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A Deep Learning Framework for Adaptive E-Learning: Integrating Learning Style Detection in Web-Based Platforms

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Abstract: *Modern digital learning has made the creation of the adaptive e-learning systems a priority because different needs of learners require individual approaches. The conventional approaches usually do not consider the learning styles of individual students, therefore, leading to less engagement and unequal academic results. To solve this, a deep learning-based model is proposed, which combines learning style identification with student performance forecasting with the Student Feedback Dataset of Kaggle. The framework uses sophisticated text preprocessing, extraction of features based on Word2Vec, as well as the classification based on LSTM model that is optimized on sequential data. The LSTM has excellent performance on experimental evaluation, reaching 99.29% accuracy (ACC), 94% precision (PRE), 95% recall (REC), and a 95% F1-score (F1) and validation loss of 0.2-0.4. Relative analysis indicates that LSTM is much better than SVM (75.55% ACC), BPNN (78.83), and ANN (79.11%). The framework is more inclusive, knowledge-retaining, and motivating by dynamically adjusting course delivery to personal learning preferences. Moreover, it provides teachers with practical knowledge to formulate powerful learning plans. Deep learning can transform online learning environments to be smarter, more customized and larger. This could be translated to better performance in school in the long-term.*

Keywords: Web-Based Platforms E-Learning, LSTM, Adaptive Learning Systems, Deep Learning, Educational Technology, Machine Learning in Education, Data-Driven E-Learning Personalization.

I. INTRODUCTION

Traditional methods of instruction are obsolete in today's world due to the exponential growth of information technology, the intense rivalry for talent development, and the lightning-fast advancements in science and industry. In today's digital world, scholars place a higher value on sustainable development education [1]. Creativity, initiative, self-awareness, and the capacity for continuous learning are characteristics essential to the advancement of time [2]. Sustained development education revolves around skills, and the question of how to develop such abilities has always been an important one.

E-Learning, or electronic learning, is quickly becoming the norm in classrooms throughout the globe. The availability of appropriate electronic and web-enabling technology is a critical component in the efficacy of e-learning [3]. Extending conventional learning techniques into new, more dynamic models, the Internet and network-centric computers provide a solid groundwork for e-learning experiments [4]. The Internet and other forms of contemporary electronic technology have seen tremendous growth in their usage in educational settings in the past several years. Careful scientific design incorporating student-centric methods and adaptive methodologies is essential for good e-learning systems [5][6].

Developing a successful adaptive e-learning system relies on building a thorough student model that takes into account various student attributes. Each student's learning style is shaped by his or her own distinct approach to learning [7]. The way people choose to process and interpret information is reflected in their styles. For e-learning systems to effectively personalize material and learning pathways for each student, it is essential to recognize various styles.

One of the most important aspects of any educational setting is a teaching method that priorities students' unique needs and interests [8]. By engaging in certain behaviors, such as reading, perceiving, watching, or imitating, students are able to enhance their focus while learning [9]. The manner through which an individual receives new information and does school-related tasks is referred to as his/her learning style.

The artificial intelligence is spreading exponentially, and the educational system is not left out of this. Analysis of complex student data enables the customization of the learning process, which is made possible by AI, that is, through ML and DL [10][11]. DL is more concerned with learning processes of the students on a deeper level. The combination of e-learning systems and deep learning can help eliminate the shallow and fragmented learning that is caused by learning style detection and knowledge transfer as well as building holistic knowledge. Deep learning is highly significant to develop the learning abilities of the students to locate, examine and resolve issues and it is an important means of developing creative thinking in students.

The proposed research consider an adaptive e-learning system, which will be rooted on deep learning. This system is able to identify the learning styles preferred by the students and reform the online content in accordance to come up with a more personalized and effective learning experience.

