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Original Article

The Convergence of Deep Learning and ICT: Revolutionizing Student Performance Prediction

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***Abstract** - Education includes transferring knowledge, integral judgment, and mature wisdom in addition to teaching and practising certain skills. Empowering educators and policymakers to make creative decisions that develop better student engagement, achievement, and equity in education, which ultimately prepares students for future challenges and opportunities, is crucial. Integrating Information and Communication Technology (ICT) into education boosts the learning capabilities that impact societal development, economic prosperity, and individual growth. This study aims to predict student performance using a Deep Neural Network (DNN) optimized with a feature optimization technique for effectively predicting student outcomes on ICT-enhanced learning. The dataset includes various attributes like gender, language skill, computer knowledge, learning type, location, and subject scores. The study evaluates the effects of ICT-enabled learning and finds critical elements impacting student performance by thoroughly examining the dataset and the neural network application. The proposed DNN employs a sequential architecture with multiple hidden layers with a classification accuracy of 93.0%, precision of 93.21%, recall of 93.0%, and an F1-score of 92.91. These findings highlight the model's high effectiveness in predicting student grades. This research underscores the potential of ICT-enhanced education to improve learning outcomes. It provides a robust predictive tool for early detection of at-risk students, thereby enabling prompt and targeted interventions.*

***Keywords** - Academic Success, Deep Neural Network, Education, Information and Communication Technology, Learning Type.*

1. Introduction

Education is the key component of society that influences shaping individuals and impacts social structures. It offers the information and abilities required for financial success and personal growth [1]. Through education, people can attain social mobility and end cycles of poverty and inequality. It encourages critical thinking, which empowers people to engage in democratic processes and make judgments. Education also helps to close gaps between varied populations by promoting tolerance and cultural understanding. A highly educated workforce is necessary for innovation and competitiveness in today's knowledge-based economy. Education also improves public health by raising knowledge and comprehension of health-related topics. It also contributes significantly to environmental sustainability by emphasizing the value of resource conservation and appropriate use. The educational environment is evolving along with technology, bringing both new opportunities.

Integrating ICT into education enhances learning experiences by providing interactive and accessible resources for students and teachers. This technological advancement promotes digital literacy, preparing students for a future in the digital world [2]. The International Federation of ICT defines ICT as an expanded form of Information Technology (IT) that highlights the significance of cohesive connectivity and the incorporation of telecommunications (phone lines and wireless signals) and computing devices, as well as the need for enterprise software, storage, middleware, and audiovisual. These elements are necessary to allow users to have substantial exposure to store, transfer, fully comprehend, and modify data.

ICT is a general term that refers to all technological advancements in digital data control and communication. ICT includes modern computer-related development careers that help people, businesses, and organizations [3]. ICT is difficult to communicate since it is hard to update with the rapid developments. ICT sends, retrieves, limits, and tracks computerized data. It is defined as the processing and communication of organizations that provide various assistance for training, learning, and the practice of education.

Understanding and predicting student outcomes is essential for creating personalized and effective educational experiences. It also makes it possible to recognize at-risk students early on and offer appropriate solutions to prevent dropouts and improve academic success [4]. Educators can address learning gaps and provide appropriate challenges by employing instruction to individual needs, predicting better student engagement and achievement. Predictive insights also guide efficient resource allocation, ensuring support for students. This data-driven approach informs curriculum development, helping to enhance instructional strategies and overall educational quality. Policymakers can provide informed education policies to promote equity and improve system-wide performance. Additionally, insights into student outcomes increase parental involvement by providing a clearer understanding of their child's progress and needs. Predicting student outcomes develops continuous improvement, innovation, and education research, driving efforts to prepare students for future challenges and ensuring equal opportunities for all learners [5]. The main objectives of the suggested method are given below:

- To develop a novel Deep Neural Network (DNN) using feature optimization techniques for predicting student performance based on different attributes
- To identify the most influencing factor that affects student outcomes.
- To analyze the influence of ICT-enabled education on improving learnability.

The remaining portion of this paper is structured as follows: Section 2 presents a review of the existing methods, identifying areas that require further exploration, mainly in the context of ICT-enhanced education. Section 3 details the methodology for developing the predictive model and analyzing student performance. Section 4 provides an in-depth discussion of the results obtained from the suggested method. Section 5 gives the conclusion of the paper by concluding the main outcomes,

2. Literature Review

Gocen and Bulut [6] employed qualitative case studies with undergraduate students of teacher education programs to explore the methodologies based on ethics. By integrating case-based and digital approaches, the model developed an open-minded attitude among the lecturers and students, using Socratic and active learning strategies. The formative evaluation throughout the academic year ensures an understanding of ethical concepts. The main shortcomings include focusing on particular preservice teachers and lacking a control group.

Parveen et al. [7] used the Technology Acceptance Model (TAM) to explore the role of ICT at the intermediate level in the Sialkot District in Pakistan. The data gathered from the principals of governmental intermediate institutions showed that ICT highly influenced teachers and students in enhancing interactive learning and resource assessment. The study's limitations include the limited sample size, dependence on self-reported information, and regional focus.

Karl et al. [8] developed a refined pedagogical evaluation system using artificial intelligence (WTCAi - When the Child Asks with AI) focused on the generation gap between teachers and students utilizing a learner-centered approach and constructive pedagogical methods. The system provides real-time data on performance and comprehensive feedback from students, parents, and teachers. However, the limitation included potential bias from self-reported data.

Vuong [9] assessed the reliability of a questionnaire based on the Teachers Attitudes Towards Computers (TAC) Questionnaire (V6) by focusing on the attitude of EFL primary school teachers towards ICT use in Vietnam. Data from 598 participants and 202 pilot samples performed Exploratory component Analysis (EFA) to demonstrate a reliable seven-factor structure. The rapid technological advancements, changes in ICT integration and potential sample-specific biases necessitate re-examination.

Avsec et al. [10] investigated the contributions of ICT and student engagement using multivariate regression and a sequential mediation model. Findings indicated that system thinking directly influences the outcomes of design-based courses. The limitation involved inhibiting structural equation modelling due to the limited sample sizes per group. Jaouadi et al. [11] integrated a hybrid model with ICT and Generative Artificial Intelligence (GAI) to provide personalized and engaged learning experiences utilizing components and uncover the benefits for educators and students. The main challenge involved in the infrastructure and data privacy handling.

Versteijlen and Wals [12] developed a sustainability-oriented learning model that blended online and on-campus learning using pedagogical design principles. The study included principles that were analyzed for developing sustainability competencies but noticed further validations of the design principles. Hoq et al. [13] developed a machine learning model to predict student performance based on the assessment of programming assignment submissions using a stacked ensemble model with SHAP framework for ensuring transparency in effect of programming procedures on students' achievement. Limitations involved the exploration of more intricate student profiles and detect plagiarism and cheating in programming codes.

Badal and Sungkur [14] analyzed the shift to online learning platforms during COVID-19, considering students' academic history and online engagement. Random Forest classifier surpassed others, achieving 85% grade prediction accuracy and 83% for engagement. Al-Azazi et al. [15] proposed a deep learning method using Artificial Neural Network-Long Short-Term Memory (ANN-LSTM) in

Massive Open Online Courses (MOOCs), which surpassed state-of-the-art models by 6–14%. Alhazmi & Sheneamer [16] used dimensionality reduction by the T-SNE algorithm, focused on data mining for clustering and classification techniques for investigating the correlation between different factors. Nonetheless, the difficulty persists in solving complex student performance issues.

An ensemble machine learning model with various classifiers with an accuracy of 93% was employed by Saluja et al. [17]. The importance of SMOTE (Random Under Sampler) and stacking approaches was emphasized in the study for enhancing prediction accuracy. Hussain and Khan [18] focused on predicting final grades using data from the Board of Intermediate & Secondary Education (B.I.S.E) Peshawar using regression models and decision tree classifiers, achieving high-grade prediction accuracy and low Root Mean Square Error in mark prediction.

