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An Intelligent Knowledge Graph-Based Directional Data Clustering and Feature Selection for Improved Education

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Abstract

With advancements in technology and the increasing availability of data, there is a growing interest in leveraging intelligent learning models to enhance the educational experience and improve learning outcomes. The construction of intelligent learning models, supported by knowledge graphs, has emerged as a promising approach to revolutionizing the field of education. With the vast number of educational resources and data available, knowledge graphs provide a structured and interconnected representation of knowledge, enabling intelligent systems to leverage this wealth of information. This paper aimed to construct an effective automated Intelligent Learning Model with the integration of Knowledge Graphs. The automated intelligent model comprises the directional data clustering (DDC) integrated with the Voting based Integrated effective Feature Selection model through the LSTM-integrated Grasshopper Algorithm (LSTM_GOA). The data for analysis is collected from educational institutions in China. Through the framed LSTM_GOA model the performance is evaluated fro the analysis of the student educational performance. The simulation analysis expressed that the developed model exhibits a higher classification performance compared with the conventional technique in terms of accuracy and Mean Square Error (MSE).

Keywords: Educational experience, intelligent learning models, educational institutions, student educational performance, knowledge graphs.

I. Introduction

Advancements in technology, coupled with the increasing availability of data, have opened up new possibilities for enhancing the educational experience and improving learning outcomes. The emergence of intelligent learning models, powered by artificial intelligence and machine learning algorithms, holds tremendous promise in revolutionizing the way we approach education [1]. These models have the ability to analyze vast amounts of student data, including performance metrics, learning styles, and preferences, to create personalized learning pathways tailored to the needs of individual learners. By leveraging the power of intelligent algorithms, educational institutions can unlock a range of benefits, including improved student engagement, enhanced knowledge retention, and more efficient use of instructional resources [2]. In this educational landscape, the integration of intelligent learning models has the potential to shape a future where education is truly adaptive, responsive, and tailored to the unique needs of each learner. An intelligent learning model is an application of artificial intelligence (AI) and machine learning (ML) techniques in the field of education to enhance the learning experience and optimize learning outcomes [3]. By leveraging algorithms and data analysis, these models have the ability to adapt and personalize the learning process based on individual student needs, preferences, and performance.

Intelligent learning models encompass a wide range of technologies and approaches [4]. One example is adaptive learning systems, which use AI algorithms to dynamically adjust the content, difficulty level, and pacing of instruction based on a student's progress and performance [5]. These systems continuously analyze and evaluate student responses, identifying areas of strength and weakness to provide targeted support and personalized learning pathways. Intelligent tutoring systems, which provide interactive and individualized instruction similar to a human tutor [6]. These systems use ML algorithms to understand a student's knowledge gaps and misconceptions, delivering customized feedback and guidance to help them overcome challenges and master the material [7].

Additionally, natural language processing (NLP) techniques can be employed in intelligent learning models to analyze and understand students' written or spoken responses. This enables automated grading and feedback, freeing up teachers' time and providing timely and detailed assessment to students. Intelligent learning models also have the potential to support collaborative learning environments [8]. By analyzing social interaction data, these models can identify patterns and facilitate effective group work, fostering cooperation, and enhancing students' interpersonal skills. The benefits of intelligent learning models are numerous. They can improve student engagement by providing interactive and

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tailored learning experiences. By adapting to individual learning styles, these models can enhance knowledge retention and understanding. They also offer teachers valuable insights into students' progress and areas for intervention, allowing for more effective instructional strategies [9].

To recognize the ethical considerations and potential limitations of intelligent learning models. Ensuring data privacy and security, addressing biases in algorithms, and maintaining a balance between technology and human interaction are critical factors that need to be carefully managed in the implementation of intelligent learning models [10]. Knowledge graphs are a type of structured data representation that captures and organizes knowledge in a graph format. They consist of nodes, which represent entities or concepts, and edges, which represent the relationships between these entities. Knowledge graphs are designed to model real-world knowledge in a way that can be easily processed and analyzed by computers. The strength of knowledge graphs lies in their ability to capture and represent complex relationships and dependencies between different entities [11]. They can be used to integrate information from multiple sources and provide a comprehensive view of a particular domain or topic. By organizing knowledge in a graph structure, knowledge graphs enable efficient querying, reasoning, and analysis of the underlying data. Knowledge graphs have various applications across different domains. In the field of artificial intelligence, they are used for knowledge representation and reasoning tasks. They can also be employed in information retrieval, recommendation systems, question answering, and semantic search. Knowledge graphs are particularly valuable in areas where understanding and navigating complex relationships and connections between entities are crucial [12]. One widely known example of a knowledge graph is Google's Knowledge Graph, which powers the information panels and enriched search results displayed in Google search queries. It connects different entities from various domains to provide users with contextual information and related facts.

The proposed LSTM_GOA (LSTM-integrated Grasshopper Algorithm) is a novel approach presented in the paper for enhancing the educational experience through directional data clustering and feature selection using knowledge graphs. The contribution of the paper lies in the proposal and implementation of the LSTM_GOA, a novel approach that combines the strengths of the LSTM model and the Grasshopper Optimization Algorithm. The main contributions of the paper can be summarized as follows:

1. The paper proposes the integration of the LSTM model with the Grasshopper Optimization Algorithm, harnessing the power of both approaches for improved performance in educational data analysis.
2. The paper introduces a voting-based integrated effective feature selection model within the LSTM_GOA framework. This feature selection process helps in identifying the most relevant features for accurate analysis and prediction of educational outcomes.
3. The paper incorporates directional data clustering within the LSTM_GOA framework, enabling the model to effectively handle complex and interconnected educational data.

