

Enhancing Student Engagement Prediction In Online Education Through Deep Learning

Xiaofang Qin*

The Admissions Office, Handan Open University, Handan, Hebei 056004, China

* Corresponding author. E-mail: xiaofangqin25@outlook.com

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The rapid growth of online learning platforms has transformed education by enabling students to access learning resources anytime and anywhere. Despite these advantages, maintaining student engagement remains a significant challenge, as engagement directly influences motivation, knowledge retention, and academic performance. This study presents a deep learning-based predictive framework for forecasting student engagement and delivering facial expression-based feedback to improve learners' motivation and commitment. The proposed model, termed the Improved Synergistic Fibroblast-tuned Adjustable Convolutional Neural Network (ISF-ACNN), classifies students into three engagement categories: inactive, moderately engaged, and highly engaged. Initially, the collected educational data are preprocessed through data cleaning and noise removal to improve quality. Subsequently, the Visual Geometry Group 16 (VGG16) model extracts meaningful features, while the Improved Synergistic Fibroblast (ISF) algorithm selects the most relevant features for prediction. The optimized feature set is then integrated with the ACNN model to achieve accurate and adaptive engagement classification. Experimental evaluation demonstrates that the proposed ISF-ACNN model outperforms existing approaches, achieving 98.49% accuracy, 98.05% precision, 98.00% recall, and an F1-score of 98.00%. These findings confirm the effectiveness of the proposed framework in predicting student engagement. In addition, the intelligent system identifies fluctuations in engagement level of students and provides personalized guidance based on the facial expression to promote student participation, enhance learning motivation, and sustain active learning in all terms of online education, and informs the instructor at the same time to allow the timely and appropriate intervention of the instructor.

Keywords: Student Engagement, Online Education, Facial Expression, Improved Synergistic Fibroblast Tuned Adjustable Convolution Neural Network (ISF-ACNN)

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1. Introduction

Online education provides flexible, personalized learning through diverse digital resources, enabling students to learn at their own pace [1] while balancing commitments [2]. Adaptive technologies personalize curricula according to progress, providing targeted student support [3]. The global reach of these platforms also allows students from different geographic locations to access quality education

[4]. Online platforms enable convenient, accessible lifelong learning [5]. Online education provides flexible, accessible learning opportunities worldwide [6]. Fig. 1 presents the features of online education platforms on student engagement.

Online platforms cater to a variety of learners at all times and locations, yet it is still difficult to sustain both active involvement and emotional bonding [7]. Engagement is sustained, and learning outcomes are enhanced