Galarce-Miranda et al. [19] examined the impact of ICT on online platforms during COVID-19 and highlighted the disparity in ICT integration due to limited internet access. Students recognized the benefits of ICT but were concerned about the social connection and motivational aspects. The study lacks the focus of the educator's role. Alshabandar et al. [20] investigated the expansion of MOOCs in distance learning using predictive models to evaluate participation and performance in prior sessions. Using the OULAD dataset from Open University UK, the results showed that the accuracy was feasible. The main shortcomings were the absence of timing clues to predict the students' evaluation grades model.

3. Materials and Methods

Predictive modelling improves student outcomes in ICT-enhanced education by enabling personalized learning, early intervention, resource allocation, curriculum development, data-driven decision-making, continuous improvement, and research and innovation. So, a deep learning-based model is employed in this paper for effective student performance prediction and analysis of ICT-enabled education's influence on improving learnability. The workflow of the whole methodology is depicted in Figure 1. The student data is pre-processed and done with exploratory data analysis. After data analysis, the feature is optimized using a feature optimization technique. A deep neural network is proposed to predict student outcomes effectively.

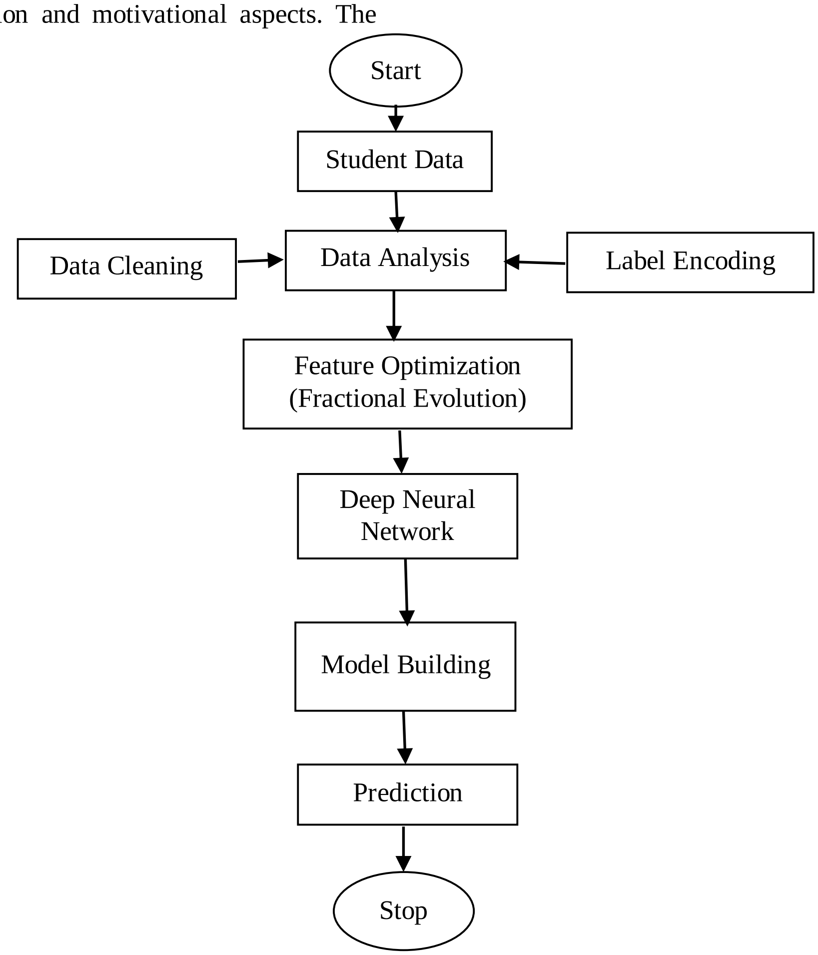

Fig. 1 Block diagram of suggested methodology

3.1. Dataset Description

The dataset provided encapsulates student information relevant to predictive modelling within an ICT-enhanced educational framework. It includes diverse attributes, including gender, language skill, computer knowledge, learning type, location, and subject scores in mathematics, physics, and chemistry, as in Figure 2. With gender representing the biological distinction, language skill delineates proficiency levels, ranging from basic to proficient, while computer knowledge reflects the spectrum of expertise from beginner to advanced. The learning type denotes the pedagogical approach, specifically emphasizing ICT integration. Moreover, the geographical factor of location distinguishes between rural and urban settings. The primary objective of this study is the development of predictive models to discuss student performance across subjects, employing deep learning techniques to unravel intricate patterns and correlations within the dataset. By enhancing the complex interaction of these variables, educators and policymakers gather insights crucial for optimizing educational strategies adapted to individual needs and contexts.

```
df = pd.read_csv('/content/gdrive/My Drive/student_data.csv')
df.head(15)
```

	gender	language_skill	computer_knowledge	learning_type	location	math_score	physics_score	chemistry_score
0	female	basic	advanced	ict	rural	72	72	74
1	female	intermediate	basic	ict	urban	69	90	88
2	female	basic	proficient	ict	rural	90	95	93
3	male	beginner	intermediate	normal	rural	47	57	44
4	male	intermediate	basic	ict	rural	76	78	75
5	female	basic	intermediate	ict	rural	71	83	78
6	female	basic	basic	ict	urban	88	95	92
7	male	basic	basic	normal	rural	40	43	39
8	male	advanced	fundamental	normal	urban	64	64	67
9	female	basic	fundamental	normal	rural	38	60	50
10	male	intermediate	intermediate	ict	rural	58	54	52
11	male	advanced	intermediate	ict	rural	40	52	43
12	female	basic	fundamental	ict	rural	65	81	73
13	male	beginner	basic	ict	urban	78	72	70
14	female	beginner	proficient	ict	rural	50	53	58

Fig. 2 Sample dataset

3.2. Data Analysis

Data analysis is essential for uncovering patterns and relationships within the dataset, facilitating the determination of important variables and the development of predictive models to estimate student outcomes. The process of obtaining and fixing mistakes and inconsistencies in data is known as data cleaning. This stage is important because inconsistent data might lead to false or erroneous conclusions. Data cleaning involves several steps like handling missing values, checking for duplicates, checking for data types and unique values of each column as in Figure 3, checking for different categories present in other categorical column and Figure 4, and checking the data set statistics.

```
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   gender              1000 non-null   object
 1   language_skill      1000 non-null   object
 2   computer_knowledge  1000 non-null   object
 3   learning_type       1000 non-null   object
 4   location            1000 non-null   object
 5   math_score          1000 non-null   int64
 6   physics_score       1000 non-null   int64
 7   chemistry_score     1000 non-null   int64
dtypes: int64(3), object(5)
memory usage: 62.6+ KB
```

(a)

```
df.nunique()

gender                 2
language_skill         5
computer_knowledge     6
learning_type          2
location               2
math_score            81
physics_score         72
chemistry_score       77
dtype: int64
```

(b)

Fig. 3 (a) Data type, and (b) Number of unique values of each column.

```
df.describe()
```

	math_score	physics_score	chemistry_score
count	1000.00000	1000.000000	1000.000000
mean	66.08900	69.169000	68.054000
std	15.16308	14.600192	15.195657
min	0.00000	17.000000	10.000000
25%	57.00000	59.000000	57.750000
50%	66.00000	70.000000	69.000000
75%	77.00000	79.000000	79.000000
max	100.00000	100.000000	100.000000

Fig. 4 Statistics of dataset

The numerical data description above shows that all means fall between 66 and 68.05. Additionally, all standard deviations fall within the range of 14.6 to 15.19. The minimum score for math is zero, but the minimum for physics is ten, and for chemistry, it is seventeen. EDA is used to examine and analyse the datasets to summarize the important characters portrayed by the dataset by employing data visualizations. The process involves identifying unique categories for each categorical variable in the dataset, which includes 'gender', 'language skill', 'computer knowledge', 'learning type', and 'location'. This step aids in understanding the diversity of values within each categorical feature, which is essential for data exploration. The numerical and categorical columns are distinguished based on their data types, preparing the data for further analysis. The numerical and categorical features and their respective counts provide a clear overview of the dataset's structure to facilitate subsequent analytical tasks. Columns of total score and average are included as in Figure 5.