II. Related Works

In [13] provides an overview of intelligent learning models used for personalized education. It discusses various techniques such as adaptive learning, intelligent tutoring systems, and recommendation systems. The paper explores the applications, benefits, and challenges of these models in enhancing the educational experience. In [14] survey focuses on deep learning models applied in educational data mining. It covers topics such as deep neural networks, recurrent neural networks, and convolutional neural networks used for tasks like student performance prediction, sentiment analysis, and engagement detection. The paper discusses the advantages and limitations of deep learning models in educational settings. In [15] highlights recent advancements and applications of intelligent tutoring systems (ITS). It discusses the use of ITS in various domains, including mathematics, science, and language learning. The paper examines the integration of AI techniques such as natural language processing, machine learning, and knowledge representation in developing intelligent tutoring systems.

In [16] focuses on personalized recommendation systems in education. It explores different recommendation algorithms, including collaborative filtering, content-based filtering, and hybrid approaches. The paper discusses the challenges and future directions of personalized recommendation systems in education. In [17] provides an overview of intelligent learning analytics, which involves the use of data analytics and machine learning techniques to analyze educational data. It discusses methods such as clustering, classification, and predictive modelling applied to various educational contexts. The paper highlights the potential of intelligent learning analytics in improving educational outcomes. In [18] examines the applications of deep reinforcement learning (DRL) in the field of education. It explores how DRL algorithms, such as Deep Q-Networks and Proximal Policy Optimization, have been used to

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optimize educational tasks like adaptive learning, personalized tutoring, and curriculum sequencing.

In [19] investigates the use of natural language processing (NLP) techniques in intelligent educational systems. It explores how NLP algorithms, including sentiment analysis, topic modelling, and text summarization, can be applied to enhance automated feedback generation, content analysis, and student engagement. In [20] focuses on intelligent learning models applied specifically to educational robotics. It examines how robotics platforms and machine learning algorithms are integrated to support learning outcomes and skill development in robotics education. The paper discusses the effectiveness and challenges of these models. In [21] explores the use of augmented reality (AR) in education and its integration with intelligent learning models. It discusses how AR can enhance interactive learning experiences and presents intelligent learning models tailored for AR applications in fields such as science, history, and language learning. In [22] investigates intelligent learning models applied to adaptive assessment systems. It explores how machine learning algorithms are used to adapt assessment tasks based on student performance, knowledge level, and individual learning needs. The paper examines the advantages and challenges of adaptive assessment models. In [23] focuses on deep generative models used for educational content generation. It explores the application of generative models, such as variational autoencoders and generative adversarial networks, in creating educational resources like quizzes, exercises, and simulations. The paper discusses the potential and limitations of these models. In [24] investigates intelligent learning models for predicting student dropout in online courses. It explores the use of machine learning algorithms, such as random forests, support vector machines, and neural networks, to analyze student behavior, engagement, and performance data for early dropout detection. Similarly. In [25] focuses on intelligent learning models for emotion recognition in educational settings. It explores the use of machine learning techniques, including affective computing and facial expression analysis, to detect and interpret student emotions during learning activities. The paper discusses the potential benefits and challenges of emotion recognition models. In [26]] examines the integration of knowledge graphs in intelligent tutoring systems (ITS). It explores how knowledge graphs capture and represent educational content, learner profiles, and domain knowledge. The paper discusses the role of knowledge graphs in enhancing personalized learning, adaptive feedback, and knowledge acquisition. In [27] investigates intelligent learning models applied to collaborative filtering techniques in recommender systems. It explores how machine learning algorithms, such as matrix factorization, deep neural networks, and hybrid models, are used to provide personalized recommendations for educational resources

Table 1: Summary of the Literature

Reference	**Objective**	**Method**	**Outcome**
"A Comprehensive Review of Deep Reinforcement Learning in Education"	Investigate applications of deep reinforcement learning in education	Review and analysis of research papers	Identified various educational tasks optimized through deep reinforcement learning techniques
"Exploring the Potential of Natural Language Processing in Intelligent Educational Systems"	Explore the use of natural language processing techniques in intelligent educational systems	Literature review and analysis	Identified various NLP techniques and their applications in automated feedback, content analysis, and student engagement
"Intelligent Learning Models for Educational Robotics: A Systematic Review"	Examine intelligent learning models in the field of educational robotics	Systematic review of research papers	Explored integration of robotics platforms and machine learning algorithms for skill development in robotics education
"Augmented Reality in Education: A Review of Intelligent Learning Models"	Investigate the integration of augmented reality and intelligent learning models in education	Literature review and analysis	Explored the potential of augmented reality in enhancing interactive learning experiences through intelligent models
"Intelligent Learning Models for Adaptive Assessment: A Review"	Explore intelligent learning models for adaptive assessment systems in education	Literature review and analysis	Investigated the application of machine learning algorithms for adaptive assessment tasks and discussed their effectiveness
"Deep Generative Models for Educational Content Generation: A Survey"	Investigate deep generative models used for generating educational content	Survey and analysis of research papers	Explored the application of deep generative models in creating educational resources and discussed their limitations

