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Predicting Student Performance with Secure Data Handling and Deep Learning-Based Classification Models

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ABSTRACT

Predicting student academic performance is a critical task for educational institutions, as it enables early identification of at-risk students and supports informed academic decision-making. This study proposes a binary classification framework for predicting student performance using deep learning techniques, specifically Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) models.

The proposed approach formulates the prediction task as a classification problem, where students are assigned to predefined performance categories rather than predicting exact numerical scores. Prior to model training, data preprocessing and feature standardization are applied to enhance learning efficiency. To ensure data confidentiality and integrity, the Advanced Encryption Standard (AES) is employed to encrypt the student dataset before storage.

The performance of the proposed models is evaluated using standard classification metrics, including accuracy, precision, sensitivity, and F1-score. Experimental results demonstrate that the RNN model achieves superior performance with an accuracy of 96%, outperforming the LSTM model, which attains an accuracy of 75%. These findings highlight the effectiveness of deep learning models for student performance classification and emphasize the importance of secure data handling in educational prediction systems.

Keywords: Deep Learning, RNN, LSTM, student academic performance, AES, Data Encryption

INTRODUCTION

In order to provide diverse learning systems, information systems have been integrated into education. These tools can help teachers and students by raising academic achievement. The performance and progress of students can be seen on a learning dashboard [1]. Course-management systems can also supplement traditional classroom instruction by providing digital lecture materials, homework, and a discussion board [2]. Information systems are used to deal with Big data in education, also referred to as data analysis, has lately played a crucial influence in the restructuring of education, especially in research on education and innovative teaching methods [3]. instructive Big data includes a variety of applications that can help examinations of pupils' educational practices to determine their learning styles, This could then be used to improve learning environments [4]. To help teachers develop instructional strategies that raise students' academic achievement, big data in education is crucial. However, identifying those students who are at-risk or likely to fail is crucial to improve both the students' academic performance [5] and the success rates of each course [6].

As a result, before a course ends, student performance prediction has been used to identify students who are at danger [7]. Initially, deep learning (DL) models and traditional machine learning were utilized for performance prediction since these models can handle heterogeneous data types and can be quickly implemented in predictive tasks with little need for data pretreatment. Nevertheless, complex datasets present a major challenge for these classical models, which calls for the addition of more advanced model architecture to improve prediction model accuracy.

DL has garnered significant attention in addressing this issue because of its strong information processing capabilities. As a result, there is a trend toward using DL for learning analytics. Due to its ability to increase the efficiency of processing large volumes of data from student logs for prediction using operation counts from learning management systems (LMS), massive open online courses, or e-books to categorize student performances, deep learning (DL) has been used in educational data mining [8], [9], [10]. Furthermore, because educational data contain time-related information that influences performance prediction, numerous research have used a recurrent neural network (RNN), a model that can handle time-sequence data [11], [12], [13], to process data sequences or capture temporal dependencies.

Thus, for interventions with at-risk students that enable teachers and students to recognize patterns of activity generally associated with successful engagement, it is critical to comprehend the reasoning behind a model's decision to select significant features for prediction [14], [15].

The ability of Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks to handle sequential data and capture temporal relationships has made them popular. These qualities make them especially well-suited for forecasting student success, as past academic records might offer insightful information about what to expect in the future.

Even with RNNs and LSTMs' promise, tweaking these models to reach the maximum level of predicted accuracy still presents difficulties. Advanced modeling strategies that can take individual differences and the dynamic nature of learning into account are necessary due to the complexity of student performance data, which is influenced by a multitude of factors. Furthermore, it is critical to protect sensitive educational data because breaches might jeopardize the reliability of prediction models in addition to student privacy [16],[17].

In this study, student performance prediction is formulated as a binary classification task, where students are categorized into performance levels rather than predicting exact numerical grades
This study advances the fields of predictive analytics and educational data mining by:

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1-Using sophisticated deep learning models: RNN and LSTM networks are used to predict student performance, and their efficacy in capturing the nuances of academic data is investigated.

2- Taking care of worries about data security: Putting AES encryption into practice will safeguard the dataset's confidentiality and integrity and guarantee that the prediction models are built on safe, unmodified data.