	gender	language_skill	computer_knowledge	learning_type	location	math_score	physics_score	chemistry_score	total score	average
0	female	basic	advanced	ict	rural	72	72	74	218	72.666667
1	female	intermediate	basic	ict	urban	69	90	88	247	82.333333
2	female	basic	proficient	ict	rural	90	95	93	278	92.666667
3	male	beginner	intermediate	normal	rural	47	57	44	148	49.333333
4	male	intermediate	basic	ict	rural	76	78	75	229	76.333333
5	female	basic	intermediate	ict	rural	71	83	78	232	77.333333
6	female	basic	basic	ict	urban	88	95	92	275	91.666667
7	male	basic	basic	normal	rural	40	43	39	122	40.666667
8	male	advanced	fundamental	normal	urban	64	64	67	195	65.000000
9	female	basic	fundamental	normal	rural	38	60	50	148	49.333333

Fig. 5 Adding columns for total score and average

Also, a violin plot visualization, as in Figures 6 and 7, is provided as it is crucial for intuitively comparing the distribution and density of various scores across different learning types. It provides valuable insights into how different educational approaches may impact the student's performance.

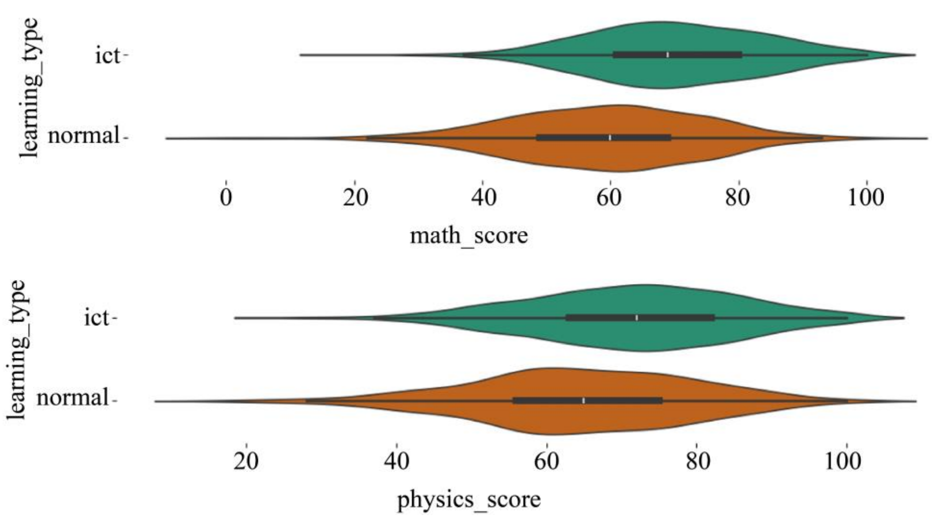

Fig. 6 Learning type v/s Maths score and Learning type v/s Physics score

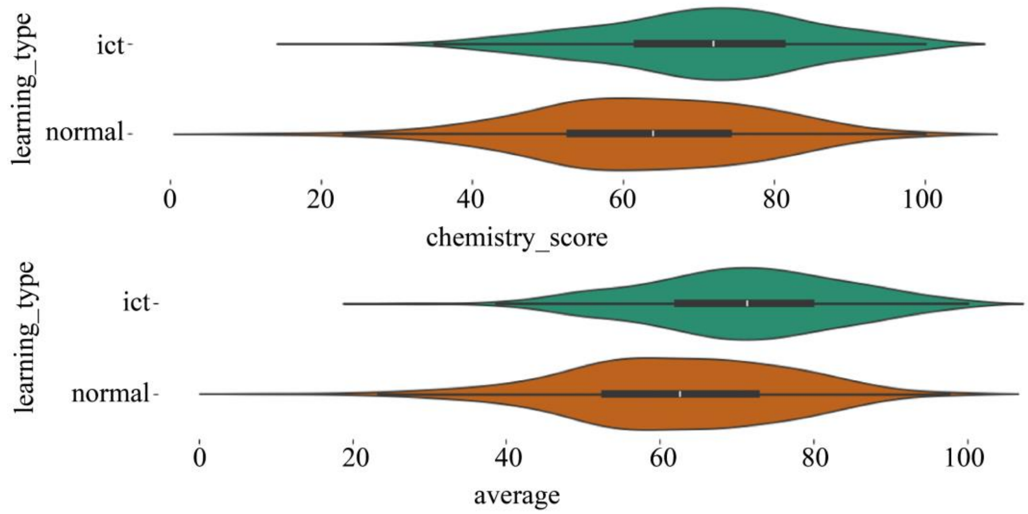

Fig. 7 Learning type v/s Chemistry score and Learning type v/s Average score

When considering the average score, students focusing on ICT education scored more marks than normal students. To visualize and analyze the average score distribution of students, histograms and Kernel Density Estimation (KDE) plots are employed. First, the average score for each student is calculated based on their math, physics, and chemistry scores. A histogram is then plotted to show the frequency distribution of these average scores, providing insights into the central tendency, spread, and frequency of score ranges. This helps identify common score intervals and any outliers. A smooth estimate of the probability density function is also produced using a KDE plot, which displays the distribution's general shape, including any potential skewness and multiple modes. Together, these visualizations offer a comprehensive understanding of student performance, highlighting areas where students excel or need improvement, thus aiding in informed decision-making and targeted educational interventions. The histogram analysis based on the gender category is given in Figure 8.

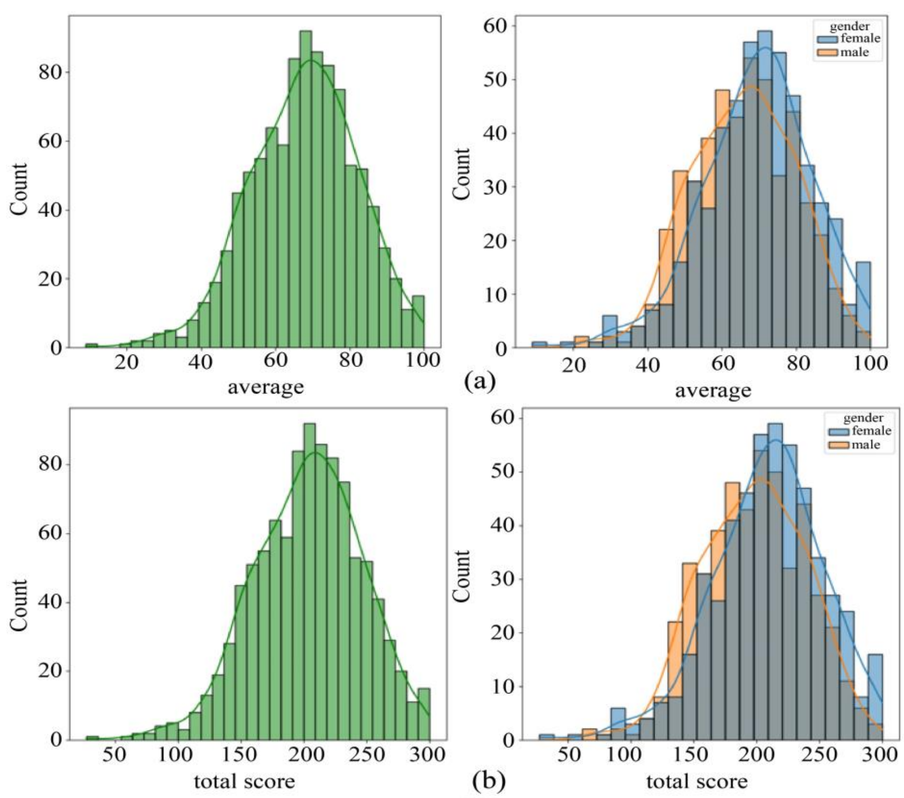

Fig. 8 Performance Analysis based on (a) Average score, and (b) Total score for gender category.