A. Motivation and Contributions of the Study

The reason behind conducting this research was that increasing usage of web-based e-learning systems generate vast volumes of data on student interactions on a daily basis. Knowing the individual learning styles and being able to predict the student performance correctly is essential to providing them with personalized learning experience, increasing their engagement, and increasing the academic outcomes. Conventional methods of teaching usually do not consider the needs of the various learners and this leads to reduced motivation and increased dropouts. The proposed study tackles these issues by combining the latest techniques of NLP with deep learning algorithms, in order to process student feedback and activity records. The proposal to identify significant trends in this data facilitate the adaptive strategies of learning and present educators with practical information, which help create a more successful and efficient digital learning process, as well as a more inclusive one. These are the major contributions of this study:

- Leveraged the Student Feedback Dataset from Kaggle, encompassing diverse student responses and activity logs from web-based e-learning platforms.
- Developed a comprehensive text-cleaning pipeline, including word tokenization, lowercase conversion, removal of numbers and punctuations, stemming and lemmatization, and exclusion of symbols and hyphens.
- Used Word2Vec method to encode textual feedback into numerical vectors which can be used in DL models.
- Trained and developed a deep learning model which was an LSTM based LLDP and SPP student predictor of their performance.
- Determined the effectiveness of the model by objective and reliable tests such as the REC, ACC, PRE, F1, and loss function.
- Proposed a framework which can help in individualized methods of learning and decision making in the digital learning systems.

B. Significance of the Study

The proposed study significant as it will assist in bridging the gap between the traditional e-learning and the ever-growing adaptive and learner-centered systems. The framework is also able to outperform traditional methods in both identification of learning styles and prognostication of academic performance by utilizing the capability of LSTM-based deep learning. It is dynamic unlike the static models which means that content delivery should be adjusted dynamically to ensure that learners with different needs are given personalized support. This flexibility helps increase motivation, lessen the number of dropouts and increase the general level of knowledge retention. Moreover, the combination of sophisticated NLP methods and Word2Vec-based feature extraction makes the student behavior analysis deeper. The work provides a scalable and intelligent structure that promotes inclusivity, innovativeness and long-term academic excellence.

C. Organization of the Paper

The following is the outline of the paper: Adaptive online learning in the classroom is discussed in Section II. Model development and the suggested approach are described in Section III. Discoveries from the experiments are detailed in Section IV. In Section V, provide conclusions and suggest avenues for further research on adaptive e-learning.

II. LITERATURE REVIEW

The literature on e-learning emphasizes the use of DL for predicting student performance, enhancing accuracy, feature extraction, and scalability, while revealing gaps in personalized learning style adaptation, real-time feedback, and multi-subject content optimization.

Riva et al. (2023) used Bayesian Networks, K-means Clustering, and DT to construct an adaptive online learning system based on the Felder-Silverman Learning Style Model. Using the approach, students were able to achieve 28.8%, 41.4%, 31.9%, and 32.9% performance improvements in the Electromagnetic Spectrum, Light, Electricity, and Magnetism modules, respectively. Decision Tree accuracy was 87.5%, K-Means clustering was 0.7, and Bayesian Network distribution was 95.1%; all of these metrics demonstrate that the adaptive system effectively applied the ML approaches [12].

Jebbari et al. (2023) emphasize the role of digital mediums in enhancing the efficiency and communication between teachers and pupils, especially in view of the present COVID-19 pandemic. A strategy for successful e-learning on E-platforms is proposed through study of learner answers and comparison of machine learning algorithms such as NN, RF, DT, BN, ANN, and SVM. According to the research, the NN algorithm had a 98.7 percent success rate in predicting the learning styles of the participants. The effectiveness of online education on digital platforms depends on this strategy [13].

Abu-Naser et al. (2022) investigate the potential of online education, a paradigm shifts in the delivery of technical courses that eliminates geographical and temporal constraints. During the COVID-19 pandemic, unprepared educational institutions faced technological challenges with online learning. Utilized a Kaggle dataset to project students' levels of flexibility following the course, allowing for an evaluation of the effectiveness of online education. The Decision Tree Classifier was determined to be the best machine learning approach with an impressive 92% F1-score, accuracy, precision, and recall. As an alternative, the proposed deep learning system achieved a 94.67% accuracy, precision, recall, and F1-score [14]

Alshmrany (2022) proposes using a convolutional neural network with long short-term memory (CNN-LFM) to do adaptive e-learning style prediction. In order to predict if a student is more of a sequential/global, visual/verbal, active/reflective, sensing/intuitive, or sensing/reflective type, the algorithm takes traits from a set of massive open online courses (MOOCs). When compared to alternative approaches, the JAVA-built model obtains better classification accuracy (97.09%), specificity (94.76%), sensitivity (92.12%), and precision (97.56%) [15].