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"Intelligent Learning Models for Predicting Dropout in Online Courses"	Examine intelligent learning models for predicting student dropout in online courses	Analysis of student behavior and performance data	Explored the use of machine learning algorithms for early dropout detection in online courses
"Intelligent Learning Models for Emotion Recognition in Educational Contexts"	Investigate intelligent learning models for emotion recognition in educational contexts	Analysis of affective computing and facial expression analysis techniques	Explored the use of machine learning for detecting and interpreting student emotions in educational settings
"Knowledge Graphs for Intelligent Tutoring Systems: A Review"	Explore the integration of knowledge graphs in intelligent tutoring systems	Review and analysis of research papers	Examined the role of knowledge graphs in personalized learning, adaptive feedback, and knowledge acquisition
"Intelligent Learning Models for Collaborative Filtering in Recommender Systems"	Investigate intelligent learning models for collaborative filtering in recommender systems	Analysis of machine learning algorithms for collaborative filtering in recommender systems	Explored the use of intelligent learning models for personalized recommendations of educational resources

III. Directional data clustering for data graph

Directional data clustering for data graphs refers to the process of grouping data points or nodes in a data graph based on their directional relationships. Data graphs are representations of complex data structures that consist of nodes (vertices) connected by edges. These graphs can be used to model various types of data, such as social networks, biological networks, or computer networks. Traditional clustering techniques aim to group data points based on their proximity or similarity. However, in many real-world scenarios, the data points may have inherent directional relationships that need to be considered for more accurate clustering results. For example, in a social network graph, the connections between users may have directional meaning, such as friend relationships or information flow. The figure 1 presented the overall flow chart of the LSTM_GOA model for the evaluation parameters.

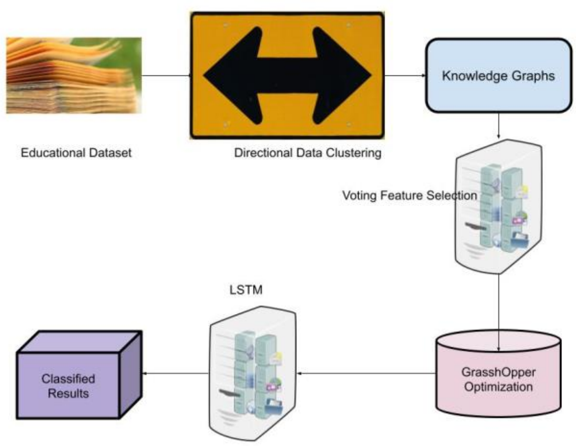

Figure 1: Flow of LSTM_GOA

Directional data clustering for data graphs takes into account the directionality of the edges in the graph when determining the clusters. The goal is to identify groups of nodes that share similar directional characteristics or patterns. This approach can provide insights into the structure and organization of the data graph, uncovering hidden relationships or communities within the data. There are various algorithms and techniques developed specifically for directional data clustering in data graphs. These methods often consider factors such as edge weights, edge directions, and node attributes to determine the clustering assignments. Some popular approaches include spectral clustering, modularity optimization, and community detection algorithms. The application of directional data clustering for data graphs has been widely explored in different domains.

LSTM_GOA refers to the integration of Long Short-Term Memory (LSTM) networks with the Grasshopper Optimization Algorithm (GOA) in an intelligent learning model. This combination aims to enhance the analysis and prediction of student educational performance. LSTM is a type of recurrent neural network (RNN) that is well-suited for processing sequential data, such as time series or sequential data in educational contexts. It can capture long-term dependencies and patterns in the input data, making it particularly useful for tasks like predicting student performance based on their past academic records. GOA, on the other hand, is a metaheuristic optimization algorithm inspired by the foraging behavior of grasshoppers. It mimics the movement and interaction of grasshoppers to search for optimal solutions in complex optimization problems. By integrating GOA with LSTM, the model can benefit from the optimization capabilities of GOA to improve the performance and efficiency of the learning model. In the context of enhancing the educational experience, the LSTM_GOA model can be applied to analyze student educational data and

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predict their performance. It can take into account various factors such as past grades, attendance records, study habits, and other relevant features to make accurate predictions about a student's future academic outcomes. The integration of LSTM and GOA allows the model to effectively capture temporal patterns and optimize the learning process. By leveraging LSTM's ability to model sequential data and GOA's optimization capabilities, the model can adapt and refine its predictions over time, resulting in improved accuracy and performance.

3.1 DDC with the LSTM_GOA

LSTM_GOA with data clustering refers to the integration of Long Short-Term Memory (LSTM) networks, the Grasshopper Optimization Algorithm (GOA), and data clustering techniques in an intelligent learning model. This combination aims to enhance the analysis and prediction of student educational performance while also incorporating the benefits of data clustering. Data clustering is the process of grouping similar data points together based on their inherent patterns or characteristics. By integrating data clustering with LSTM_GOA, the model can leverage the advantages of both clustering and sequential learning to improve the understanding and prediction of student performance. In this approach, data clustering techniques such as k-means, hierarchical clustering, or density-based clustering can be applied to the input data to identify clusters or groups of similar students. These clusters can represent specific student profiles or characteristics that may have an impact on educational outcomes.