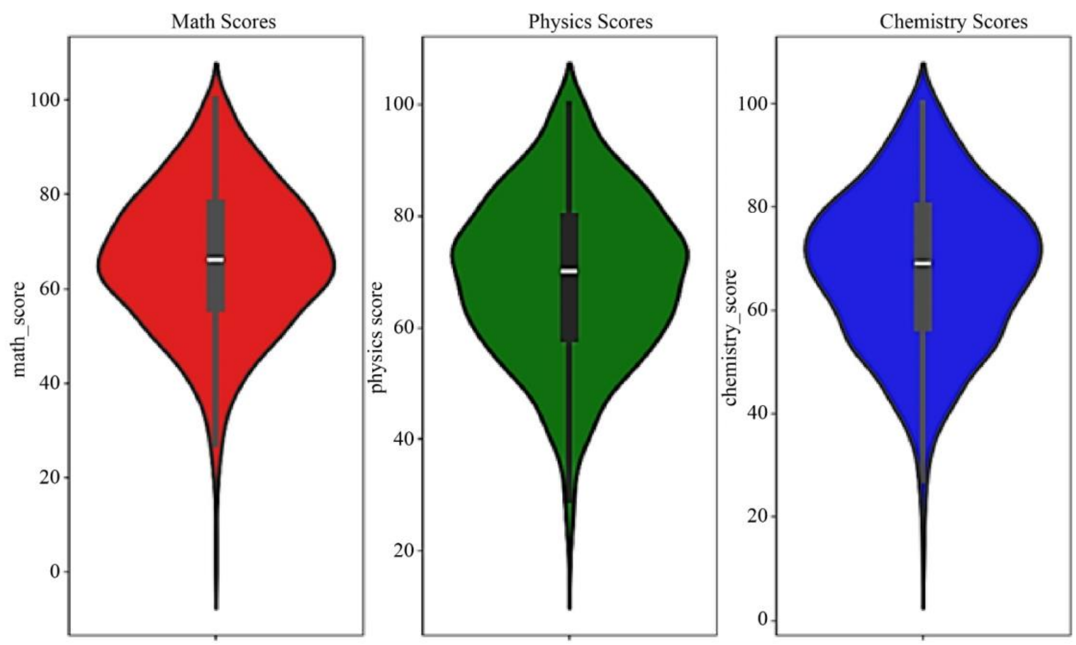

Fig. 9 Maximum score of students in all three subjects

From Figure 8, it is clear that the performance of female students is better compared to male students. Figure 9 represents the plot showing the maximum score of students in all three subjects.

It is evident from the three plots above that most students achieve scores between 60 and 80 in math, while most achieve scores between 50 and 80 in physics and chemistry. Figure 10 represents the distribution of the data.

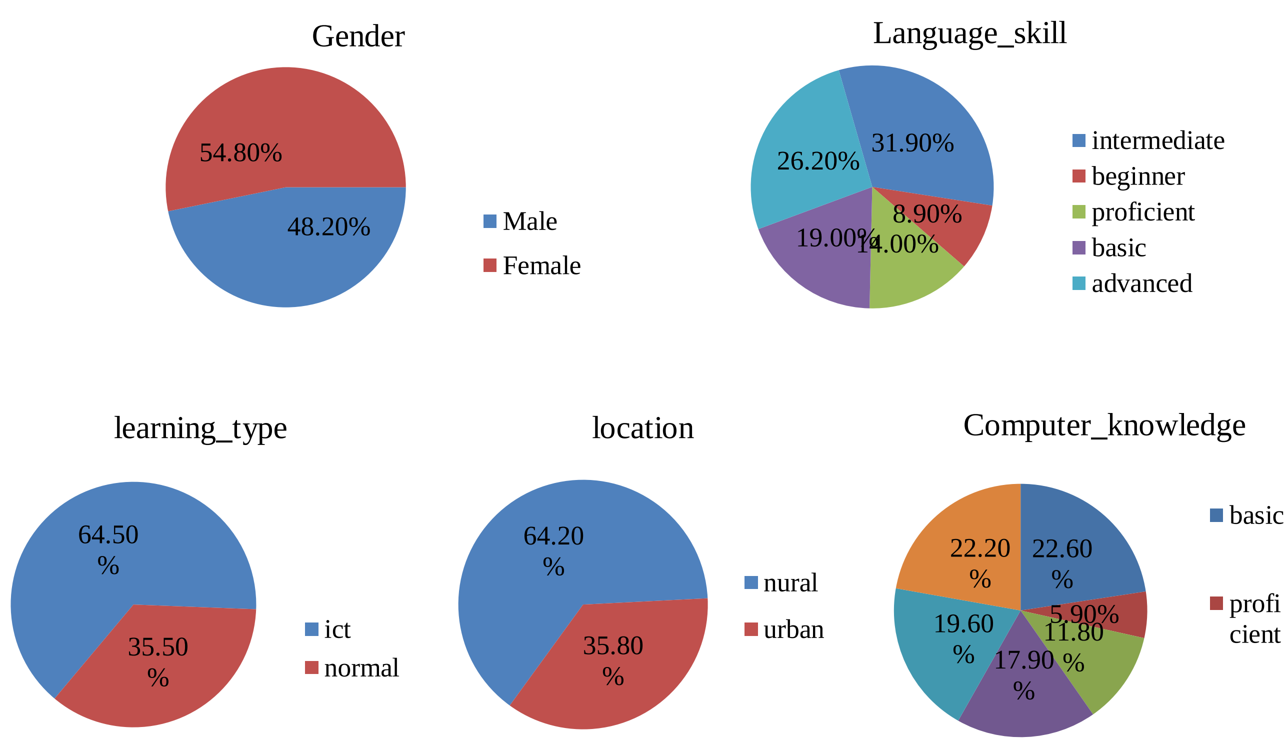

Fig. 10 Distribution of data

The dataset shows an almost equal number of male and female students, with most having intermediate language skills. Most of them are engaged in ICT-enhanced learning and come from rural areas. In terms of computer knowledge, most students have basic skills, closely followed by those with intermediate skills. These insights help inform targeted educational strategies and resource allocation. The analysis investigates the impact of language skills and learning types on student performance through univariate and bivariate analyses. Bivariate analysis reveals that proficient students achieve the highest marks while beginners score the lowest, indicating that language proficiency significantly affects academic outcomes, as represented by Figure 11. Students with lower language skills consistently perform worse across all subjects. Univariate analysis of the learning type shows that ICT-enhanced learning is more common among students than traditional methods. Further bivariate analysis indicates that students engaged in ICT-enhanced learning tend to perform better than those using normal learning methods, underscoring the positive impact of technology-integrated education on student performance, as in Figure 12. These insights emphasize the critical role of language proficiency and modern learning approaches in enhancing academic achievement.

The provided steps create a system to evaluate and categorize student performance. First, a pass mark of 40 determines if students pass or fail based on their average scores. Students are labeled as either 'Pass' or 'Fail' accordingly. Then, a grading system is implemented to assign letter grades based on their average scores and pass/fail status. The grades range from 'E' for failing scores to 'O' for scores between 90 and 100, with intermediate grades ('D', 'C', 'B', 'A') covering specific score ranges. This system is applied to all students, creating a new column categorising their performance. Finally, the distribution of these grades is analyzed to understand how many students fall into each category, providing insights into overall student performance as in Figure 13. The final dataset is illustrated in Figure 14, which includes the status of performance (pass/fail) and the grades corresponding to the score (A, B, C, D, E, O).