Gambo and Shakir (2021) investigate the role of emerging mobile and smart technology in revolutionizing classrooms. An autonomous smart learning environment model that identifies five metacognitive skills essential for success in online learning settings is introduced by the authors as the metacognitive smart learning environment model (MSLEM). A neural network (ANN) learning agent that can classify students' preferred learning styles using the Felder-Silverman Learning Style Model (FSLSM) is presented in this study. The ROC curve showed that the model was successful, and it averaged a 93% accuracy rate. There were six distinct iterations of training and testing, with data categorized according to training accuracy scores [16].

Aziz, El-Khoribi and Taie (2021) created a model for an adaptive e-learning recommender system that takes into account both learning styles and knowledge levels (AERM-KLLS). The approach examines the learner's style and current knowledge level to automatically adjust to their needs, interests, and current level of knowledge. From the locations with the lowest pre-test scores, the model selected objects to provide. The use of AERM-KLLS algorithm enhanced the overall performance of 321 respondents and the accuracy was 90.97% This model was offered to English course learners in University [17].

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Table I provides the summary of the literature in the field of Learning Style Detection in web-based environment and student performance prediction. It summarizes the methods used, significant findings, the significant strengths, limitations, and recommendations of each study.

Table 1: Literature Review Table of Student Performance Prediction on Web-Based Platforms

Reference	Methodology	Dataset	Results	Research Gaps	Recommendations
Riva et al., (2023)	Integrating K-Means Clustering, Decision Tree, and Bayesian Network with FSLSM	Student learning data	Performance improved (28.8%–41.4%), DT accuracy = 87.5%, Bayesian acceptance = 95.1%	Limited scalability across diverse domains; focus only on physics modules; shallow ML models used (no deep learning integration).	Extend framework with deep learning for more complex patterns; test across multiple subjects and larger datasets.
Jebbari et al., (2023)	Compared ML algorithms (NN, RF, DT, BN, ANN, SVM) for predicting learning styles (VARK)	Learner responses dataset	NN achieved highest accuracy (98.7%)	Focused only on prediction of LS, not integration into adaptive delivery; lacks real-time personalization.	Incorporate LS detection into adaptive content delivery; explore deep learning for higher generalizability in dynamic environments.
Abu-Naser et al., (2022)	ML (Decision Tree) and DL models to predict adaptability levels	Kaggle e-learning dataset	DT = 92% accuracy, DL = 94.67% accuracy	Focused on adaptability, not LS integration; dataset limited to adaptability responses.	Extend adaptability models with LS detection; integrate DL into adaptive e-learning frameworks.
Alshmrany, (2022)	CNN with Levy Flight Distribution (CNN-LFD) for LS prediction (FSLSM dimensions)	MOOC dataset	Accuracy = 97.09%, Precision = 97.56%, Sensitivity = 92.12%	Prediction only, no adaptive content delivery; platform-specific implementation (JAVA-based).	Expand to full adaptive e-learning pipeline; implement CNN-LFD in web-based platforms for scalability.
Gambo & Shakir, (2021)	ANN-based classification of LS mapped to FSLSM; MSLEM framework	Student dataset	Accuracy = 93% (ROC validation)	Limited to ANN and small datasets; LS integration not directly connected to adaptive materials.	Explore deep learning for LS detection with large-scale student data; integrate with adaptive systems for personalized delivery.
Aziz, El-Khoribi & Taie, (2021)	Adaptive recommender model (AERM-KLLS) combining LS and Knowledge Level	Learner questionnaires + course knowledge overlay model	Accuracy = 90.97% for 321 learners; improved post-test scores	Model limited to English course; based on questionnaires (static input); shallow ML approach.	Extend model to multi-domain subjects; use deep learning for dynamic LS detection from real-time learner interactions.