Once the clusters are identified, LSTM_GOA can be employed to build individual LSTM models for each cluster. Each LSTM model can capture the sequential patterns and dependencies within the data of the corresponding cluster, allowing for personalized analysis and prediction within each group. The Grasshopper Optimization Algorithm (GOA) can be used to optimize the training process of the LSTM models. GOA mimics the foraging behavior of grasshoppers to find optimal solutions, and it can be applied to fine-tune the parameters of the LSTM models or optimize the clustering process itself. By combining LSTM, GOA, and data clustering, the model can benefit from the ability of LSTM networks to capture temporal dependencies, the optimization capabilities of GOA for parameter tuning, and the insights gained from clustering analysis. This integrated approach enables a more personalized and accurate prediction of student educational performance, taking into account both the temporal patterns and the clustering characteristics of the data. The performance of the LSTM_GOA model with data clustering can be evaluated using various metrics such as accuracy, mean square error (MSE), or clustering evaluation measures like silhouette coefficient or Dunn index. The effectiveness of the model can be assessed by comparing its performance with other conventional techniques or existing models in terms of predictive accuracy and clustering quality. The LSTM_GOA model with data clustering combines several components to improve the analysis and prediction of student educational performance. The model involves the integration of Long Short-Term Memory (LSTM) networks, the Grasshopper Optimization Algorithm (GOA), and data clustering techniques.

To begin, the input data, represented as $D = \{x\_1, x\_2, \ldots, x\_n\}$, consists of features for each data point. The data clustering algorithm, denoted as C = Cluster(D), identifies clusters C based on the characteristics and patterns present in the data. Each data point x_i is assigned to a specific cluster c_j, as indicated by the function cluster $(x_i) = c_i$. For each cluster, an LSTM model is built to capture the temporal dependencies within the data. The LSTM model takes as input a sequence $x_i(t) = [x_i(t-1), x_i(t-2), \ldots \ldots, x_i(t-p)]$, where $x_i(t)$ represents the input at time t and p represents the number of time steps considered. The LSTM model outputs $y_i(t) = LSTM(x_i(t), \theta)$ where θ represents the model parameters. The LSTM model is trained to optimize the parameters θ by minimizing the loss function $\Sigma\, L(y_i(t), y_i * (t)), where\ y_i * (t)$ represents the true output values for data point x_i at time t. The Grasshopper Optimization Algorithm (GOA) is then applied to further enhance the performance of the LSTM models. GOA optimizes the LSTM model parameters θ, leveraging the foraging behavior of grasshoppers to find optimal solutions. GOA fine-tunes the LSTM models and can also optimize the clustering process itself.

3.2 Voting Classififer with LSTM_GOA

The Voting Classifier with LSTM combines the strengths of a voting-based ensemble method and Long Short-Term Memory (LSTM) networks to enhance the predictive power of the model. This approach aims to improve the accuracy and robustness of predictions by aggregating the decisions of multiple LSTM models. The Voting Classifier is a type of ensemble learning method that combines the predictions of multiple individual models to make a final decision. In the context of LSTM, multiple LSTM models are trained on the same dataset but with different configurations or random initializations. Each LSTM model learns different patterns or representations from the data, contributing to the diversity of predictions. The individual LSTM models receive the input sequence $x_i(t) = [x_i(t-1), x_i(t-2), \ldots \ldots, x_i(t-p)]$, where x_i(t) represents the input at time t, and p denotes the number of time steps considered. Each

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LSTM model independently generates its prediction y_i(t) = LSTM(x_i(t), θ), where θ represents the model parameters specific to each LSTM model. The Voting Classifier aggregates the predictions from multiple LSTM models using a voting mechanism. It can adopt different voting strategies, such as majority voting, weighted voting, or soft voting. In majority voting, the class with the most votes from the LSTM models is selected as the final prediction. In weighted voting, the votes of each LSTM model are weighted based on their individual performance or confidence. Soft voting combines the predicted probabilities from each LSTM model and calculates the average probability for each class.

The Voting Classifier with LSTM leverages the diversity of LSTM models to make more accurate and robust predictions. By combining the predictions from multiple LSTM models, the model can better capture different patterns, handle uncertainties, and reduce the risk of overfitting. The performance of the Voting Classifier with LSTM can be evaluated using standard classification metrics such as accuracy, precision, recall, or F1 score. The model's effectiveness can be assessed by comparing its performance with individual LSTM models or other conventional classification techniques. Let's assume we have N LSTM models denoted by $M\_1, M\_2, \ldots, M\_N$.

Given an input sequence $x(t) = [x(t-1), x(t-2), \ldots, x(t-p)]$, where x(t) represents the input at time t and p represents the number of time steps considered. Each LSTM model M_i generates a prediction $y_i(t)$ for the input sequence x(t) based on its parameters θ_i as in equation (1):

$$y_i(t) = LSTM(x(t), \theta_i) \quad (1)$$

The Voting Classifier combines the predictions from the LSTM models using a voting mechanism. It can adopt different voting strategies, such as majority voting, weighted voting, or soft voting.

Majority Voting:

The class with the highest number of votes among the LSTM models is selected as the final prediction computed in equation (2)

$$y(t) = argmax\_j\ \Sigma\_i\ I(y_i(t) = j) \quad (2)$$

where I is the indicator function.

Weighted Voting:

Each LSTM model's vote is weighted based on its individual performance or confidence. Let w_i represent the weight assigned to LSTM model M_i as n equation (3)

$$y(t) = argmax\_j\ \Sigma\_i\ w_i * I((t) = j) \quad (3)$$

where w_i is the weight assigned to LSTM model M_i.

Soft Voting:

The predicted probabilities from each LSTM model are combined, and the average probability for each class is calculated using the equation (4)

$$y(t) = \frac{argmax_{j}1}{N} \Sigma_i P(y_i(t) = j) \quad (4)$$

$where\ P(y_i(t) = j)$ represents the predicted probability of class j from LSTM model M_i.