3-Encouraging individualized education means figuring out the main causes of academic difficulties so that teachers may provide solutions that are specific to each student's requirements and raise grades all around.

With these contributions, the study hopes to further our understanding of how deep learning may be used to assist focused educational practices, protect educational data, and forecast student achievement.

The format for the remaining portion of the paper is:
A summary of relevant research is given in section 2. The materials and methods utilized are explained in section 3. The performance metrics are described in section 4. section 5 provides a detailed outline of the suggested model. The findings and potential directions for further research are finally presented in section 6.

RELATED WORK

With the advent of computerized instructional software, learning management systems, computerized assessment systems, and learner engagement in the last ten years, the field of education has advanced. A number of variables contribute to kids' subpar academic performance. These include geographic location, the historical and cultural background of the pupils, educational strategies like frightening teaching methods, unsuitable assessment tools, and the fundamental knowledge of the students. A learner's performance is influenced by biological, psychological, and social factors. Due to their strong information processing capabilities. DL models have garnered significant interest due of their potent information processing capability. The trend of applying deep learning (DL) to learning analytics, including early prediction, has resulted from this. RNN and its derivative models are useful when examining learning logs with temporal features to inform students' learning patterns. An RNN model was employed in these research to manage data sequences and take learning behavior continuity into account.

Reference [18] concentrated on applying RNN from six Information Science courses offered by two teachers to predict students' final grades early. Additionally, they retrieved characteristics (i.e., anonymous learning activity attributes) that might be used to characterize students' learning activities).

Using an embedding layer, bidirectional long short-term memory, and global max pooling (GMP), Reference [19] developed GritNet, which makes weekly graduation prediction of students from the Udacity dataset easier.

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Reference [20] investigated why so many MOOC participants drop out of their courses and what motivates students to study. This research proposes a Context-aware Feature Interaction Network that leverages student interactions based on attention mechanisms to predict user dropout behavior. In order to look at feature contributions, including the goals of the online intervention techniques, they also performed feature ablation.

Reference [21] predicted students' academic achievement by examining their activities on campus, which provide insight into their habits and learning styles. The capacity of traditional approaches to quickly and thoroughly comprehend student actions is constrained since they manually extract statistical features from pre-stored data. In order to solve this, the authors suggest a two-stage architecture called Sequence-based Performance Classifier (SPC), which encodes recent behaviors of students using a Hybrid Recurrent Neural Network (HRNN) with attention mechanisms and then utilizes a Support Vector Machine (SVM) to forecast performance. This method attempts to capture the sequential nature of students' behaviors in order to produce a more accurate and automated prediction.

Based on daily click frequencies in the LMS, Reference [22] used LSTM to assess time-sequence data for the early identification of at-risk kids.

Reference [23] suggested a novel combined neural network model integrating RNN and the gated recurrent unit (GRU) to fit static and sequential data. The model used personal demographics and sequential learning behavior data to identify at-risk students.

Using demographic and click stream data generated during interactions with the learning platform, Reference [24] proposed an attention-based multilayer LSTM for performance prediction in online courses. The model could enable individual predictions in any course, at any time.

A hybrid deep learning model that combines DL and RNN was presented in Reference [25] in order to forecast high-risk students and examine the learning behavior sequences of students. This study emphasizes how better student performance prediction can be achieved by combining temporal and general behavioral data.

Using demographic and activity click stream data, Reference [26] developed an ANN-LSTM model for early prediction. This model makes use of LSTM's capacity to retain prior learning knowledge and fuse it with the present learning information in order to enhance prediction performance.

In reference [27], a multi-source sparse attention convolution neural network was presented. It combines global attention, multiple input heads, and multi-scale convolution kernels to collect structured data and show the relationships between courses to forecast course grades.

By employing an attention-based neural network technique to forecast learning outcomes based on students' experiences, Reference [28] investigated how service learning affects students' growth. In order to encode latent contextual information in a student post-experience

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questionnaire, they presented a Context-Reinforced Experience Attention Modeling network. According to this study, attention processes enhanced predictive accuracy in learning environments.

