. The models were evaluated using four performance metrics (Accuracy, Precision, Recall and F1-Score) to ascertain the model effectiveness and robustness in predicting the eLearning System performance and user satisfaction.

Dataset Characteristics

The dataset used in this study comprised usability-related data collected from eLearning system interactions, encompassing a diverse set of features such as user demographics, system performance metrics, and interface usability factors as shown in figure 2 below.

```
Dataset loaded successfully. Here's a preview:
            Age  Gender YearOfStudy Semester      EducLevel      Course  \
0         18-24  Female       First      1st  Undergraduate     Science
1         25-31    Male      Second      2nd   Postgraduate        Arts
2         32-37  Female       Third      1st  Undergraduate Engineering
3  38 and above    Male      Fourth      2nd   Postgraduate    Business
4         18-24  Female       First      1st  Undergraduate     Science

  SmartphoneSystem EducTools easyinteraction collaboration  ...  \
0              iOS       LMS             Yes           Yes  ...
1          Android      Zoom              No            No  ...
2              iOS     Teams             Yes           Yes  ...
3          Android    Moodle              No            No  ...
4              iOS       LMS             Yes           Yes  ...

  screendesignAttractive userproductivity usercontrol consistentscreenlayout  \
0                    Yes             High        High                    Yes
1                     No              Low         Low                     No
2                    Yes             High        High                    Yes
3                     No              Low         Low                     No
4                    Yes             High        High                    Yes

  engagingInterface userinsurance usersafety systemresources recommendatio  \
0               Yes           Yes        Yes         Optimal           Yes
1                No            No         No      Overloaded            No
2               Yes           Yes        Yes         Optimal           Yes
3                No            No         No      Overloaded            No
4               Yes           Yes        Yes         Optimal           Yes

  totalsatisfaction
0              High
1          Moderate
2               Low
3              High
4          Moderate

[5 rows x 72 columns]
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Figure 2: Features of OC2 eLearning Dataset

The dataset in figure 2 above consist of 100,000 records representing a wide range of users with varying levels of technological proficiency. It includes various features such as Age, Gender, YearOfStudy, Course, SmartphoneSystem, and other usability-specific attributes such as textsize, timetakenload etc.

RESULTS AND DISCUSSION

The performance of the three machine learning models Support Vector Machine (SVM), Decision Tree, and Neural Network was evaluated using key metrics such as accuracy, precision, recall, and F1-score. Among these models, the Neural Network demonstrated the most consistent performance, achieving the highest overall accuracy and balanced precision and recall across satisfaction levels. The Decision Tree model also performed well, offering high interpretability and competitive accuracy, particularly for identifying key usability factors. The SVM model, while effective, showed slight limitations in handling complex, non-linear patterns in the dataset. Additionally, the training process for the Neural Network revealed clear trends in loss and accuracy, with a steady decline in loss and a corresponding improvement in accuracy over 20 epochs. These results underscore the strength of the Neural Network in capturing intricate relationships between features and satisfaction levels while highlighting the Decision Tree's simplicity and the SVM's suitability for linear separable patterns. Together, these models provide complementary insights into the usability evaluation framework. Table 1 below shows the results of SVM with key evaluating metrics obtained from the model development.

Table 1: Support Vector Machine Model

	Accuracy	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	1.00	13344
1	1.00	1.00	1.00	1.00	6656
Macro avg		1.00	1.00	1.00	20000
Weighted avg		1.00	1.00	1.00	20000

The results from the Support Vector Machine (SVM) model indicate exceptional performance, achieving a perfect accuracy of 100%. The classification report demonstrates equally high precision, recall, and F1-score values of 1.00 for both classes (0 and 1), signifying that the model correctly classified all instances in the dataset without any errors. The class distribution shows a support of 13,344 samples for class 0 and 6,656 samples for class 1, ensuring the model's robustness across an imbalanced dataset. Furthermore, the macro and weighted averages for precision, recall, and F1-score also stand at 1.00, confirming the model's ability to handle varying class distributions effectively. This result underscores the SVM's strength in achieving perfect separability for this dataset, making it a reliable choice for identifying usability factors influencing user satisfaction. For Decision Tree Model, the results showed in Table 2 below achieved an accuracy of 100% for predicting usability factors impacting eLearning System and user satisfaction.