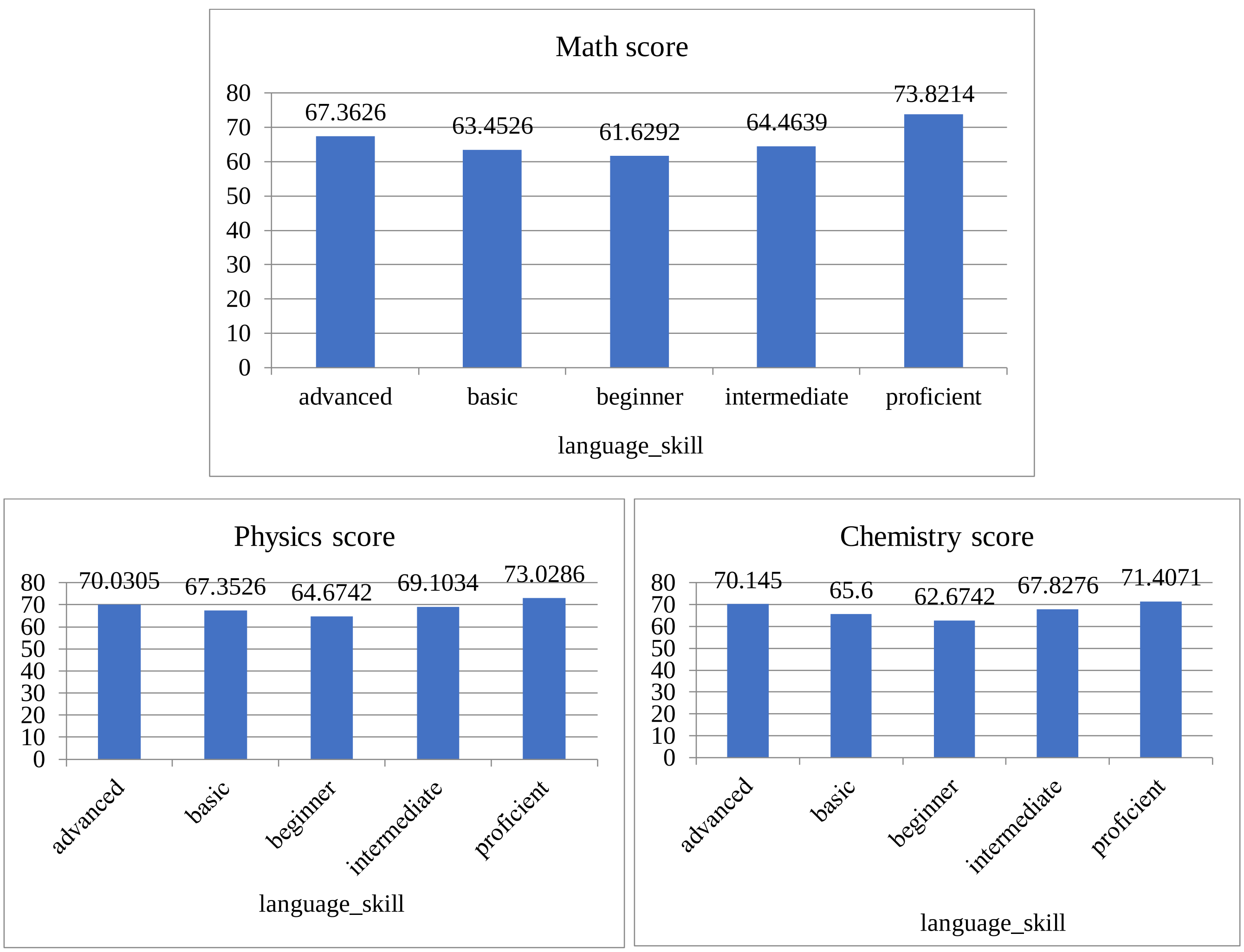

Fig. 11 Impact of Language Skill on Student's Performance

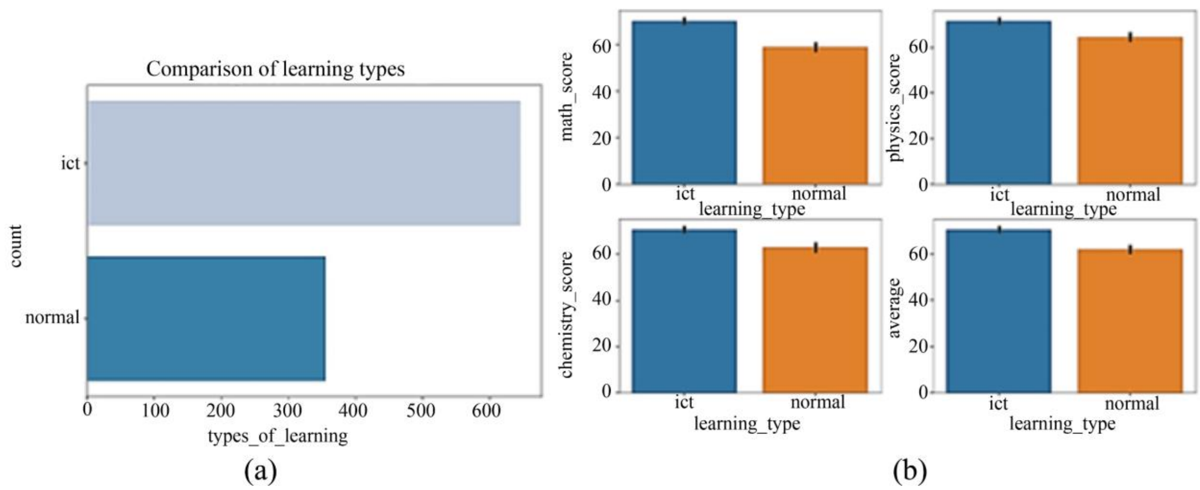

Fig. 12 Analysis of Learning Type (a) Univariate, and (b) Bivariate.

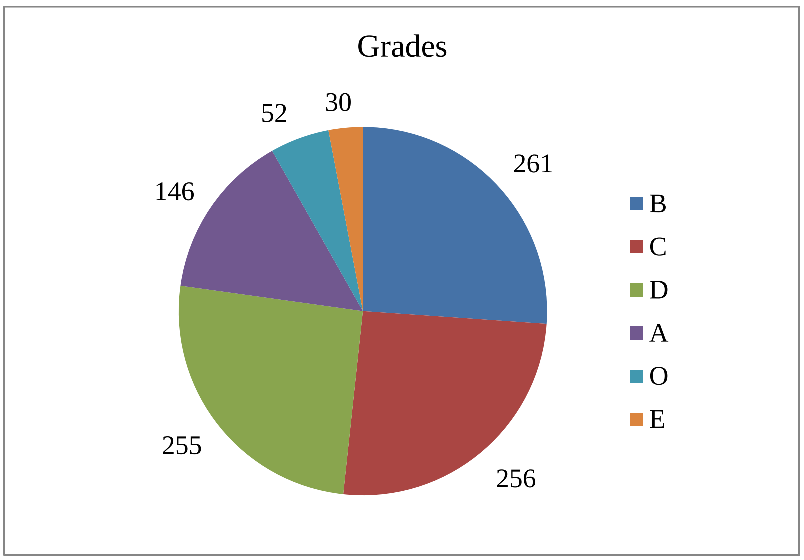

Fig. 13 Counts and distribution of various grades among the students

```
[27] df.head(15)
```

	gender	language_skill	computer_knowledge	learning_type	location	math_score	physics_score	chemistry_score	total score	average	status	grades
0	female	basic	advanced	ict	rural	72	72	74	218	72.666667	Pass	B
1	female	intermediate	basic	ict	urban	69	90	88	247	82.333333	Pass	A
2	female	basic	proficient	ict	rural	90	95	93	278	92.666667	Pass	O
3	male	beginner	intermediate	normal	rural	47	57	44	148	49.333333	Pass	D
4	male	intermediate	basic	ict	rural	76	78	75	229	76.333333	Pass	B
5	female	basic	intermediate	ict	rural	71	83	78	232	77.333333	Pass	B
6	female	basic	basic	ict	urban	88	95	92	275	91.666667	Pass	O
7	male	basic	basic	normal	rural	40	43	39	122	40.666667	Pass	D
8	male	advanced	fundamental	normal	urban	64	64	67	195	65.000000	Pass	C
9	female	basic	fundamental	normal	rural	38	60	50	148	49.333333	Pass	D
10	male	intermediate	intermediate	ict	rural	58	54	52	164	54.666667	Pass	D
11	male	advanced	intermediate	ict	rural	40	52	43	135	45.000000	Pass	D
12	female	basic	fundamental	ict	rural	65	81	73	219	73.000000	Pass	B
13	male	beginner	basic	ict	urban	78	72	70	220	73.333333	Pass	B
14	female	beginner	proficient	ict	rural	50	53	58	161	53.666667	Pass	D

Fig. 14 Final dataset

3.3. Dataset Encoding

The process involves transforming categorical variables into numerical formats to prepare the dataset for machine learning analysis. First, label encoding is applied to the location and learning type, converting them into numerical values. The language skill column is manually mapped to a numerical scale from 1 to 5, representing different proficiency levels from beginner to proficient. The computer knowledge is also label-encoded, and the frequency of each category is counted. Similarly, the gender and status are label-encoded. The dataset is then split into features and targets, with the target being the grades. Finally, a histogram is plotted for each feature to visualize their distributions, as in Figure 15, aiding in understanding the data's characteristics and ensuring it is ready for modeling. Label encoding transforms the categorical grades into a series of integers, which are then converted into a binary class matrix using one-hot encoding. This matrix represents each grade as a binary vector suitable for classification tasks.