MATERIALS AND METHODS

The proposed approach addresses a binary classification problem aimed at predicting student academic performance by assigning students to predefined performance categories rather than predicting exact numerical scores. Accordingly, the prediction task focuses on identifying whether a student belongs to a specific performance level based on historical and behavioral data. The primary methods and supplies used in this work are summarized in this section.

1. Feature Standardization

Before entering the data for the methods used, work was done on feature scaling, which involves changing values using one of two basic techniques: normalization or standardization. During normalization, the input values are changed to fall between 0 and 1. By using standardization techniques, the numbers are transformed to have a zero-centered value and a standard deviation of 1. The normalizing technique was utilized in this paper [3].

2. Long Short-Term Memory (LSTM)

LSTM is a specific instance of an RNN. It is designed to address the problem of abrupt or nonexistent slopes. The basic architecture of the LSTM consists of many gates and a memory cell. These memory cells and gates were initially added to each neuron in the network in 1997 [29].Recurrent neural networks (RNNs), the most sophisticated method for processing sequential input, are used by both Google and Apple's Siri. Because of its internal memory, it is the first algorithm to remember its input, which makes it ideal for machine learning issues requiring sequential data. The idea behind how RNNs operate is that they may forecast an output by upholding and enhancing the output of a layer that came before it. The first section determines whether or not the data from the previous timestamp should be recalled. This cell uses the input from the second component to try and learn new information. Subsequently, the cell updates the data from the third segment's current timestamp to the subsequent timestamp. Gates mentions three components of the LSTM cell. The forget gate, input gate, and output gate are the names given to the first, second, and third parts, respectively. An LSTM's hidden state is the same as a conventional RNN's; H(t-1) indicates the hidden state of the previous timestamp and the current timestamp, respectively, to represent an LSTM's cell state, and H(t) indicates the hidden state of the current timestamp. For the LSTM, a cell state is represented by the timestamps C(t-1) and C(t), which stand for the previous and current timestamps, respectively [30]. Two different activation function types are included in LSTM: sigmoid, which has a range of 0 to 1 and is used in conjunction with the forgetting gate because it tends to forget less significant phrases, and tanh, which has a range of -1 to 1, which is used to help remember essential words.

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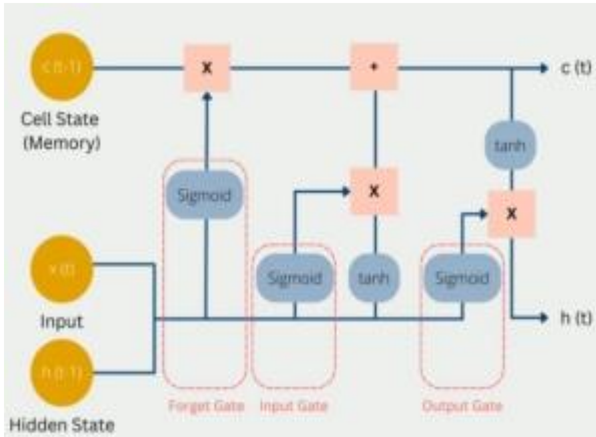

FIGURE 1. Structure of Long Short Term Memory [31]

The following stages are used to implement this algorithm:
Step 1: The forget gate is used to determine what should be forgotten based on knowledge from a prior time step;
Step 2: New information is sought via input gate and tanh for updating cell state;
Step 3: The information from the two gates above is used to update the cell state;
Step 4: Information is usefully provided by the squashing operation and the output gate. [31]

3. Recurrent Neural Network (RNN)

Apple's Siri, Google voice search, and recurrent neural networks (RNNs) are voice search systems based on the most sophisticated sequential data analysis algorithm. It is the first algorithm to remember its input because of its internal memory, which makes it perfect for machine learning problems needing sequential data. RNN operates (as illustrated in Fig.1) according to the idea that it can forecast an output layer by storing the output of that layer and feeding it back into the input [32]. The nodes from several layers of the neural network are condensed to form a single layer of recurrent neural networks. For buried layers, RNN employs the sigmoid or tanh function. The performance of the tanh function is superior. It is only thought that the identity activation function is linear. There are no linear activation functions left [33].