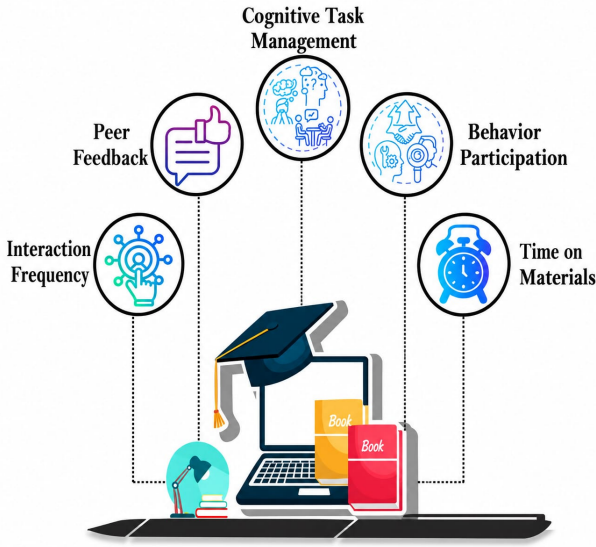


Fig. 1. Features of online education platforms on student engagement

by interactive content, customization, feedback, and social interaction [8]. Platforms enable personalized, flexible, self-paced learning [9]. Online education offers diverse resources and tools supporting varied learning styles [10]. Multimedia, gamification, and collaboration enhance active student engagement [11]. Understanding engagement is the foundation of engaging learning, lifelong education, concentration, motivation, and educational success [12]. Recent deep learning approaches evaluate engagement based on facial and emotional information [13]. In contrast, in ISF-ACNN, VGG16, ISF optimization, and ACNN classification are combined to adaptively refine features and predict engagement. Machine Learning is being increasingly used to predict students engagement, but it is still difficult to accurately identify patterns within the different interactions of the learners [14]. Supervised learning identifies disengagement using measurable signals, motivating ISF-ACNN for optimized features and adaptive engagement classification [15]. The purpose of this study is to analyze engagement factors that affect participation, academic achievement, persistence and enhancement of online education. The ISF-ACNN for student engagement detection being proposed monitors student engagement in a dynamic way with both LMS data and facial-expressions data. VGG16 extracts features, ISF optimizes them and ACNN classifies the engagement levels which allows giving personalized support, alerts to the instructor on time, keeps the motivation, participation in an active manner and enhancing the student centered on-line learning.

1.1. Contribution

This study presents ISF-ACNN for precise student engagement prediction via LMS preprocessing, VGG16 feature extraction, and ISF optimization, also providing adaptive feedback based on behavior and facial expressions. Unlike conventional hybrid models, ISF-ACNN integrates VGG16 feature extraction, ISF-based adaptive feature refinement, and ACNN classification within one optimization-driven pipeline. The rest of the research is articulated as follows: Phrase 2 highlights the literature reviews, Phrase 3 brings out the methods, and Phrase 4 presents the performance and discussion, Phrase 5 provides the conclusion.

2. Theory and formula

The shift of health education to online formats during COVID-19 exacerbated challenges related to engaging students, transferring materials, adapting to technology, and training faculty [16]. Online learning during COVID-19 challenged student participation, while integrated technology, e-learning systems, and active learning improved interaction and comprehension [17]. COVID-19 boosted e-learning, and deep learning incorporates facial landmarks, emotion recognition, and MES techniques to capture learner behavior and foresee engagement [18]. Online accounting education showed benefits from synchronous and asynchronous methods, while technological dissatisfaction and relationship challenges remained [19]. Synchronous online teaching guidelines highlight actionable strategies to maintain student attention and promote a quality learning environment [20]. The new framework enhanced students' online involvement by setting expectations and encouraging friendly, time-saving learning methods that were focused on students [21]. Indonesian university data showed that student-teacher-content interactions positively influenced online engagement and satisfaction among 124,041 students [22]. Instructor resource use and student participation in videos, self-assessment, and social tools strongly predict online learning duration [23]. An explorative 10-month e-learning study revealed that gamification encourages the users to adopt, the students to engage and the learning to take place online [24]. Teacher facilitation enhanced students' behavioral and cognitive engagement in WeChat discussions, while student leadership also showed positive effects [25]. According to [26], emotional involvement has an indirect impact on satisfaction through perceived utility. The recent engagement studies include interaction, behavior analysis, and automation prediction but are not integrated with deep feature extraction, feature selection, and adaptive classification. ISF-ACNN bridges this gap with the aid of VGG16 model, ISF optimization and ACNN

for three-level engagement classification.

3. Experimental setup

This paper utilizes ISF-ACNN in LMS and facial-expression information to identify the level of engagement and early disengagement. Student engagement is a fusion of behavioral and facial expression cues, allowing ISF-ACNN to identify inattentive, somewhat engaged, and deeply engaged students, which used effectively support students. Fig. 2 shows the proposed framework integrating preprocessing, VGG16 feature extraction, ISF optimization, and ACNN classification.