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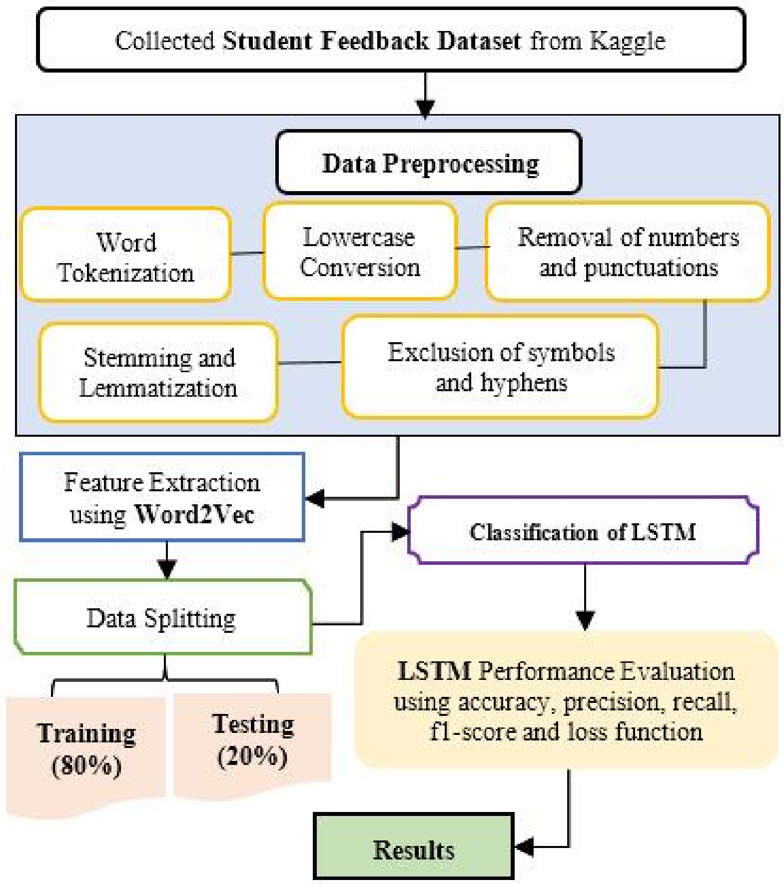

Figure 1: Flowchart of the Proposed Deep Learning-Based Adaptive E-Learning Framework

III. METHODOLOGY

This paper aims to present a deep learning system that improves online e-learning platforms through an automatic recognition and adaptation of personal learning styles. The method enhances the individualization of the learning process, engagement, and academic results. The methodology starts with the Student Feedback Dataset downloaded on Kaggle and then a thorough data preprocessing phase also includes word tokenization, lowercase, deleting numbers and punctuations, stemming and lemmatization, and eliminating symbols and hyphens. Feature extraction using the Word2Vec approach, which converts textual data into numerical vectors, follows preprocessing. A total of 80 records are used for training, while 20 records are used for testing. An LSTM-based classification model is trained on training data and then evaluated on test data. The results of the model's ACC, PRE, REC, F1, and loss tests reveal how well the model can predict students' future performance and identify their preferred learning modes. The methodology steps are as depicted in the proposed methodology as in the following Figure 1.

A. Data Collection and Analysis

The dataset of this study is the Student Feedback Dataset on Kaggle. It consists of six major categories, namely: teaching quality, and course content, examinations, and laboratory activity, library facilities, and extracurricular activities. The data intended to give the understanding of different facets of the academic environment, which can assist institutions to discover their strengths and weaknesses. Each category has two columns, each of which may contain any of the three possible labels, i.e. 0 (neutral), 1 (positive) and -1 (negative). There are different visualizations giving information about different aspects of the dataset, which are presented below:

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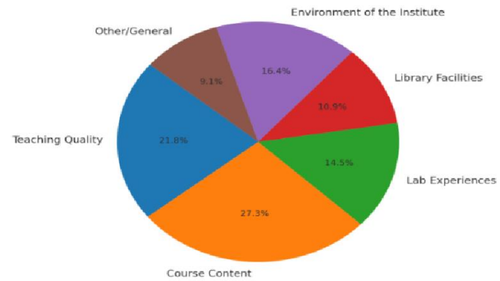

Figure 2: Overall Distribution of Student Ratings

The pie chart shows the distribution of student feedback on various aspects of the educational institution in Figure 2. Course Content represents the largest portion at 27.3%, indicating it is the most significant factor according to students. Teaching Quality accounts for 21.8%, while the Environment of the Institute makes up 16.4%. Other categories include Lab Experiences (14.5%), Library Facilities (10.9%), and Other/General (9.1%). Each slice indicates the proportion of responses for each category, reflecting the relative importance or satisfaction level of these components.