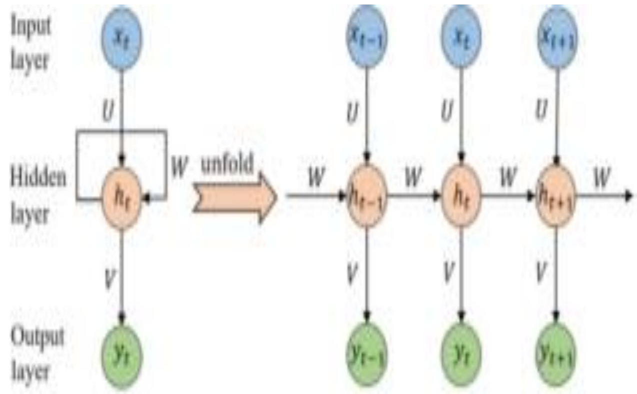

FIGURE 2. Structure of Recurrent Neural Networks [34]

The following steps enable the algorithm to work:
Step 1: Initialization. Before implementing the basic RNN unit, we first determine the dimensions of the individual parameters U, V, W, b, and c;

Step 2: Forward pass;

Step 3: Compute the loss;

Step 4: Backward pass;

Step 5: Update the weights;

Step 6: Repeat steps 2-5; [34]

Advanced Encryption Standard (AES)

Advanced Encryption Standard(AES) is one of the common symmetric-key encryption paradigm [35]. AES is an iterative cipher that is based on two operations: “substitution” and “permutation”. Essentially, it consists of a number of interconnected processes, some of which require swapping inputs for particular outputs(substitutions), while others involve randomizing bits (permutations) [36]. AES never use bits for its calculation; instead, it uses bytes. Therefore, AES treats a plaintext block of 128 bits as 16 bytes. For processing as a matrix, these 16 bytes are organized into four columns and four rows [7].

It uses keys with lengths of 128, 192, and 256 bits to encrypt plain text divided into blocks of 128 bits. The number of rounds in AES is configurable and is based on the size of the key. For 128-bit keys, 192-bit keys, and 256-bit keys, AES uses 10, 12, and 14 rounds, respectively. Four stages, namely: s**ubstitution of the bytes, shifting the rows, mixing the columns, and** a**dding the round key,** make up each round of AES, except for the last round that excludes the mix columns stage in encryption process, and also the inverse mix columns stage is omitted in the decryption process, see Fig. 3 [37].

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Figure 3. AES Encryption System [37]

In the adding round key stage, the 128-bit key is initially xored with plain text. The 128-bit plaintext block is partitioned into 16 bytes. These bytes are represented as a 4 x 4 matrix called the *State*. Every single State byte is transformed into a new byte that is created by intersecting row and column elements. Inverse State is used for substituting byte transformation during decryption. During shifting the rows stage, the first row of the State matrix remains the same, whereas the second, third, and fourth row experiences a one-byte circular left shift, a two-byte circular left shift, and a three-byte circular left shift, respectively. The matrix multiplication of the state is used to carry out mixing the columns stage. The expanded key is xored with the state in the adding the round key stage to obtain the ciphered message [37].

Performance Metrics

Four evaluation metrics are used in this study i.e. F1-score, accuracy, precision, and sensitivity: accuracy-the number of times the classifier correctly catches the data in the entire data set – as a measure of accuracy; The percentage of cases that were accurately classified to all cases that were correctly classified is how it is displayed. The ratio of correctly labeled positive instances to all cases that were either incorrectly or correctly identified as positive is referred to as precision. Otherwise said accuracy measures the count of times that an assertion can be correctly identified as positive. Sensitivity measures how well the system can make positive cases by taking the total count of positive instances inclusive of the falsely classified negative specimens and dividing it by the total position count. Precisions and sensitivity scores are put together to produce the F1 score which in itself is a measure of how correct a classifier is Four scores out of these four measures have been calculated using below equations [38][39].