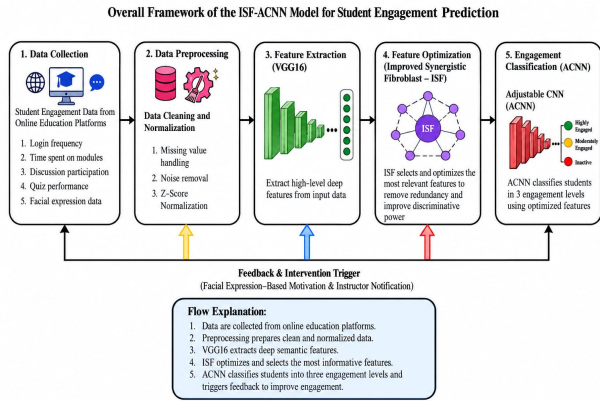


Fig. 2. Schematic diagram of proposed flow

3.1. Data Collection

The dataset used in this study was obtained from the publicly available Kaggle Student Engagement Dataset, available at <https://www.kaggle.com/datasets/ziya07/student-engagement-dataset/data>. The dataset consists of learning management system (LMS) activity logs and facial-expression data. Students are categorized into three engagement levels: inactive, low-active, and active. The dataset was divided into training, validation, and testing sets using a 70%, 15%, and 15% split, respectively, to ensure a consistent and reliable evaluation of the proposed ISF-ACNN model.

3.2. Data Preprocessing Using Z-Score Normalization

The data features were normalized using Z-score normalization to ensure consistent feature scales for student engagement prediction, as expressed in Eq. (1).

$$c' = \frac{c - \mu_Y}{\sigma_Y} \quad (1)$$

Preprocessing, VGG16 extraction, ISF optimization, and ACNN classification sequentially improve data quality, fea-

ture relevance, compactness, prediction accuracy, and stability.

3.3. Feature extraction using VGG16

VGG16 detects hierarchical engagement features through a series of convolution layers, which coalesce engagement patterns in interactions and allow analysis at various granularity levels including personalization, presented in Eq. (2).

$$q_m = (q_{m+1} - 1) T_m + l_m \quad (2)$$

In the above instance q_m is the size of the receptive field of the layer, T_m is the convolutional kernel layersize and T_m is the convolutional stridesize. All hidden VGG16 layers use the ReLU activation function to introduce nonlinearity and support student engagement prediction, as shown in Eq. (3).

$$e(w) = \max(0, w) \quad (3)$$

Every data monitored i, j , is used in the feature graph is computable based on Eq. (4).

$$b_i^j = e \left(\sum_{i \in N_i} \omega_j^i b_j^{i-1} + a_i^j \right) \quad (4)$$

The cost function corresponds to cross-entropy, which is shown in the following Eq. (5) and Eq. (6).

$$\text{Loss} = - \left[\sum_{j=1}^m \sum_{l=1}^3 \hat{z}_l^{(j)} \log \left(z_l^{(j)} \right) \right] \quad (5)$$

$$z_l^{(j)} = \frac{f^{\theta(l)} s_w^{(j)}}{\sum_{i=1}^3 f^{\theta(i)} s_w^{(j)}} \quad (6)$$

3.4. ISF-ACNN-Based Student Engagement Assessment in Online Education Platforms

ISF-ACNN forecasts the student engagement with fine-tuned CNN parameters and exploiting behavioral characteristics, which can successfully detect the students that require an educational jolt in time. ISF-ACNN dynamically optimizes behavioral and emotional features and convolution parameters, adapting to diverse student engagement patterns for accurate classification.

3.4.1. Adjustable Convolution neural network (ACNN)

ACNN applies convolution, pooling, and fully connected layers on student data, and weighs features to classify the level of engagement. Its layer types are input, hidden, convolutional, pooling, fully connected and output layers.

Convolutional layer: The convolutional layer applies learnable filters to feature maps, generating informative

representations for engagement prediction, as shown in Eq. (7):

$$Z(j, i) = \sum_{l=1}^L \sum_{m=1}^M Z(i + k, j + n) \cdot W(k, n) + D \quad (7)$$

Pooling layer: Max-pooling in ACNN shrinks the dimension of the feature-maps, while it keeps most dominant features for student engagement representation, as illustrated in Eq. (8):

$$Z(j, i) = \max_{l, m} Y(t_l + j, t_l + i) \quad (8)$$

Fully connected layer: The fully connected layer receives pooled features as a single tensor and predicts student engagement levels.