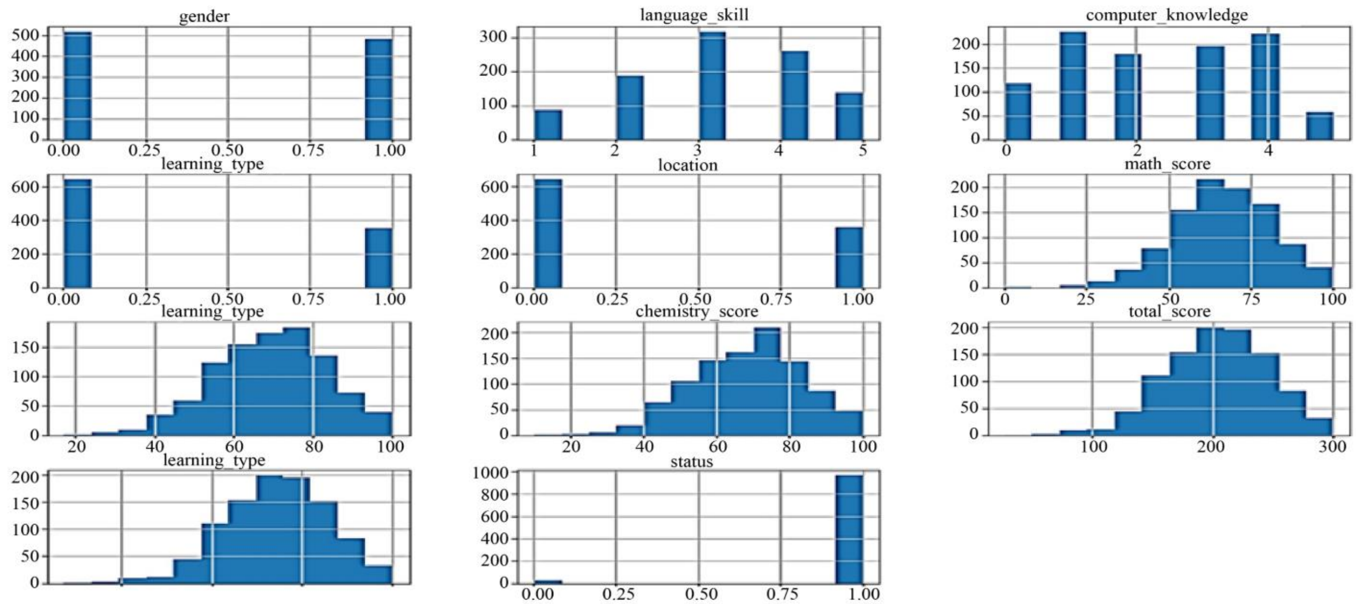

Fig. 15 Feature distribution of encoded data

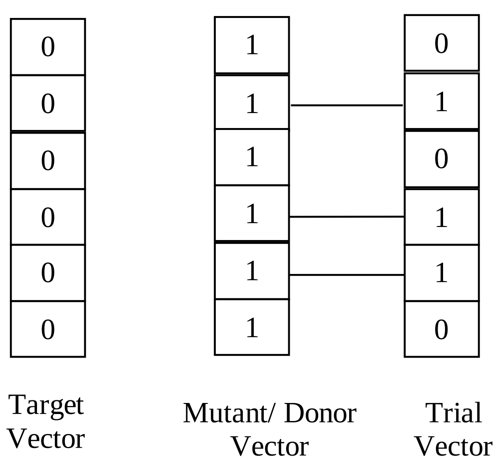

Fig. 16 Fractional evolution process

3.4. Feature Optimization

Fractional evolution, like a genetic algorithm, uses mutation as the primary operator to search for better solutions. The optimization process starts with mutation, followed by evaluating the fitness of individual solutions. The algorithm employs mutation to explore the search space and selection to guide the search toward promising regions. During mutation, a donor vector is generated using a base vector and a difference vector derived from other vectors in the population. This donor vector undergoes crossover with a target vector, which represents a potential solution, to produce a trial vector, as in Figure 16. The final selection involves choosing between the target vector (parent) and the trial vector (offspring) based on their fitness, ensuring that the better-performing vector is retained for the next generation. This iterative process continues, gradually evolving the population towards optimal solutions. The flow chart of the fractional evolution process for feature optimization is given in Figure 17.

3.5. Proposed Deep Neural Network

A DNN is a type of Artificial Neural Network (ANN) that has many layers between the input and output layers. It intends to gradually extract higher-level features from unprocessed input to discover intricate patterns in data. As shown in Figure 18, a DNN comprises an input layer, multiple hidden layers, and an output layer. Each layer contains interconnected neurons, also known as nodes or units. Weights are carried by the connections between neurons and are changed throughout training to reduce the disparity between expected and actual outputs.

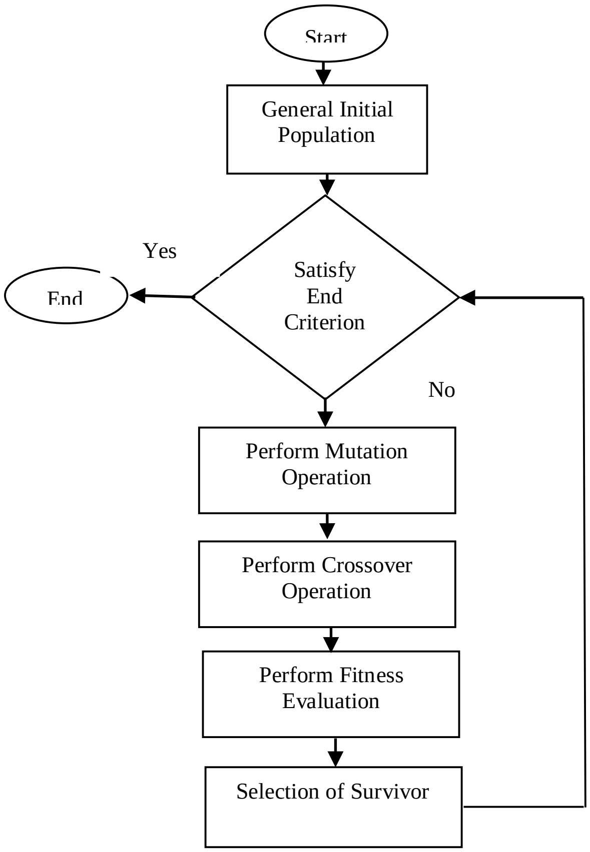

Fig. 17 Flowchart of fractional evolution process

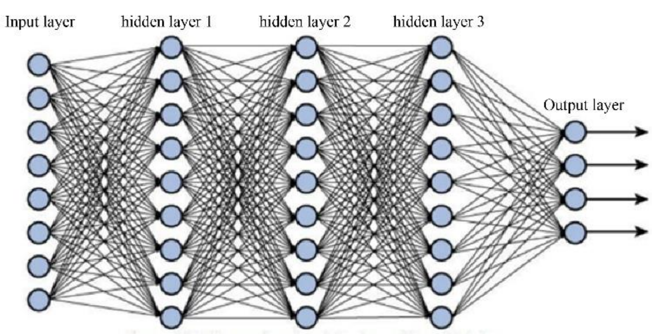

Fig. 18 Basic architecture of DNN

Forward propagation is a process of computing the output of the neural network given an input. The input layer will have nodes corresponding to the dataset's features, including gender, language skill, computer knowledge, learning type, and location. The number of features will determine the number of nodes in the input layer. The data, X, is delivered to the input layer. The hidden layers will perform feature extraction and representation learning. The proposed DNN include multiple hidden layers to capture complex relationships in the data. Each hidden layer will have a varying number of neurons, determined through experimentation to find the optimal architecture. All neurons in the preceding layer send inputs to each neuron in a deep layer. The output layer has nodes corresponding to the predicted outcomes. The output z of each neuron in layer l is computed as a weighted sum of the inputs passed through an activation function f represented by Equation (1),