$$ACCURACY = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (1)$$

$$PRECISION = \frac{TP}{(TP + FP)} \quad (2)$$

$$SENSITIVITY = \frac{TP}{(TP + FN)} \quad (3)$$

The acronyms above are interpreted in the following contexts:

- **TP: True Positive** – a case that is positively diagnosed correctly.
- **FP: False Positive** – a negative that is mistakenly diagnosed as positive.
- **TN: True Negative** – a negative that is correctly diagnosed.
- **FN: False Negative** – a positive case determined to be negative.

$$F1\_score = \frac{2 * Precision * Sensitivity}{Precision * Sencitivity} \quad (4)$$

Proposed System

This study demonstrates the possibility of predicting the academic level of students' performance by taking advantage of a set of general characteristics of each student. This study also aims to help educational institutions such as schools and universities know the level of performance of their students, shed light on students whose academic and educational level is low, and work to exert more effort. Follow-up by the educational staff in order to raise the level of this group of students. In this study, we compare the performance of LSTM and RNN.

In order to preserve student data and protect it from tampering, it will be encrypted using the AES algorithm and stored in the database.

The system is composed of two phases, as illustrated in Fig.4 prediction of the student dataset and encrypt this dataset. Below is a detailed explanation of these phases.

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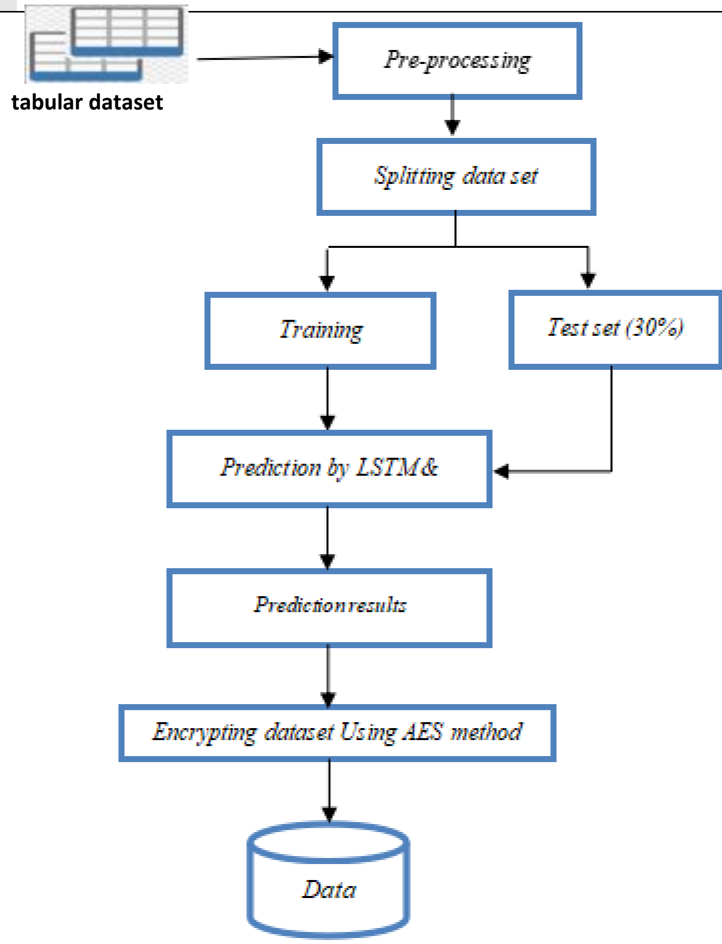

FIGURE 4. The Architecture of the Proposed System

1. Preprocessing stage

In this study, we used a dataset* from the Kaggle website consisting of 15 features such as (age, gender, Parental Education, Study Time Weekly, Parental Support...etc.). This means that these features need to be pre-processed before classification. Although there are other ways to perform the preprocessing work, the option we recommend uses feature scaling methods. This is a method of evenly distributing independently occurring features within a preset range of the data. It has a large control volume or range of values. Without feature scaling, machine learning algorithms usually rely on values regardless of the unit; therefore, large values, even larger, are preferred to small values. As part of the normalization process, equation (5) is used to rescale the feature values to produce a distribution with a mean of 0 and a variance of 1.

$$V_{new} = \frac{V_i - V_\mu}{V_\sigma} V_{new} = \frac{V_i - V_\mu}{V_\sigma} \quad (5)$$

Where V_i denotes a dataset feature value, V_new denotes a scaled feature value, V_µ denotes the feature value average, and V_σ is the standard deviation of the feature value.