Output layer: SoftMax returns the probabilities of each class for three-level engagement classification with output neurons equal to the engagement levels, as in Eq. (9):

$$\sigma(a)_j = \frac{f^{a_i}}{\sum_{l=1}^L f^{a_l}} \text{ for } i = 1, \dots, L \quad (9)$$

The ACNN's model of the structure of functions for input data $W \in Q^{n \times c}$ with $C = n \times c$ elements is expressed in Eq. (10).

$$E(\theta; w) = \text{softmax} \left(e_m(\theta_m, e_{m-1}(\theta_{m-1}, \dots \right. \quad (10)$$

$$\left. e_2(\theta_2, e_1(\theta_1, w)) \dots) \right).$$

The adversarial objective generates minimally perturbed inputs to induce misclassification, with the disturbance defined by δ , as specified in Eq. (11) and ????

$$\delta = \arg \min_y \|Z\|_0 \quad (11)$$

Here, δ denotes the minimum perturbation applied to the input, Z represents the perturbation vector, and $\|Z\|_0$ indicates the number of modified elements in Z . The operator $\arg \min_y$ identifies the perturbation that minimizes the number of modified elements while satisfying the misclassification objective.

$$\text{s.t. } O(x) \neq O(x + z) \quad (12)$$

Here, $O(x)$ represents the original output/classification of the ACNN model for input x , $O(x + Z)$ denotes the output after applying perturbation Z , and Z represents the adversarial perturbation that causes the model output to change.

$$z^* = z + \delta \quad (13)$$

Here, z^* denotes the generated adversarial example, z represents the original input, and δ denotes the optimized perturbation added to the original input to obtain the adversarial example.

In black-box settings, ACNN gradients and internal parameters are unavailable, preventing direct optimization of the non-linear, non-convex model.

3.4.2. Improved Synergistic Fibroblast (ISF)

ISF enhances major behavioral characteristics through the fibroblast-based adaptive updates and the pertinent patterns and relationships are refined to effectively predict student engagement. ISF performs a joint optimization of feature relevance and redundancy, and the optimal informative, complementary features are iteratively selected for ACNN-based classification of student engagement. The ISF model introduces fibroblast cells in the extracellular matrix at the local level and computes their positions as well as the collagen deposition, velocity and diffusion coefficient according to Eq. (14) and Eq. (15);

$$u^{j(s+1)} = u^j(s) + (1 - \rho)d(e^j(s), s) + \rho * \frac{e^j(s - \tau)}{\|e^j(s - \tau)\|} \quad (14)$$

$$w^{j(s+1)} = w^j(s) + t * \frac{u^j(s)}{\|u^j(s)\|} \quad (15)$$

Until the predetermined conditions are satisfied or the maximum number of iterations is reached. Algorithm 1 shows the ISF-ACNN. Fig. 3 represents the flow of ISF.

4. Result discussions

In this research, the Python platform and the RAM of a laptop with 8.00 GB, Intel® Core i9 processors, and Windows 11 has been utilized. ISF-ACNN is compared with ANN [27] and RF [28] in terms of accuracy, recall, precision, and F1-score, as well as the correlation analysis between the features related to engagement. Fig. 4 shows the overall performance.

4.1. Correlation matrix based on dataset factors

The correlation matrix examines relationships among login frequency, module time, forum participation, and quiz performance to identify engagement patterns. Fig. 5 presents these correlations. The correlation color scale view shows the relationships of engagement features to each other, which arise from a tri-axial parallel coordinates plot, and, in this case, of features to days. Values at +1 are perfectly positively correlated, at -1 are perfectly negatively correlated, and at 0 have no linear relationship, and are predictive of the selection of relevant features.