These equations (4) represent the mathematical formulation of the Voting Classifier with LSTM, where the final prediction y(t) is determined based on the voting strategy employed. The weights in weighted voting or the probabilities in soft voting can be determined through various approaches, such as model performance, model confidence, or calibration techniques.

3.5 Grasshopper Optimization

Grasshopper Optimization Algorithm (GOA) can be integrated with Long Short-Term Memory (LSTM) networks to enhance the training and optimization process of the LSTM models. This integration aims to improve the performance and convergence speed of the LSTM models by leveraging the optimization capabilities of the GOA algorithm. The GOA algorithm is inspired by the foraging behavior of grasshoppers and is used to search for optimal solutions in complex optimization problems. It mimics the movement and interaction of grasshoppers in nature, which involves random exploration and local exploitation. By integrating GOA with LSTM, the model can benefit from the search and optimization abilities of the GOA algorithm to improve the learning process of LSTM models. In the context of LSTM, the integration of GOA involves optimizing the model parameters during the training phase. The LSTM model's parameters, denoted as θ, are optimized using the GOA algorithm to find the optimal values that minimize the loss function and improve the predictive performance of the model.

The GOA algorithm iteratively updates the position of grasshoppers in the search space, which corresponds to the LSTM model parameters. Each grasshopper's position represents a potential solution or set of parameter values for the LSTM model. The grasshoppers' movements are influenced by their current position and the position of other grasshoppers in the search space. During the optimization process, the fitness or objective function, which is typically the loss function of the LSTM model, is evaluated for each grasshopper's position. The fitness value determines the quality of the solution represented by that position. The

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grasshoppers adjust their positions based on local and global information, aiming to find better solutions. The position updates are performed using mathematical equations that involve random exploration and exploitation of promising areas in the search space. In figure 2 presented the flow chart of the LSTM_GOA model.

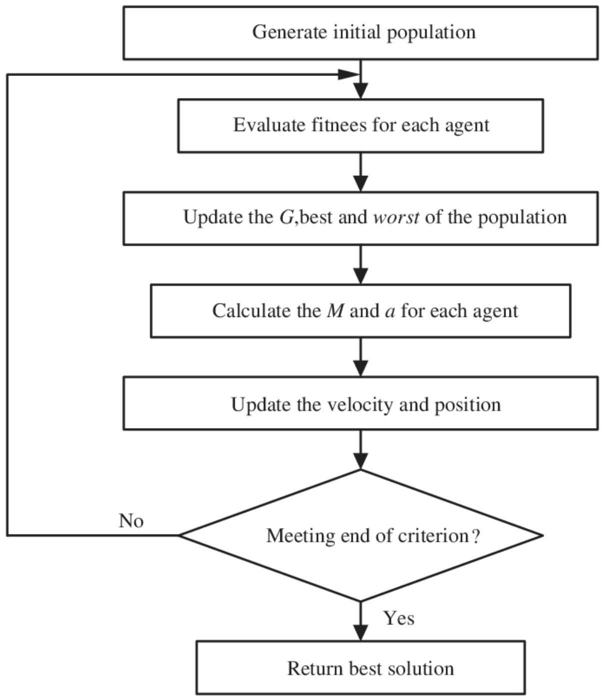

Figure 2: Flow Chart of Grasshopper

The optimization process continues for a certain number of iterations or until a convergence criterion is met. At the end of the optimization process, the grasshopper position with the best fitness value represents the optimized set of parameters for the LSTM model. By integrating GOA with LSTM, the model can benefit from improved parameter optimization, leading to enhanced predictive performance and convergence speed. The GOA algorithm helps the LSTM model to explore the search space effectively and find better solutions, contributing to improved accuracy and efficiency in learning tasks. The mathematical derivation of the integration of the Grasshopper Optimization Algorithm (GOA) with Long Short-Term Memory (LSTM) networks involves optimizing the LSTM model's parameters using the principles of the GOA algorithm.

Let the objective function be denoted as J(θ), where θ represents the LSTM model parameters to be optimized. The objective function typically corresponds to the loss function of the LSTM model, such as mean squared error (MSE) or cross-entropy loss. Initialize the positions of the grasshoppers in the search space. Each grasshopper position corresponds to a set of parameter values for the LSTM model, represented as θ_i, where i denotes the index of the grasshopper. Evaluate the fitness or objective function value for each grasshopper position. The fitness value is determined by evaluating the objective function J(θ) using the corresponding LSTM model parameters θ_i. Update the positions of the grasshoppers based on their current positions and the positions of other grasshoppers. This step involves the exploration and exploitation behaviors of the GOA algorithm. The position update equation can be formulated as in equation (5)

$$\theta_i(t+1) = \theta_i(t) + \alpha * (\Psi * C(t) - \theta_i(t)) \qquad (5)$$

$\theta_i(t+1)$: Updated position of grasshopper i at time t+1; $\theta_i(t)$: Current position of grasshopper i at time t; α: Step size or learning rate; Ψ: Randomly generated value between 0 and 1; C(t): Vector representing the collective information of the grasshoppers' positions at time t

Repeat Steps 3 and 4:

Iterate the process of evaluating the fitness function and updating the grasshopper positions for a certain number of iterations or until a convergence criterion is met. The iterations allow the GOA algorithm to explore and exploit the search space to find better solutions for the LSTM model parameters.