(*https://www.kaggle.com/datasets/tusharika802/student-performance-data-csv)

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2. Splitting data stage

After the necessary preprocessing, the data is divided into two sets: a test set, which is used to evaluate the system performance, and a training set, whose main purpose is to enable the machine learning algorithm to make precise findings. Essentially, 70% of the data comes from the training set and 30% from the test set.

3. Prediction stage

We analyze two well-known algorithms (LSTM and RNN) to determine which one is superior based on evaluation metrics because this study is important in knowing the level of students' performance and thus affects the educational level in general.

4.**Encrypt stage**

This stage includes encrypting the student data set and storing it in a database in order to protect it from tampering and change.

Experimental Results and Discussion

The proposed work consists of two phases: prediction for the performance student dataset and Encrypt the student data set and store it in a database. This section focuses on examining and evaluating the outcomes of these phases. It should be noted that the system is implemented in Python, and the dataset[1] used in these stages is publicly available, containing various features such as age, gender, ethnicity, parental education, absences, and other factors that can positively or negatively affect the level of students' educational performance.

The first stage of the proposed work includes predicting the level of students' educational performance using two of the most famous deep learning algorithms, namely RNN and LSTM, and their results were compared and discussed as shown in the following summary:

<u>Summary of RNN:</u>

Layer (type)	Output Shape	Param #
simple_rnn_10 (Simple RNN)	(None, 12, 10)	120
dropout_13 (Dropout)	(None, 12, 10)	0
simple_rnn_11 (Simple RNN)	(None, 10)	210
dropout_14 (Dropout)	(None, 10)	0
dense_8 (Dense)	(None, 1)	11

Total params: 341
Trainable params: 341
Non-trainable params: 0

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Summary of LSTM:

```
Layer (type)              Output Shape          Param #
==================================================================
 lstm (LSTM)               (None, 13, 10)         480
 lstm_1 (LSTM)             (None, 13, 10)         840
 lstm_2 (LSTM)             (None, 10)             840
dropout_2 (Dropout)        (None, 10)             0
dense_1 (Dense)            (None, 1)              11
==================================================================
Total params: 2,171
Trainable params: 2,171
Non-trainable params: 0
```

Table 1 shows the results after implementing the RNN and LSTM algorithms on the students' data set. The table shows the superiority of the performance of the RNN algorithm over the performance of the LSTM algorithm.

Table 1. The performance results of RNN and LSTM prediction techniques

Applied method	Accuracy	Precision	Sensitivity	F1_score
RNN	**96%**	**94%**	**94%**	**95%**
LSTM	**75%**	**73%**	**71%**	**74%**