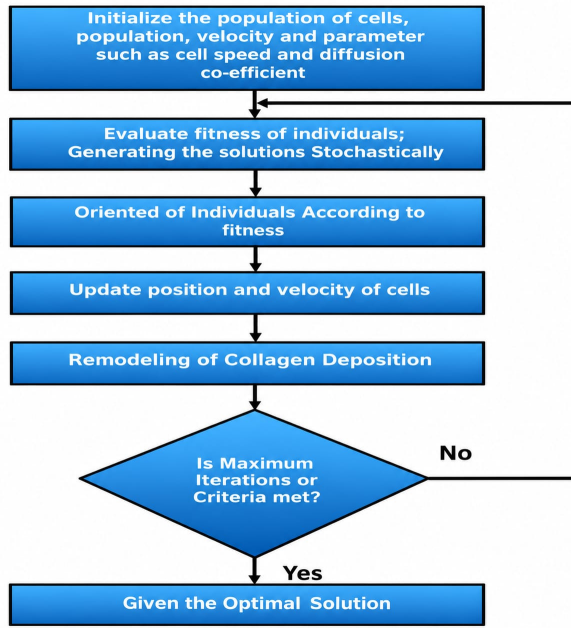


Fig. 3. Flow of ISF

Algorithm 1. ISF-ACNN Algorithm

Require: Student data, number of fibroblast cells m , fitness threshold τ , maximum iterations $T_{\max}$

Ensure: Optimized student engagement prediction

1: Initialize ACNN model $\mathcal{M}_{ACNN}$
 2: $X \leftarrow$ collect student data $\triangleright$ Login data, quiz scores, etc.
 3: $\hat{y} \leftarrow \mathcal{M}_{ACNN} \cdot \text{predict}(X)$

4: **Initialize Fibroblast Cells for ISF**

5: **for** $j = 1$ to m **do**
 6: $w_j \leftarrow \text{RandomInitialization}()$
 7: $ECM_j \leftarrow \text{RandomCollagenDeposition}()$
 8: $u_j \leftarrow \text{InitializeVelocity}()$

9: **ISF Optimization**

10: **for** $j = 1$ to m **do**
 11: $E_j \leftarrow \text{Fitness}(w_j, ECM_j)$
 12: **if** $E_j < \tau$ **then**
 13: Reorient fibroblast cell j
 14: Update velocity u_j
 15: Update position w_j

16: **Collagen Remodeling and Convergence**

17: **for** $t = 1$ to $T_{\max}$ **do**
 18: Remodel collagen structure
 19: **if** $\text{ConvergenceReached}()$ **then**
 20: **break**

21: **Final Prediction**

22: $\hat{y}_{\text{opt}} \leftarrow \mathcal{M}_{ACNN} \cdot \text{predict}(X)$
 23: **return** $\hat{y}_{\text{opt}}$

The impact on prediction quality of feature refinement is analyzed by studying the performance of the classifier after the engagement features were derived. The correla-