$$z^l = f\left(\sum_{i=1}^{n^{(l-1)}} w_i^{(l)}\, x_i^{(l-1)} + b^{(l)}\right) \tag{1}$$

Here, $w_i^{(l)}$ implies the weight of the connection between neuron i in layer l–1 and neuron j in layer l, $x_i^{(l-1)}$ is the output of neuron i in layer l–1, $b^{(l)}$ is the bias term. The network's ultimate output is computed by the output layer. The probabilities for each class described by Equation (2) are produced using the softmax activation function for classification tasks.

$$\hat{y} = softmax(z^{(L)}) = \frac{e^{z_j^{(L)}}}{\sum_{K=1}^{L} e^{z_i^{(L)}}} \tag{2}$$

Where $z_j^{(L)}$ is the output of the neuron j in the output layer and K is the number of classes. During training, the difference between the predicted output $\hat{y}$ and the actual output y is measured using a loss function L as given by Equation (3),

$$L(\hat{y}, y) = -\sum_{i=1}^{K} y_i log(\hat{y}_i) \tag{3}$$

The model summary and architecture of the proposed methodology are given in Figures 19 and 20, respectively.

```
model.summary()

Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 128)               1536

 dense_1 (Dense)             (None, 64)                8256

 dense_2 (Dense)             (None, 32)                2080

 dense_3 (Dense)             (None, 16)                528

 dense_4 (Dense)             (None, 6)                 102

=================================================================
Total params: 12502 (48.84 KB)
Trainable params: 12502 (48.84 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Fig. 19 Model summary

3.6. Hardware and Software Setup

A powerful computational infrastructure was used for the study, consisting of an NVIDIA GeForce GTX 1080Ti GPU, an Intel Core i7 processor, 32GB of RAM, and the Python-based Keras library integrated with the TensorFlow framework. The extensive computing resources of Google

Colab combined with Keras's user-friendly interface made building models easier and guaranteed that intricate neural network architectures were successfully trained and implemented. Hyperparameters are configurations or settings used to control the training process of a deep learning model. Unlike model parameters, which are learned from the data, hyperparameters are set before the training process begins and directly influence the performance and convergence of the model. Table 1 mentions the hyperparameters used in the proposed model.

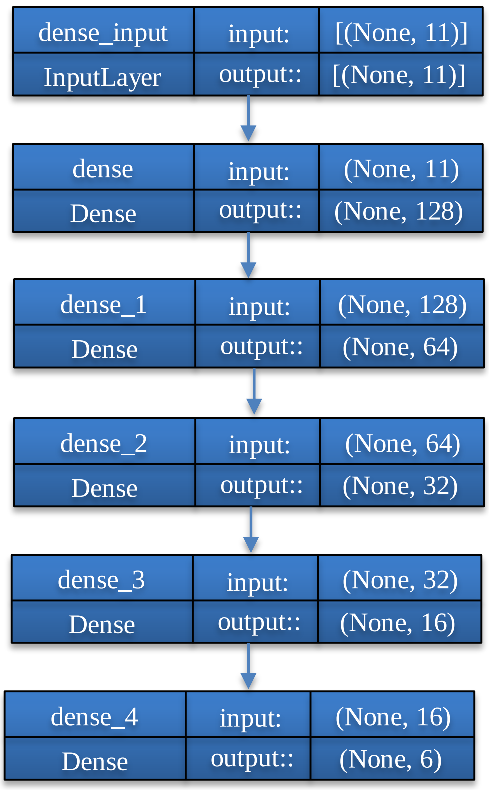

Fig. 20 Architecture of proposed model

Table 1. Hyperparameter specification

Hyperparameters	Values
Optimizer	Adam
Iterations	1000
Batch Size	128
Activation Function	ReLU, Softmax
Loss Function	Categorical Cross-Entropy

80% of the dataset is used for training, while the remaining 20% is used for testing. This ensures that the model can be trained on a significant percentage of the data while being assessed on a separate set to test its performance. The training set contains 800 samples with 11 features each, and the testing set contains 200 samples with 11 features each. The target variables for the training and testing sets are represented as 6-dimensional vectors corresponding to the one-hot encoded grades.

4. Results and Discussion

4.1. Performance Evaluation

Performance parameters are essential for evaluating the effectiveness of the deep learning model in classification tasks and understanding its strengths and weaknesses in handling different types of data and scenarios. The evaluation metrics used for the proposed methodology are given in Table 2. Using the evaluation metrics given in Table 2, the classification report of the proposed model is given in Table 3 to assess the efficiency.

Table 2. Evaluation metrics

Performance Metrics	Equations
Accuracy	$(TP + TN) / (TP + TN + FP + FN)$
Precision	$TP / (TP + FP)$
Recall	$TP / (TP + FN)$
F1 Score	$2 * (Precision * recall) / (Precision + recall)$
where TP-true positives, FP-false positives, TN-true negatives and FN-false negatives	

Table 3. Classification report

Evaluation Parameters	Results (%)
Accuracy	93.0
Precision	93.21
Recall	93
F1-Score	92.91

The classification report summarizes the performance of the classification model in predicting student outcomes based on the dataset. With an accuracy of 93.0%, the model demonstrates a high level of correctness in its predictions. The precision of 93.21% indicates that the model accurately identifies students who achieve a certain grade level. In comparison, the recall of 93.0% reflects its ability to correctly identify all students who actually attained that grade. The F1-score, at 92.91%, provides a balanced measure of precision and recall, promising the model's effectiveness in student outcome prediction. Visualizing accuracy and loss using plots validates the model's effectiveness and makes informed decisions to enhance educational interventions and support strategies. The accuracy plot illustrates the trend of model accuracy over the training epochs, as shown in Figure 21. As the model learns from the data during training, the accuracy plot allows us to monitor how well the model performs over time. A consistently increasing accuracy plot shows that the model is effectively learning the patterns in the data and improving its predictive capabilities.

Meanwhile, the loss plot depicts the model's loss function trend over the training epochs, as in Figure 22. The loss function measures the disparity between the model's predictions and the actual outcomes, with lower values indicating better model performance. In the study, a decreasing loss plot signifies that the model converges towards optimal parameter values and improves its predictive accuracy.

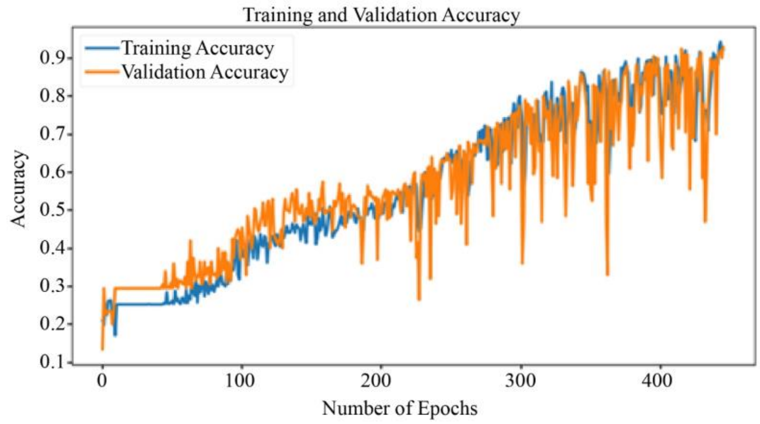

Fig. 21 Accuracy plot of suggested methodology

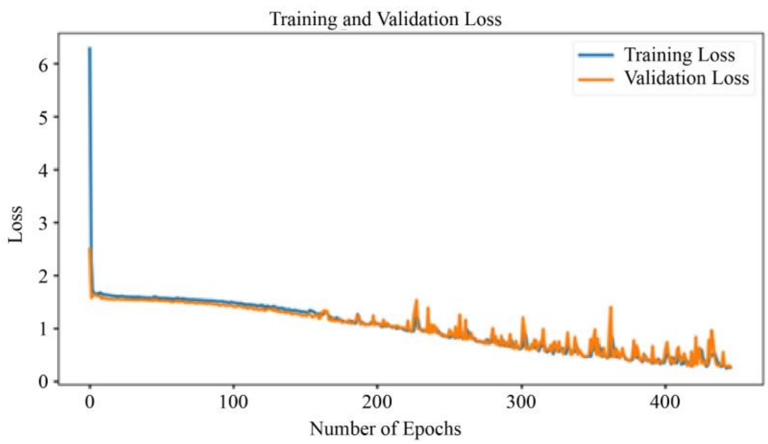

Fig. 22 Loss plot of suggested methodology

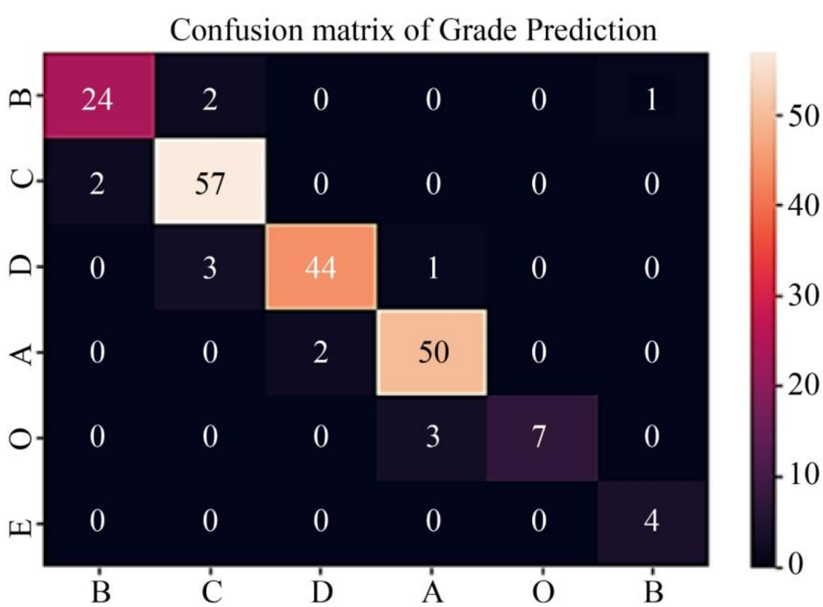

Fig. 23 Confusion matrix of proposed methodology

The confusion matrix thoroughly analyses the model's effectiveness in grading students based on predictive modelling of student outcomes. The evaluation of the model's accuracy in assigning students to various grade levels is analysed by the confusion matrix, as shown in Figure 23.

This allows us to identify specific areas of misclassification and make necessary adjustments to improve accuracy. Understanding the model's errors can ensure reliable performance across all grade levels.

The output obtained after predicting the student performance for analyzing the influence of ICT-enabled education for enhancing learnability is given in Figure 24. The prediction results obtained by the proposed DNN model are illustrated in Table 4.

Table 4. Prediction outputs

Input Data	Predicted Grade
[0,2,1,1,0,72,72,74,218,72,1]	B
[1,1,0,0,0,54,43,44,141,47,1]	E
[1,4,4,1,0,84,90,85,259,86,1]	A
[1,2,2,0,0,34,30,45,109,36,0]	O

4.2. Performance Comparison

The proposed deep neural network with feature optimization technique is compared with some conventional learning methods. Figure 25 illustrates the accuracy comparison graph of the suggested model with existing methods where the proposed DNN model outperformed the other existing materials.