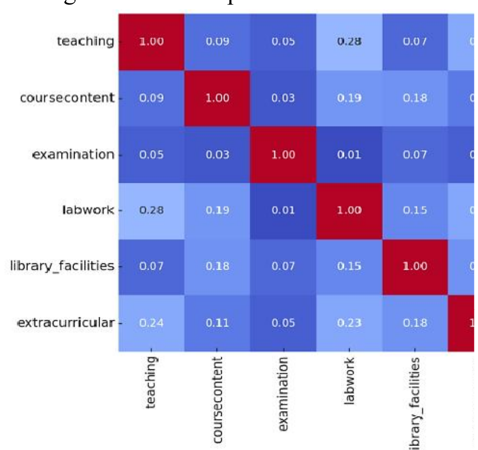

Figure 3: Correlation Heatmap of Student Feedback Variables

The heatmap represents in Figure 3 a correlation matrix based on the Student Feedback Dataset. The axes are labeled with six categories: teaching, coursecontent, examination, labwork, library_facilities, and extracurricular. The colors in the grid indicate correlation strength, with the color bar on the right showing the scale from blue (low correlation) to red (high correlation). Diagonal cells are dark red with a value of 1.00, showing perfect self-correlation. Off-diagonal cells display correlations between different variables, such as 0.28 between teaching and labwork and 0.03 between course content and examination, indicating a very weak relationship. The heatmap visually summarizes the linear relationships among student feedback factors.

B. Data Preprocessing

A critical phase in the preparation of unprocessed data for machine learning or analysis is data preprocessing. Efficient computing requires data cleansing, transformation, and organization. A more trustworthy dataset is the result of thorough preparation that guarantees its accuracy, consistency, and structure [18]. A detailed description of the preprocessing procedure is provided below:

Word Tokenization:

Tokens are the smallest independent textual units that carry specific grammatical and semantic meaning. A piece of text, such as a paragraph, can be broken down into smaller components. The most common methods of tokenization, such word and phrase tokenization, break down texts into individual phrases and words. The basic idea behind tokenization is to divide text into smaller, more manageable pieces called tokens.

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Lowercase Conversion:
The modification of the case of words or sentences simplifies tasks, such as matching specific words or tokens. In most cases, two distinct kinds of conversion processes see heavy usage. A whole chunk of text can be transformed into all lowercase or all uppercase using these methods [19]. Additional varieties exist, such as sentence case and title case. In lowercase, all the letters are smaller than in uppercase, which means that they are all capitalized.

Removal of Numbers and Punctuations:
This step eliminates unnecessary numbers and punctuation from textual data to reduce noise and standardize content for analysis. Care is taken to preserve meaningful numeric values, such as measurements or quantities, using customized rules suited to the specific business or research context.

Exclusion of Symbols and Hyphens:
Depending on the context, special characters such letters and symbols can be either non-alphanumeric or numerical, adding to the text's unstructured noise. In most cases, use common, basic words to remove them.

Stemming and Lemmatization:
Stemmed and lemmatized words are both reduced to their fundamental form; however, stemming may generate non-dictionary stems, whereas lemmatization consistently produces valid words (lemmas). Stemming is faster, applying fixed rules to strip affixes, whereas lemmatization considers context, syntax, and semantics, using resources like WordNet in NLTK. Lemmatization is slower due to its dictionary lookup step, but more accurate.