Table 2: Decision Tree Model

	Accuracy	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	1.00	13344
1	1.00	1.00	1.00	1.00	6656
Macro avg		1.00	1.00	1.00	20000
Weighted avg		1.00	1.00	1.00	20000

The results from the Decision Tree model show exceptional performance, achieving an accuracy of 100%, with perfect precision, recall, and F1-score values of 1.00 for both classes (0 and 1). The classification report highlights the model's ability to correctly classify all 13,344 samples in class 0 and all 6,656 samples in class 1 without any misclassifications. The macro average and weighted average metrics also reflect perfect scores of 1.00 across all evaluation criteria, indicating the model's effectiveness in handling the dataset's class distribution. These results suggest that the Decision Tree model successfully captured the underlying patterns and relationships within the data, providing highly reliable predictions. Validation on an independent dataset is recommended to ensure the model's robustness and generalizability. Table 3 below shows result obtained from Neural Network

Table 3: Neural Network Model

	Accuracy	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	1.00	13344
1	1.00	1.00	1.00	1.00	6656
Macro avg		1.00	1.00	1.00	20000
Weighted avg		1.00	1.00	1.00	20000

The results obtained from figure 5 above shows a promising performance achieving 100% of all the metrics (Accuracy, Precision, Recall and F1-Score). The model demonstrated its ability to classify 13, 344 samples in class 0 and 6,656 samples in class 1 without any misclassification. Also the across all evaluation criteria, the macro average and weighted average metrics achieved an accuracy of 100%. Therefore the model was perfect in predicting the usability scores based on the factors identified. To further validate the said three models above, confusion matrix was implemented for each model and none of the model shows any misclassification therefore, the three said models correctly classified the sample class of 0 and one accurately as shown in figure 6,7 and 8 for Support Vector Machine, Decision Tree and Neural Network respectively.

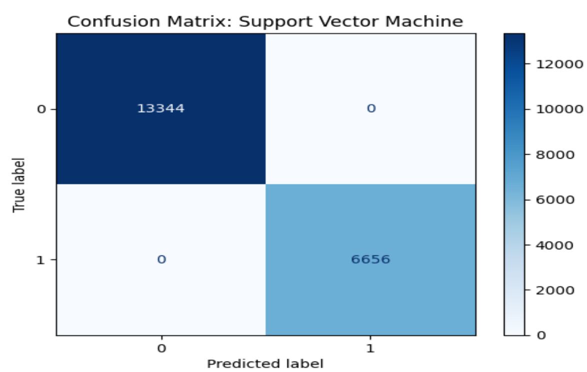

Figure 3: Confusion Matrix of SVM

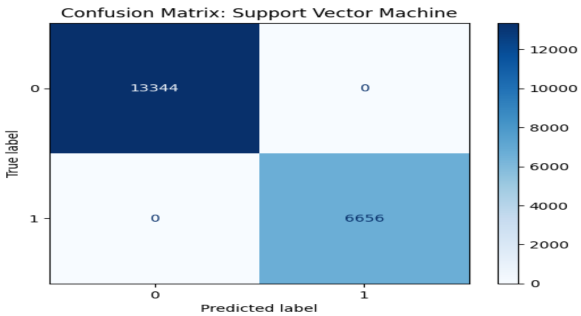

Figure 7: Confusion Matrix of DT

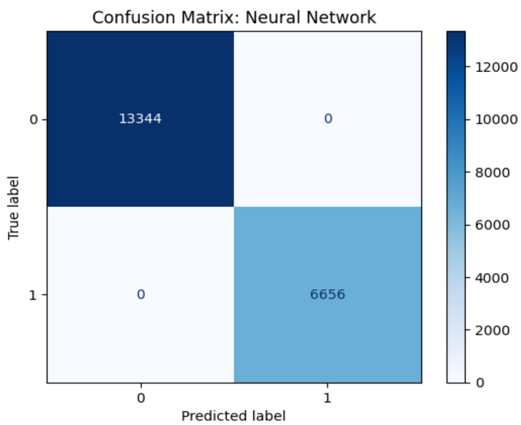

Figure 8: Confusion Matrix of NN

The confusion matrices for the SVM, DT and NN models demonstrated a perfect classification performance, with no misclassifications in either class. For class 0, all 13,344 samples were correctly predicted, while for class 1, all 6,656 samples were accurately classified. This indicates that both models exhibit 100% precision, recall, and F1-scores for all classes. The absence of false positives and false negatives highlights the models' exceptional ability to distinguish between classes effectively hence, results underscore the models' robustness effectively.

CONCLUSION

The study concludes that integrating machine learning techniques into usability evaluation can significantly enhance the design and functionality of eLearning systems. The identification of key usability factors, such as text size and system responsiveness, provides valuable insight for targeted improvements. The exceptional performance of machine learning models in predicting user satisfaction underscores their potential as reliable tools for usability assessment. Future research can extend this study by utilizing a more diverse dataset with additional factors to further refine the identification of usability issues and improve system design. Additionally, alternative machine learning models beyond Support Vector Machines (SVM), Decision Trees (DT), and Neural Networks (NN) can be explored to assess their effectiveness in predicting usability scores based on the identified factors.

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