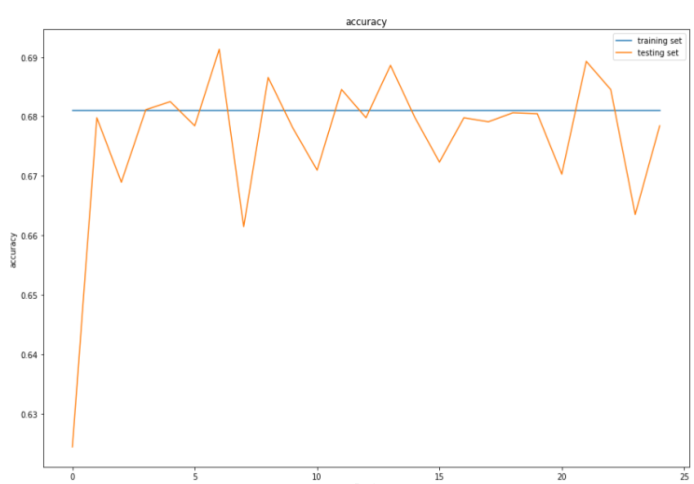

FIGURE 5. The accuracy of LSTM

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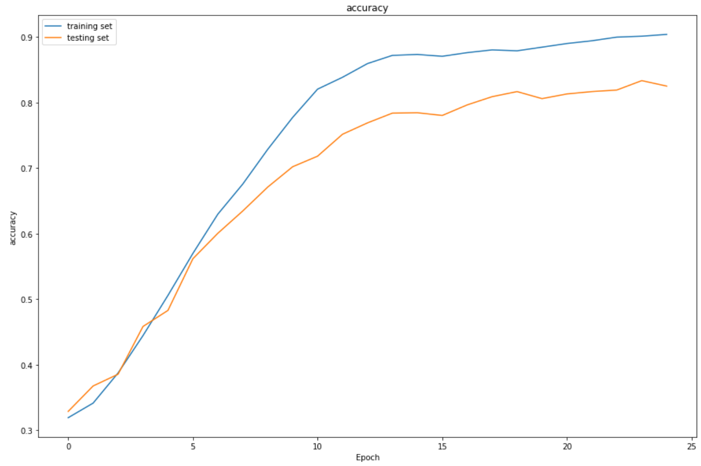

FIGURE 6. The accuracy of RNN

From Table 1 and Figures 5 and 6, it becomes clear to us that the accuracy obtained after implementing the LSTM algorithm is very low. The reason for this is due to the size of the data set used in this work, as this algorithm needs huge data in order to be implemented and give high accuracy and can be solved. This problem involves replacing the used data set with another, larger data set, or increasing the size of the used data set using a specific technique such as the CTGAN method.

Fig. 7 shows a comparison between the LSTM algorithm and RNN algorithm depending on the metrics employed in this work.

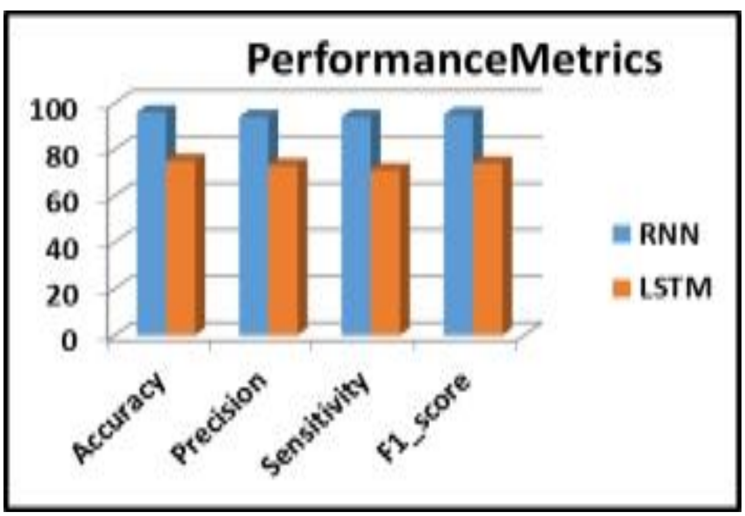

FIGURE 7. The performance comparison between LSTM and RNN

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The second stage includes encrypting the students' data set using the best and most famous encryption algorithm, which is AES. The purpose of this stage is to maintain the confidentiality of the students' data and protect it from manipulation or change.