```
# Input format [gender, language_skill, computer_knowledge, learning_type, location, math_score, physics_score, chemistry_score, average, status]
input = [0,2,1,1,0,72,72,74,218,72.6667,1]
input_array = np.asarray(input)
input_reshaped = input_array.reshape(1,-1)
prediction = model.predict(input_reshaped)
pred = np.argmax(prediction, axis=1)
print("Predicted Grade is")
print(encoder.inverse_transform(pred))

1/1 [==============================] - 0s 119ms/step
Predicted Grade is
['B']
```

Fig. 24 Prediction outputs

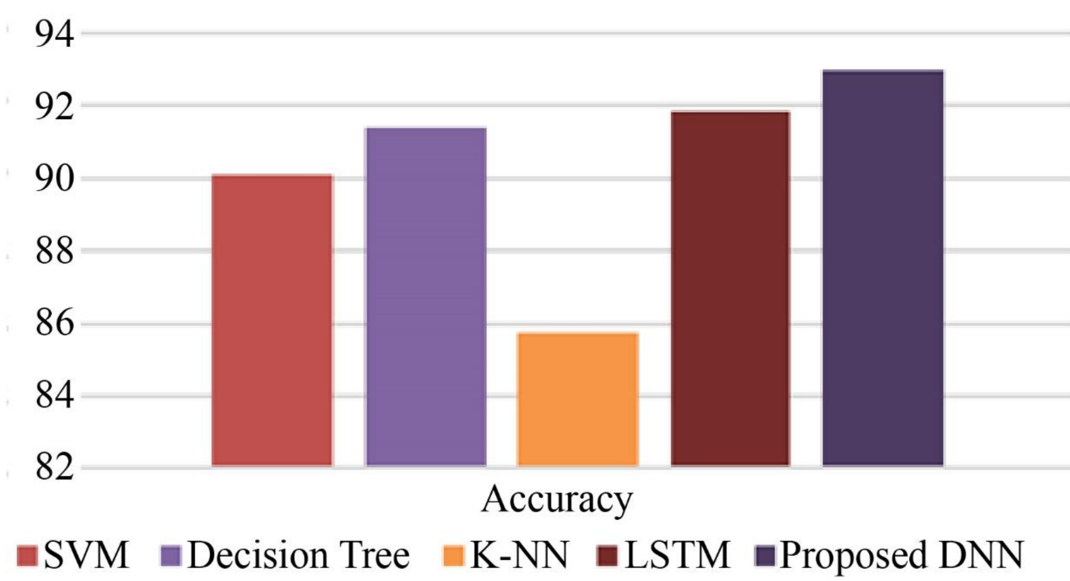

Fig. 25 Grade prediction system accuracy

5. Conclusion

ICT has become an integral part of the modern education. With the expansion of technology, various digital tools and resources are helping students and educators learn more effectively with enhanced support learning. The study proposed a novel method for predicting student performance in ICT-enhanced education using a deep neural network with feature optimization. By analyzing diverse student attributes such as gender, language skill, computer knowledge, learning type, and location, a robust predictive model was developed, demonstrating high accuracy, precision, recall, and F1-score. The evaluation metrics yielded promising results, with an accuracy of 93.0%, precision of 93.21%, recall of 93.0%, and F1-score of 92.91%. These outcomes underscore the effectiveness of the proposed model in predicting academic outcomes and identifying key factors influencing student performance. The comparison of the suggested model with the accuracy of the existing methods showcases the effectiveness in prediction. The study contributes valuable insights for educators, policymakers, and stakeholders to enhance personalized learning strategies, early intervention initiatives, and data-driven decision-making in education.

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