C. Feature Extraction using Word2Vec:
One of the most important steps, feature extraction converts text that people can understand and read into the numerical format that can be easily understood by the machine learning classifier. Using the process, text data can be analyzed and comprehended, and its functions can, among other things, sentiment analysis and document classification [20]. The characteristics of the given work are achieved with the assistance of Word2Vec that is a significant advancement in the field of NLP that converts the textual data into digital high-dimensional vectors. This new method, introduced by Google in 2013, employs a neural network network-based approach, in this case, a hidden layer, to test the complex syntactic and semantic connections among words. Adding the use of skip-gram and continuous bag of words (CBOW) training models.

D. Data Splitting
Machine learning Data partitioning Data splitting Data partitioning in machine learning Data partitioning is the practice of splitting a dataset into smaller parts to be used in training and testing. An 80:20 split gives the model the opportunity to learn patterns and correlations on 80% of the data, and to test its performance on data that it has never encountered is possible using the remaining 20%.

E. Classification of Deep Learning Model
This study introduces an adaptive e-learning framework that attempts to identify learning styles and forecast student achievement with the help of a LSTM. The extracted platform characteristics increase the performance of the system and its detection accuracy.

LSTM Model
The RNN has a more advanced version, which is the LSTM network. Two fields where it outperforms include classification and time-series prediction since it can learn long-term dependencies, which most RNNs lack [21]. The architecture of an LSTM network comprises of a memory cell, an input gate, an output gate and a forget gate. In both LSTM networks, each LSTM unit takes as input ht at time t (t= 1,2,…,) and uses the state of the previous time step to

produce an output ht. Long short-term memory (LSTM) can connect sequential data in this cycle like this. The computation of h t can be described in one way as in the Equations (1) to (5).

$$i_t = \lambda W_{ix} + W_{ih}h_{t-1} + W_{ic}c_{t-1} + b_i \quad (1)$$

$$f_t = \lambda\left(W_{fx}x_t + W_{fh}h_{t-1} + W_{fc}c_{t-1} + b_f\right) \quad (2)$$

$$o_t = \lambda(W_{ox}x_t + W_{oh}h_{t-1} + W_{oc}c_{t-1} + b_o) \quad (3)$$

$$c_t = f_t c_{t-1} + i_t\sigma(W_{cx}x_t + W_{ch}h_{t-1} + b_c) \quad (4)$$

$$h_t = o_t\sigma(c_t) \quad (5)$$

An important element dedicated to the management of data flow in the LSTM unit is the input, forget and output gates set. These gates together with weighted input summation and nonlinear activation functions allow the LSTM element to acquire complex temporal dynamics of sequential data and provide long range dependencies, which are not accessible to traditional RNNs [22]. The selective forgetting and remembering property of the LSTM coupled with its gated control architecture has been found to have facilitated the LSTM to become a powerful technology in temporally related tasks, language modelling, and other sequential prediction problems.

F. Model Evaluation

The model's efficacy is assessed using well recognized evaluation indicators. Performance is assessed using the loss curve, F1, REC, ACC, and PRE [23]. Here are the main concepts of these performance measures:

- TPR: determines the model's success rate in detecting true positives.;
- FPR: ratio of false positives incorrectly classified as negatives;
- TNR: determines the percentage of true negatives that are appropriately detected;
- FNR: proportion of correctly classified positive results incorrectly classified as negative.

Accuracy: The proportion of total predictions the model classified correctly [24]. Equation (6) of accuracy is shown below:

Accuracy: The proportion of total predictions the model classified correctly [24]. Equation (6) of accuracy is shown below:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} (6)$$

Precision: Prediction ACC is measured by the proportion of true positive forecasts. Equation (7) is applied.

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

Recall: The true positive rate, also known as sensitivity, is a measure of how many true positives the model correctly recognizes. This is what it means: Equation (8).

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

F1-score: A balanced measure that strikes a harmonic middle ground between REC and ACC, useful when situations call for both. Calculated using Equation (9):

$$F1\ Score = \frac{2\,(Precision \times Recall)}{Precision \times Recall} \quad (9)$$

Loss Function: A numerical indicator of how much the model's output deviates from the desired values. Better training and evaluation results are indicated by a lower loss.

This comprehensive evaluation process enables a detailed evaluation of different aspects of model performance, which enables choosing and identifying the most effective models.