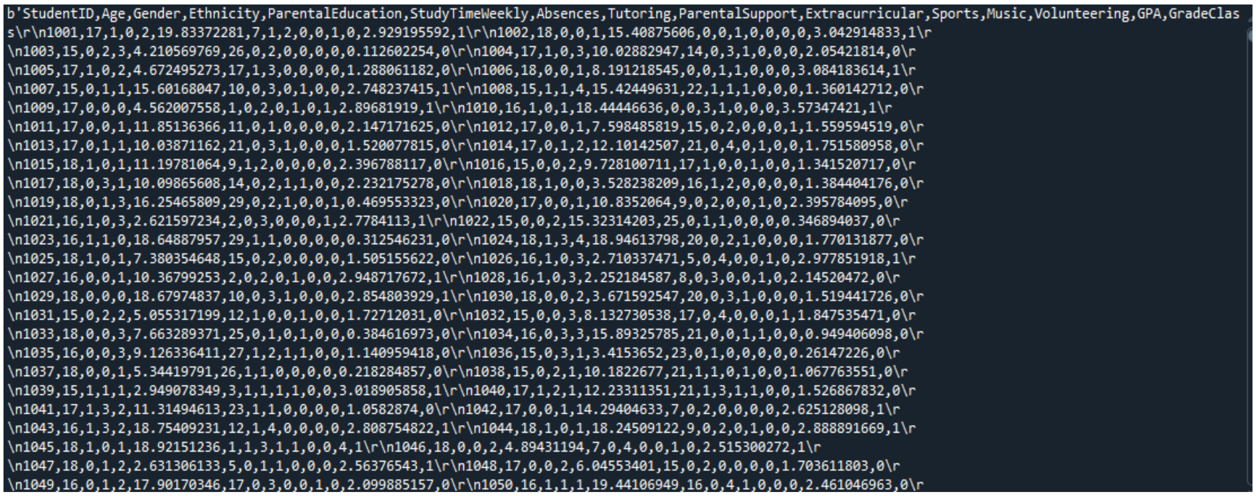

FIGURE 8. The Original Students' Dataset

Fig. 8 shows a sample of the original students' data set before coding. While, Fig. 9 shows the same set of student data, but after encryption with the AES algorithm.

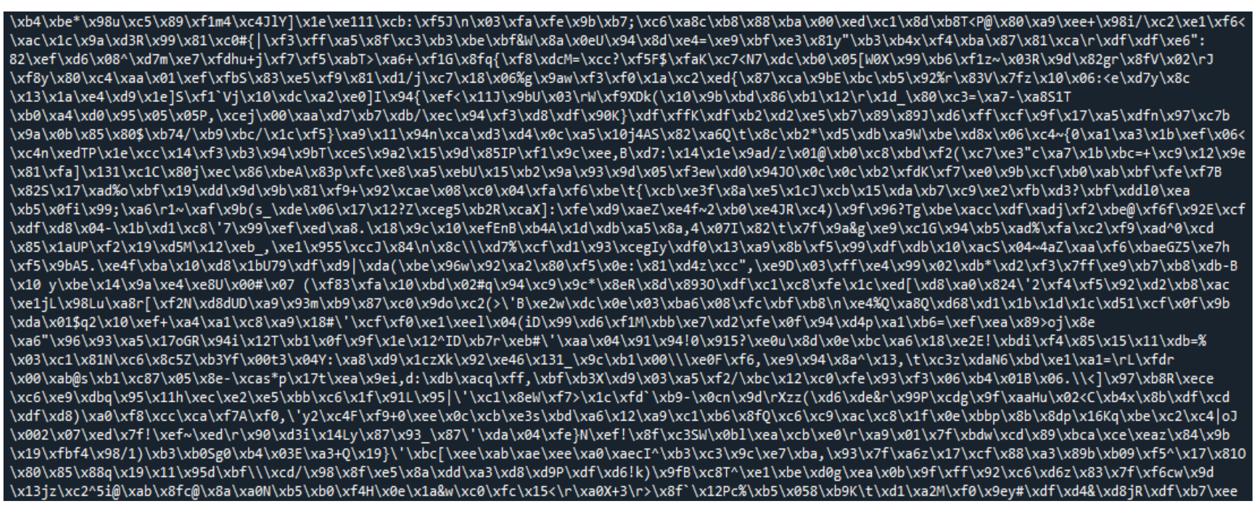

FIGURE 9. Encrypted Student Dataset

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CONCLUSION

In this study, LSTM and RNN algorithms were used on the student dataset. After implementing the above-mentioned algorithms to predict the academic level of students' performance, we obtained an accuracy of 96% and 75% for RNN and LSTM, respectively. The students' data set was also encrypted with the AES algorithm this is to maintain the confidentiality and security of dataset and protect it from tampering. It is possible in future research to use a specific method to increase the size of the data set, such as the CTGAN method, or to use a data set larger than the data used in this study, because the aforementioned algorithms need huge data in order to give higher accuracy.

Conflict of interests.

There are non-conflicts of interest.

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