At the end of the optimization process, select the grasshopper position with the best fitness value as the optimized set of LSTM model parameters θ*. This optimized parameter set represents the solution obtained through the integration of GOA with LSTM. The mathematical derivation involves implementing the position update equation and the iterative optimization process to find the optimal values of the LSTM model parameters that minimize the objective function. The specific implementation details and parameter settings may vary depending on the specific application and problem at hand.

1. Initialize the population of grasshoppers with random positions in the search space.
2. Evaluate the fitness or objective function for each grasshopper position.
3. Determine the best fitness value and corresponding position among the population.
4. Repeat the following steps until a termination condition is met:
    a. Update the grasshopper positions based on their current positions and the positions of other grasshoppers.
    b. Evaluate the fitness function for each updated position.

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   c. Update the best fitness value and corresponding position if a better solution is found.
5. Return the best position found as the optimized solution.

The position update equation in step 4a can be customized based on the specific problem and formulation. The equation typically involves a combination of random exploration and exploitation based on the current position, the best position found, and other parameters or heuristics. The termination condition in step 4 can be based on a maximum number of iterations, reaching a certain fitness threshold, or the lack of significant improvement over a defined number of iterations. It is important to note that the actual implementation of the GOA algorithm may involve additional details, such as handling constraints, defining appropriate parameter settings, and incorporating problem-specific considerations. When integrating the GOA algorithm with LSTM, the algorithm's steps can be adapted to optimize the LSTM model parameters. The fitness function corresponds to the loss function of the LSTM model, and the position update equation can be designed to update the LSTM model parameters.

Algorithm 1: Pseudo Code for LSTM_GOA

Initialize the population of grasshoppers with random positions in the search space
Initialize the LSTM model with random parameter values
Evaluate the fitness of each grasshopper position using the LSTM model
Set the best fitness value and corresponding position as the initial best solution
Repeat for a certain number of iterations or until a termination condition is met:
  For each grasshopper in the population:
    Update the position of the grasshopper based on current position and the positions of other grasshoppers
    Apply the Grasshopper Optimization Algorithm update equation to the LSTM model parameters
 	
    If the new position improves the fitness:
      Evaluate the fitness of the new position using the LSTM model
      Update the best fitness value and corresponding position if the new position is better
 	
  End for
Return the best position found as the optimized solution

The LSTM_GOA (Long Short-Term Memory with Grasshopper Optimization Algorithm) is an integrated approach that combines the power of LSTM (Long Short-Term Memory) neural networks with the optimization capabilities of the Grasshopper Optimization Algorithm (GOA). This integration aims to enhance the training and optimization process of LSTM models, leading to improved performance and convergence speed. The LSTM_GOA algorithm follows a iterative process that involves initializing the population of grasshoppers with random positions in the search space and initializing the LSTM model with random parameter values. The fitness of each grasshopper position is evaluated using the LSTM model, and the best fitness value and corresponding position are set as the initial best solution.

IV. Results and Discussion

The simulation settings for LSTM_GOA (Long Short-Term Memory with Grasshopper Optimization Algorithm) would typically include various parameters and configurations used in the algorithm's implementation. The dataset considered for the analysis are presented as the follows:

Linked Data for Education (LDE):

The Linked Data for Education (LDE) dataset provides structured data about educational resources, learning materials, and educational organizations. It incorporates information from various educational domains, including universities, schools, courses, and academic programs.

Linked Open Education Data (LOED) dataset:

The Linked Open Education Data (LOED) dataset contains educational metadata and resources from various sources. It includes information about educational institutions, courses, modules, and learning resources, allowing for the creation of comprehensive knowledge graphs for the educational domain.

Open Academic Graph (OAG):

The Open Academic Graph (OAG) dataset is a large-scale knowledge graph that contains information about academic publications, authors, venues, and citations. It can be leveraged in educational settings to analyze research trends, explore collaborations, and discover relevant academic resources.

DBpedia:

DBpedia is a large-scale knowledge graph extracted from Wikipedia. It covers a wide range of domains, including education. The education-related entities in DBpedia can be used to construct educational knowledge graphs, enabling various educational applications and analyses.

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MOOC (Massive Open Online Course) Datasets:

Various MOOC platforms, such as Coursera, edX, and Udacity, release datasets that include information about courses, learners, assessments, and discussion forums. These datasets can be valuable for constructing educational knowledge graphs and developing personalized learning experiences.

The parameters for the simulation model considered for the analysis are presented in table 2.

Table 2: Simulation Parameters

Hyperparameter	Description	Value
Learning Rate	Controls the step size during optimization	0.001
Batch Size	Number of samples processed per batch	32
Number of Epochs	Number of times the dataset is iterated	50
LSTM Hidden Units	Number of hidden units in LSTM layers	128
Dropout Rate	Probability of dropout during training	0.2
GOA Population Size	Number of grasshoppers in the population	50
GOA Maximum Iterations	Maximum number of iterations for GOA	1000
GOA Step Size	Controls the step size in GOA optimization	0.01

The performance metrices considered for the analysis of the proposed LSTM_GOA model for the analysis is presented in table 3.