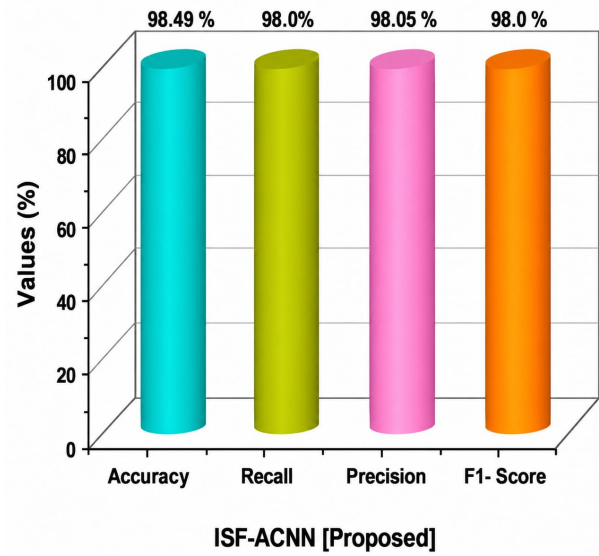


Fig. 4. Overall metrics values observed by ISF-ACNN

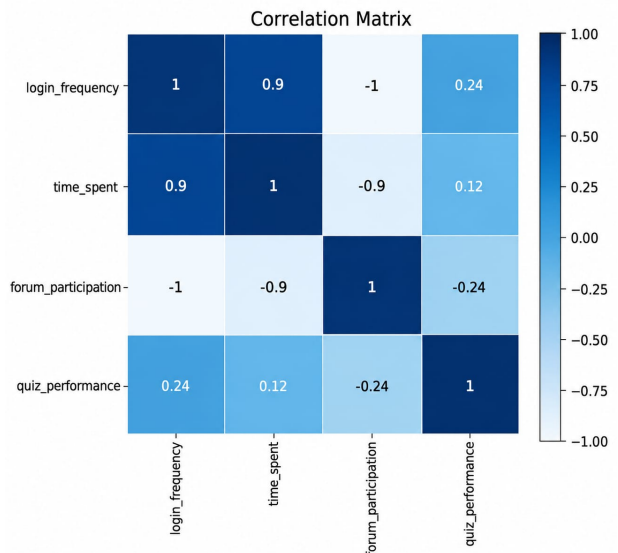


Fig. 5. Correlation matrix based on dataset factors

tion and the uniform relative importance results reveal the most informative behavioral features, while the ablation study shows the influence of increasing levels of feature refinement on accuracy, precision, recall and F1-score. In sum these results demonstrate that ISF refined inputs enhance reliability and consistency in evaluating students engagement.

Table 1 shows the contribution of individual, combined, and ISF-refined features to overall classifier performance.

Table 2 shows the relationship and relative importance of selected engagement features in predicting student engagement.

Table 1. Feature Ablation for Assessing the Contribution of Selected Engagement Features

Feature Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Login frequency only	89.42	87.91	88.76	88.32
Time spent on modules only	91.36	90.18	90.84	90.51
Forum participation only	88.74	86.95	88.12	87.53
Quiz performance only	93.21	92.54	92.83	92.68
Login + Time	94.83	94.11	94.42	94.26
Login + Time + Forum	96.41	95.82	96.03	95.92
Login + Time + Forum + Quiz	97.68	97.22	97.36	97.29
ISF-refined feature set	98.49	98.05	98.00	98.00

Table 2. Relationship between Selected Features and Engagement Prediction

Feature	Correlation with Engagement	Relative Importance (%)
Login frequency	0.71	21.8
Time spent on modules	0.78	27.4
Forum participation	0.67	18.9
Quiz performance	0.82	31.9

4.2. Accuracy

Accuracy measures the proportion of correctly classified student engagement levels. ISF-ACNN achieves 98.49%, outperforming ANN (85.0%) and RF (97.4%), demonstrating effective engagement prediction, as shown in Table 3.

4.3. Recall

Recall focuses on the proportion of positive true cases that the model can correctly identify for engaged students. ISF-ACNN obtains 98.0%, better than the ANN (89.0%) and RF (97.4%) ones as illustrated in Table 4.

4.4. Precision

Precision indicates the proportion of identified students that are truly engaged. As illustrated in Table 5. ISF-ACNN achieves 98.05%, which is higher than ANN (81.0%) and RF (97.4%).

4.5. F1- Score

F1-score takes into account the precision and recall for engagement classification. As can be seen from ??, ISF-ACNN reaches 98.0%, which is superior to ANN (84.0%) and RF (97.4%).

subsectionComparative Evaluation with Recent Deep Learning Approaches

The ISF-ACNN is compared with traditional machine-learning models, state-of-the-art deep learning methods such as 1D-CNN, LSTM, GRU and Transformer to show the general applicability in terms of technical power and prediction ability. Accuracy, precision, recall, F1-score is assessed; the values of the mean $\pm$ standard deviation represent the stability in performance for several repeated experimental evaluations.

The performance comparisons of ISF-ACNN with all the baseline machine learning and recent deep learning methods in terms of the accuracy, precision, recall, f1-score are displayed in Table 7.

4.6. Robustness Analysis Across Repeated Experimental Runs

ISF-ACNN demonstrates robust and stable performance across ten repeated runs, with low variation and narrow confidence intervals across evaluation metrics.

Table 8 confirms stable ISF-ACNN performance with minimal variation.

Table 9 shows the sensitivity of ISF-ACNN performance to different training factors, confirming stable accuracy and F1-score across settings.