IV. RESULT ANALYSIS AND DISCUSSION

The proposed solution is concerned with the accurate learning style identification and student performance prediction in web-based e-learning platforms. Experiments on the Student Performance Dataset using the LSTM model were done to determine its effectiveness. The system was equipped with ASUSTek AMD Ryzen 7 5800H (R) CPU of 2.20 GHz and VRAM of 4GB. The models are implemented using the Python language and the necessary libraries. Table II displays

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the outcomes of the LSTM model's attempt to identify students' learning styles and ascertain their performance in online e-learning platforms. The model has high accuracy of 99.29 and this means that it is a good predictor in general. Having a precision of 94.0% and a recall of 95.0, the LSTM model proves to be well-balanced with the ability to detect the relevant patterns with a high level of accuracy and a low count of false positive and false negative results. This is further validated by the fact that its F1 score is 95.0% indicating its capability to deal with the complexity of adaptive learning tasks. These findings show that LSTM model is capable of predicting sequential educational data and providing prompt e-learning systems.

Table 2: Performance of LSTM Model Student Performance Prediction on Web-Based E-Learning Platforms

Matrix	LSTM
Accuracy	99.29
Precision	94.0
Recall	95.0
F1 Score	95.0

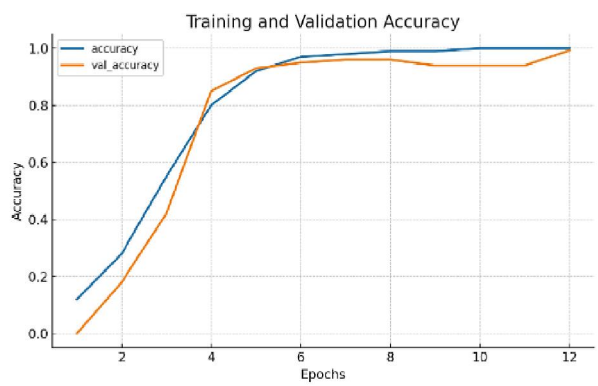

Figure 4: Accuracy and Validation Accuracy of the LSTM Model

A line graph representing the accuracy vs. the epochs is shown in Figure 4. Lines labelled "accuracy" in blue represent training accuracy and "val_accuracy" in orange represent validation accuracy. Both curves exhibit a steep rise with epoch 1 to approximately epoch 6. At this stage the accuracy of the training starts to increase gradually, and reaches about 100 percent in epoch 10. The validation accuracy also levels off with a small variation range of 95 to 98 and then increases to attain the training accuracy of epoch 12. The improvements in this graph are clearly illustrated on a visual representation of a model learning where it is seen how its performance improves as time passes on both the training and the unseen validation data.

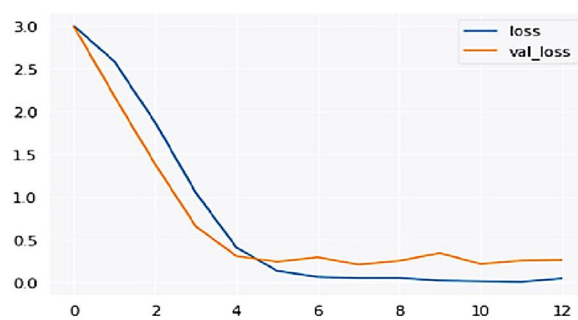

Figure 5: Loss and Validation Loss of the LSTM Model

The line graph indicates training loss (blue) and validation loss (orange) in the various epochs as indicated in the Figure 5, which is the learning process of the LSTM model. Both losses exhibit a steep decline during the initial epochs, reflecting a rapid reduction in prediction errors as the model quickly adapts to the training data. The validation loss settles into a steady state with small variations between 0.2 and 0.4 after this first phase, whereas the training loss keeps

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going downhill until it's almost nil. This behaviour emphasizes the model's resilience in adaptive e-learning tasks and implies that it has learnt effectively with little overfitting and can generalize well to unknown data.