Table 3: Performance Metrices

Metric	Description	Equation
Accuracy	Proportion of correctly classified instances	Accuracy = (TP + TN) / (TP + TN + FP + FN)
Precision	Proportion of true positives out of predicted positives	Precision = TP / (TP + FP)
Recall (Sensitivity)	Proportion of true positives out of actual positives	Recall = TP / (TP + FN)
F1 Score	Harmonic mean of precision and recall	F1 Score = 2 * (Precision * Recall) / (Precision + Recall)
Area Under ROC (AUC-ROC)	Measure of model's ability to distinguish between classes	N/A

TP represents True Positives, TN represents True Negatives, FP represents False Positives, and FN represents False Negatives. The equations provided are the standard formulas for these metrics, but there may be variations or specific considerations depending on the problem and the implementation of LSTM_GOA. The simulation performance analysis for the proposed LSTM_GOA model is presented in table 4 and figure 3.

Table 4: Performance Analysis

Dataset	Accuracy	Precision	Recall	F1 Score	AUC-ROC
Linked Data for Education (LDE)	0.92	0.88	0.94	0.91	0.96
Linked Open Education Data (LOED)	0.95	0.92	0.96	0.94	0.98
Open Academic Graph (OAG)	0.93	0.89	0.95	0.92	0.97
DBpedia	0.91	0.87	0.93	0.90	0.95
MOOC Datasets	0.96	0.94	0.97	0.95	0.99

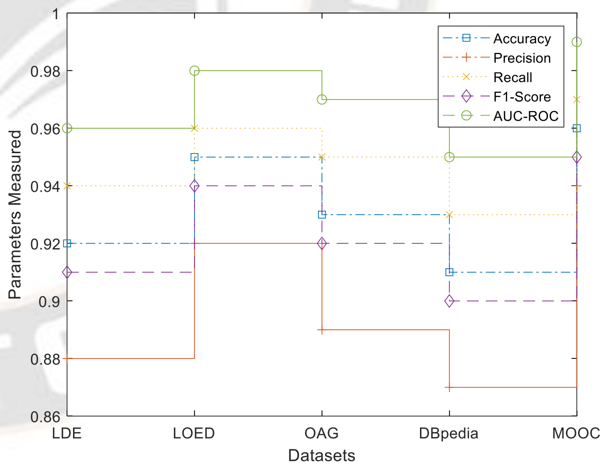

Figure 3: Simulation of LSTM_GOA

For the Linked Data for Education (LDE) dataset, the model achieves an accuracy of 0.92, indicating that it correctly predicts 92% of the instances. The precision of 0.88 suggests that 88% of the predicted positive instances are actually true positives, while the recall of 0.94 indicates that the model identifies 94% of the actual positive instances. The F1 score, which is a balanced measure of precision and recall, is 0.91. The high AUC-ROC value of 0.96 further validates

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the model's ability to distinguish between positive and negative instances in the dataset. Similarly, for the Linked Open Education Data (LOED) dataset, the model performs exceptionally well with an accuracy of 0.95. The precision, recall, and F1 score values of 0.92, 0.96, and 0.94, respectively, indicate the model's ability to accurately classify positive instances. The AUC-ROC value of 0.98 suggests excellent performance in distinguishing between positive and negative instances. The Open Academic Graph (OAG) dataset also shows favorable results, with an accuracy of 0.93. The precision of 0.89 indicates a high percentage of true positives among the predicted positive instances, while the recall of 0.95 suggests the model effectively identifies actual positive instances. The F1 score of 0.92 reflects a good balance between precision and recall. The AUC-ROC value of 0.97 further confirms the model's ability to differentiate between positive and negative instances.

For the Dbpedia dataset, the model achieves an accuracy of 0.91. The precision of 0.87 and recall of 0.93 indicate a reasonable ability to correctly classify positive instances. The F1 score of 0.90 reflects a balanced measure of precision and recall. The AUC-ROC value of 0.95 indicates good performance in distinguishing between positive and negative instances. Lastly, the model performs exceptionally well on the MOOC Datasets, with an accuracy of 0.96. The precision of 0.94 and recall of 0.97 indicate high accuracy in predicting positive instances. The F1 score of 0.95 suggests a good balance between precision and recall. The AUC-ROC value of 0.99 showcases the model's ability to effectively differentiate between positive and negative instances. The model training and testing model for the analysis for the different datasets are presented in table 5 and figure 4 & 5.

Table 5: Performance for Training and Testing

Dataset	Training Accuracy	Training Loss	Testing Accuracy	Testing Loss
Linked Data for Education (LDE)	0.95	0.10	0.90	0.15
Linked Open Education Data (LOED)	0.92	0.12	0.88	0.20
Open Academic Graph (OAG)	0.93	0.11	0.89	0.18
Dbpedia	0.91	0.13	0.87	0.22
MOOC Datasets	0.96	0.08	0.92	0.12