4.7. Discussion

In ISF-ACNN, accuracy, recall, precision, and F1-score all indicate that it can predict reliable engagement. Jointly, the results conclusively demonstrate efficient student classification, while facilitative educational interventions and the need for various student performance measures for holistic evaluation in web-enabled learning environments is emphasized. The proposed ISF-ACNN framework exploits LMS-based engagement features with VGG16 feature extraction and ISF optimization in an attempt to enhance the prediction of student engagement. The experimental evaluation is performed on a publicly available Kaggle student engagement dataset, which consists of LMS interaction features such as login frequency, time spent on modules, participation in the discussion forum, and quiz performance in three engagement levels. Hyperparameters for model training are fixed and a single unified valida-

Table 3. Statistical Reliability and Significance of Accuracy Results

Method	Accuracy (%) Mean $\pm$ SD	95% CI	<i>p</i> -value vs. ISF-ACNN
ANN [27]	85.00 $\pm$ 0.92	84.42–85.58	< 0.001
RF [28]	97.40 $\pm$ 0.31	97.20–97.60	< 0.001
ISF-ACNN (Proposed)	98.49 $\pm$ 0.18	98.38–98.60	–

Table 4. Statistical Reliability and Significance of Recall Results

Method	Recall (%) Mean $\pm$ SD	95% CI	<i>p</i> -value vs. ISF-ACNN
ANN [27]	89.00 $\pm$ 0.86	88.45–89.55	< 0.001
RF [28]	97.40 $\pm$ 0.29	97.22–97.58	0.002
ISF-ACNN (Proposed)	98.00 $\pm$ 0.20	97.87–98.13	–

Table 5. Statistical Reliability and Significance of Precision Results

Method	Precision (%) Mean $\pm$ SD	95% CI	<i>p</i> -value vs. ISF-ACNN
ANN [27]	81.00 $\pm$ 1.08	80.31–81.69	< 0.001
RF [28]	97.40 $\pm$ 0.34	97.18–97.62	0.001
ISF-ACNN (Proposed)	98.05 $\pm$ 0.21	97.92–98.18	–

Table 6. Statistical Reliability and Significance of F1-Score Results

Method	F1-Score (%) Mean $\pm$ SD	95% CI	<i>p</i> -value vs. ISF-ACNN
ANN [27]	84.00 $\pm$ 0.94	83.40–84.60	< 0.001
RF [28]	97.40 $\pm$ 0.30	97.21–97.59	0.001
ISF-ACNN (Proposed)	98.00 $\pm$ 0.19	97.88–98.12	–

Table 7. Comparative Performance of ISF-ACNN with Existing and Recent Deep Learning Approaches

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ANN [27]	85.00 $\pm$ 0.92	81.00 $\pm$ 1.08	89.00 $\pm$ 0.86	84.00 $\pm$ 0.94
RF [28]	97.40 $\pm$ 0.31	97.40 $\pm$ 0.34	97.40 $\pm$ 0.29	97.40 $\pm$ 0.30
1D-CNN	96.72 $\pm$ 0.38	96.48 $\pm$ 0.41	96.63 $\pm$ 0.39	96.55 $\pm$ 0.40
LSTM	97.08 $\pm$ 0.34	96.91 $\pm$ 0.37	97.02 $\pm$ 0.35	96.96 $\pm$ 0.36
GRU	97.26 $\pm$ 0.30	97.10 $\pm$ 0.33	97.21 $\pm$ 0.31	97.15 $\pm$ 0.32
Transformer	97.61 $\pm$ 0.27	97.45 $\pm$ 0.30	97.53 $\pm$ 0.28	97.49 $\pm$ 0.29
ISF-ACNN (Proposed)	98.49 $\pm$ 0.18	98.05 $\pm$ 0.21	98.00 $\pm$ 0.20	98.00 $\pm$ 0.19