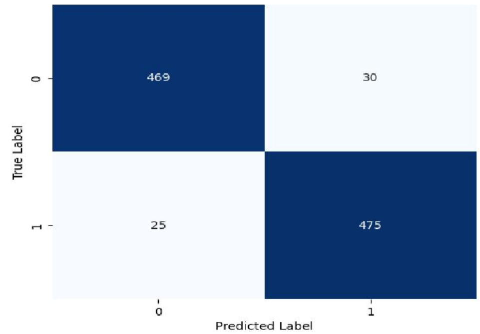

Figure 6: Confusion Matrix of the LSTM Model

Figure 6 shows a confusion matrix, a typical tool for evaluating the performance of a classification model. True labels are shown on the y-axis and forecasted labels are shown on the x-axis; each axis represents a value between 0 and 1. The number of genuine negatives, which are accurately forecasted as 0, is shown in the top-left cell, which has 469. False positives, or 1st-guess predictions gone wrong, are shown by the 30 in the top-right box. The cells on the bottom left and right show the number of false negatives (predicted as 0) and true positives (predicted as 1), respectively. The color intensity of the cells reflects the values, with darker blue indicating higher counts.

A. Comparison and Discussion

The efficacy of several ML and DL models for adaptive e-learning was assessed with respect to REC, ACC, PRE, and F1, as shown in Table III. The limited predictive power was demonstrated by the SVM, which reached an accuracy of 75.55%. The 78.83% accuracy and balanced recall and precision demonstrated by the Backpropagation Neural Network (BPNN) demonstrated an improvement in performance. In a similar vein, the ANN achieved 79.11% ACC with a good F1 and REC. On the other hand, the LSTM model was the most effective for adaptive e-learning, with a 99.29% ACC rate, 94.0% PRE, 95.0% REC, and 95.0% F1SS.

Table 3: Performance Comparison of Models for Student Performance Prediction on Web-Based E-Learning Platforms

Matrix	Accuracy	Precision	Recall	F1-score
SVM[25]	75.55	73	76	73
BPNN[26]	78.83	79.90	83.10	80.12
ANN[27]	79.11	80.90	85.12	81.14
LSTM	99.29	94.0	95.0	95.0

The LSTM-based model suggested has a number of strengths in detecting learning styles and predicting student performance on the online e-learning systems. The fact that it can efficiently deal with sequential and temporal educational data means that it can readily handle complex behavioral patterns and learning cues that may not be readily handled in a traditional model. The model can be personalized dynamically and adjusted to various interactions between students, which is why it is the most appropriate model in intelligent, adaptive learning systems, based on DL.

Deep learning methods (BPNN, ANN and most of all LSTM) are more effective in identifying learning styles and forecasting student performance than traditional machine learning models (SVM). The key feature of LSTM is its ability to capture temporal contexts when learning among learners hence giving the ability to make consistent and accurate predictions on a variety of student profiles. It is better in terms of generalization and flexibility thus proving useful in the development of adaptive e-learning, personalized support and the overall learner engagement in web-based programs.

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V. CONCLUSION AND FUTURE SCOPE

Adaptive e-learning systems possess a historical potential in transforming the digital learning with personalized experiences of various learners. The LSTM-based model proposed proved to be the best in detecting learning styles and student performance prediction with an ACC of 99.29, a PRE of 94, a REC of 95, and an F1 of 95, with a low validation loss. These findings are superior to traditional models, including SVM, BPNN, and ANN, and LSTM is the most suitable when it comes to modeling sequential relationships in learning data. The framework increases the inclusivity of modern education systems as well as the engagement and academic results of learners by dynamically providing customized content to each employee that reflects their preferences in education. However, the existing framework can only be restricted by the fact that it depends on textual feedback, which cannot be entirely descriptive of multimodal learning behaviors like voice, video interactions, or emotions. Subsequent research will resolve these shortcomings by using multimodal data to gain a more comprehensive view of the learner behaviour. In addition, the architecture of transformers or the attention mechanisms could be more closely combined to provide an additional level of flexibility and accuracy. The other possible direction is the practical application of this framework to the active e-learning platforms that would enable undergoing continuous improvement due to feedback offered in real-time. Lastly, the research can assist in the creation of robust, intelligent, and non-discriminatory adaptive learning systems that can trigger the innovation of online learning.

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