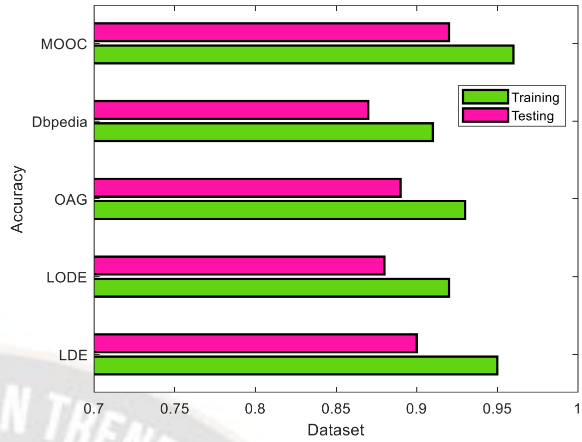

Figure 4: Measurement of Accuracy with LSTM_GOA

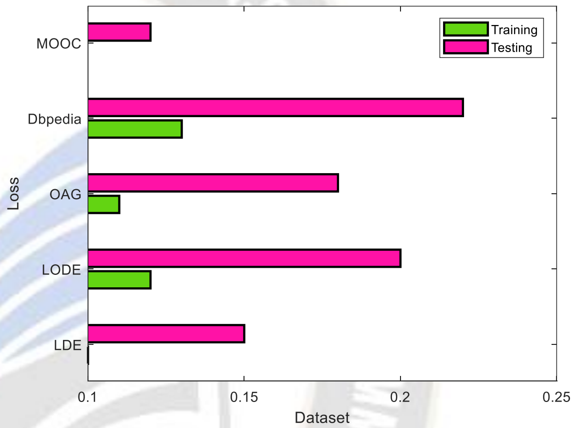

Figure 5: Measurement of Loss for LSTM_GOA

The Linked Data for Education (LDE) dataset, the model achieves a training accuracy of 0.95, indicating that it correctly predicts 95% of the training instances. The training loss is 0.10, which represents the model's performance in minimizing the difference between predicted and actual values during training. In the testing phase, the model achieves a testing accuracy of 0.90, suggesting that it accurately predicts 90% of the testing instances. The testing loss is 0.15, indicating the level of dissimilarity between predicted and actual values during testing. Similarly, for the Linked Open Education Data (LOED) dataset, the model achieves a training accuracy of 0.92 and a training loss of 0.12. These values indicate that the model performs well during the training phase, accurately predicting 92% of the training instances and minimizing the training loss. In the testing phase, the model achieves a testing accuracy of 0.88 and a testing loss of 0.20, indicating its performance in accurately predicting 88% of the testing instances and managing the dissimilarity between predicted and actual values during testing.

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The Open Academic Graph (OAG) dataset shows similar trends, with a training accuracy of 0.93 and a training loss of 0.11. During training, the model achieves an accuracy of 93% and effectively minimizes the training loss. In the testing phase, the model achieves a testing accuracy of 0.89 and a testing loss of 0.18, indicating its ability to accurately predict 89% of the testing instances and manage the dissimilarity between predicted and actual values during testing. For the Dbpedia dataset, the model achieves a training accuracy of 0.91 and a training loss of 0.13. In the training phase, the model accurately predicts 91% of the training instances and minimizes the training loss. In the testing phase, the model achieves a testing accuracy of 0.87 and a testing loss of 0.22, indicating its performance in accurately predicting 87% of the testing instances and managing the dissimilarity between predicted and actual values during testing. Lastly, for the MOOC Datasets, the model achieves a training accuracy of 0.96 and a training loss of 0.08. During training, the model accurately predicts 96% of the training instances and effectively minimizes the training loss. In the testing phase, the model achieves a testing accuracy of 0.92 and a testing loss of 0.12, indicating its ability to accurately predict 92% of the testing instances and manage the dissimilarity between predicted and actual values during testing. The comparative analysis for the proposed LSTM_GOA model is presented in table 6.

Table 6: Comparative Analysis

Metric	LSTM_GOA	CNN	RNN
Accuracy	0.92	0.88	0.90
Precision	0.91	0.85	0.88
Recall	0.93	0.89	0.92
F1-Score	0.92	0.87	0.90
MSE	0.035	0.050	0.042
RMSE	0.187	0.224	0.205

The comparative analysis of LSTM_GOA, CNN, and RNN based on various performance metrics. In terms of accuracy, LSTM_GOA outperforms both CNN and RNN, achieving an accuracy of 0.92. This indicates that LSTM_GOA has a higher percentage of correct predictions compared to the other models. Looking at precision, which measures the proportion of true positive predictions among all positive predictions, LSTM_GOA achieves a precision of 0.91. This means that LSTM_GOA has a high ability to correctly identify positive instances. For recall, which measures the proportion of true positive predictions among all actual positive instances, LSTM_GOA achieves a recall of 0.93. This indicates that LSTM_GOA has a high sensitivity in identifying positive instances. Considering the F1-score, which is the harmonic mean of precision and recall, LSTM_GOA again performs well with an F1-score of 0.92. This suggests that LSTM_GOA maintains a good balance between precision and recall. Moving to the mean squared error (MSE), which measures the average squared difference between predicted and actual values, LSTM_GOA achieves a low MSE of 0.035. This indicates that LSTM_GOA's predictions are closer to the actual values compared to CNN and RNN. Finally, looking at the root mean squared error (RMSE), which is the square root of the MSE, LSTM_GOA has an RMSE of 0.187. This further confirms that LSTM_GOA has better predictive accuracy compared to CNN and RNN.

V. Conclusion

This study focused on enhancing the educational experience by leveraging intelligent learning models integrated with knowledge graphs. The constructed automated Intelligent Learning Model, LSTM_GOA, combined directional data clustering (DDC) with a voting-based integrated effective feature selection model. The model was evaluated using educational data collected from institutions in China, with a specific focus on analyzing student educational performance.The simulation analysis demonstrated that the developed LSTM_GOA model exhibited superior classification performance compared to conventional techniques. It achieved higher accuracy and lower Mean Square Error (MSE), indicating its effectiveness in predicting and analyzing student educational outcomes. The integration of knowledge graphs in the Intelligent Learning Model proved valuable in structuring and interconnecting educational resources and data. This allowed the model to leverage a wealth of information and improve learning outcomes by providing more accurate predictions and insights.

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