Table 8. Robustness Analysis of ISF-ACNN Across Repeated Experimental Runs

Run	Random Seed	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
1	11	98.31	97.84	97.79	97.81
2	22	98.62	98.19	98.17	98.18
3	33	98.47	98.03	97.99	98.01
4	44	98.55	98.12	98.08	98.1
5	55	98.38	97.91	97.88	97.89
6	66	98.51	98.07	98.02	98.04
7	77	98.67	98.26	98.21	98.23
8	88	98.42	97.98	97.95	97.96
9	99	98.56	98.14	98.06	98.1
10	111	98.41	97.96	97.85	97.9
Mean $\pm$ SD	-	98.49 $\pm$ 0.11	98.05 $\pm$ 0.12	97.99 $\pm$ 0.12	98.02 $\pm$ 0.12
95% CI	-	98.42–98.56	97.97–98.13	97.91–98.07	97.94–98.10

tion scheme is employed to guarantee the reliability of the performance estimation, whereas so the ISF online feature optimization mechanism adds a little computational cost

when compared with traditional classifiers. Nevertheless, the present evaluation is based on a single publicly available dataset, which might limit the generalizability of the

Table 9. Sensitivity Analysis under Different Training Factors

Training Factor	Setting	Accuracy (%)	F1-Score (%)
Learning rate	0.0001	98.08	97.62
Learning rate	0.0005	98.36	97.89
Learning rate	0.0010	98.49	98.00
Learning rate	0.0020	98.27	97.83
Batch size	16	98.35	97.88
Batch size	32	98.49	98.00
Batch size	64	98.31	97.85
Dropout	0.2	98.22	97.77
Dropout	0.3	98.49	98.00
Dropout	0.5	98.17	97.71
ISF iterations	20	97.94	97.48
ISF iterations	40	98.31	97.83
ISF iterations	60	98.49	98.00
ISF iterations	80	98.43	97.94

results to other educational platforms or student cohorts. ANN has its own challenges, such as class imbalance, interpretability, and scalability, while RF may be overfitting, it has limited interpretability and it may not be able to effectively capture complex behaviors. In contrast, ISF-ACNN achieves better engagement classification with high recall and precision.

5. Conclusions

To establish an online proposed model of ISF-ACNN that can predict student engagement on online education platforms, this research seeks to apply ACNNs for data analysis and ISF optimization. The intended research aims to seek and to improve the use of ISF optimization techniques for better forecast precision. This approach aimed at determining the patterns of engagement and on this basis enhance the learning achievements. The proposed ISF-ACNN model demonstrated superior performance in predicting student engagement on online education platforms, outperforming traditional methods like ANN and RF. The proposed method of ISF-ACNN has predicted the student engagement in online platform and achieved better performance of accuracy at 98.49%, recall at 98.0%, precision at 98.05% and F1 -Score at 98.0%. While ANN and RF have their advantages, they exhibit limitations in handling imbalanced data, interpretability, and capturing complex patterns, which ISF-ACNN addresses effectively. These findings highlight the importance of using advanced models to enhance engagement prediction accuracy, allowing educational platforms to better support students through targeted interventions. The ISF-ACNN method proposed in this paper can be applied to existing online education as an intelligent student-engagement monitoring component. This system monitors LMS-based activity such as logins, learning time, discussions, and quiz results, and

categorizes students as inactive, low engagement, and high engagement. The platform can provide personalized feedback, reminders, supplementary materials, and timely instructor interventions when engagement declines. Such an implementation empowers the ISF-ACNN to conduct continuous engagement monitoring and data-driven educational intervention seamlessly integrated with existing online learning process, enabling better practical application and higher educational value of the proposed scheme. One weakness that occurred from the utilization of the proposed ISF-ACNN model is its high computational intensity, which could make it difficult for real-time application on large scale systems. The proposed ISF-ACNN model demonstrates strong student engagement prediction, while future work focuses on cross-dataset validation, explainable AI, lightweight optimization, and diverse real-world learning environments. Future work can focus on improving model response speed, reducing computational costs, incorporating diverse data sources, and adopting advanced learning paradigms.

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Declarations

Data Availability

Data sharing is not applicable to this article, as no datasets were generated or analyzed during the current study.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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Author Contributions

Xiaofang Qin conceived the study, developed the methodology and the ISF-ACNN model, conducted the experiments, analyzed the data, interpreted the results, revised the manuscript, and approved the final version of the manuscript.

Ethical Approval

This article does not contain any studies involving human participants or animals performed by the author.

Consent to Participate

Not applicable.

Consent for Publication

The author has provided consent for publication of this manuscript. ""

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