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Design a Platform for Sharing Educational Resources for Student Based on Dual Attention Graph Convolutional Networks

Abstract: - A key component of raising educational standards is always the sharing of educational resources throughout higher education institutions. The development of digital and network infrastructure among colleges and universities can propel the sharing and exploitation of excellent educational resources to new heights. Nevertheless, there is a lack of an ideal platform for resource selection and integration in the current crop of information-based teaching tools. To overcome this drawback, the methodology used in this study was described in this research in order to classify student and teacher data more precisely. Ideological and Political Education (IPE) is the source of the data collection. The Modified Hamilton filter is used to preprocess the data during the pre-processing step. The excellent course videos, classroom performance, and interactions are all successfully classified by Dual Attention Graph Convolutional Networks (DAGCN).The neural network's weight parameter is optimized using the Lotus Effect Optimization Algorithm (LEA) to improve the DAGCN. The suggested DAGNN-LEA used with the MATLAB platform. The suggested approach was calculated using performance measures such as accuracy, precision, sensitivity, F-score, computation time, and recall. In comparison to the existing method, the suggested DAGNN-LEA method yields better results in terms of high accuracy 16.65%, 18.85%, and 17.89%, high sensitivity 16.34, 12.23%, and 18.54%, high precision 14.89%, 16.89%, and 18.23%, and low computing time 82.37%, 94.47%, and 87.76%.

Keywords: Modified Hamilton filter, Ideological and Political Education, Lotus Effect Optimization Algorithm, Dual Attention Graph Convolutional Networks.

I. INTRODUCTION

The use of technological information in education has revitalized it. It has accomplished this by providing greater access to top-notch resources, innovative technical methods and solutions, and bringing fresh perspectives and strength to the subject of sustainable development. Additionally, it has promoted the reform of methods for learning and teaching while concurrently raising the effectiveness and calibre of education [1, 2]. Big data has been used extensively in several industries in recent years. It can foresee the future development trend and increase work efficiency, quality of life and the working environment, and forecast future development trends by gathering, integrating, and analyzing data in relevant fields [3, 4].The online learning approach is becoming more and more attractive to teachers and students. However, as online learning has grown more popular, issues with low intelligence sharing, severe loneliness, and little interaction among students have surfaced. These problems have hindered the progress of high-quality online education [5, 6]. Traditional online learning spaces' "isolated island" learning structure has been altered by the growth of online learning communities, which have also established interpersonal psychological compatibility and communication, highlighted the variety of learner interactions, and created an intelligent collaborative learning environment [7, 8].

The priceless sociological survey information that was acquired by devoting a significant amount of time, money, and resources is exclusively utilized by the study team and is not shared with the general public [9]. As a result, a large portion of social survey data are rarely used, effectively wasting the society's precious resources. Owing to conditions and technological restrictions, university IPE resources are dispersed. The emergence of the internet has presented ideological education with hitherto unheard-of challenges. Owing to conditions and technological limitations, university IPE resources are dispersed [10,11]. It is required to assure the efficient and ongoing use of IPE resources, increase the rate at which resources are utilized, and realize resource sharing.

College IPE is a component of staff training in universities. In daily education classes for students, IPE classes, situation and policy courses, and other educational settings, it serves as a teaching tool.

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Several key educational teams are required, such as the IPE course team and the student and worker team [12]. A platform for educational resources was established in [13, 14] as a public service that helps instructors and pupils attending public elementary and secondary schools across the nation, By enabling instructors to create online courses and establish their own homepages, networking resources serve their overall goal [15]. In order to balance supply and demand, the educational resource network, a platform that draws in commercial resources, established a link between educators and resource service units [16]. Capogna offered online videos of all grade levels and subjects taught in primary and secondary schools to students in those grades. This expanded the pool of excellent learning materials and marked a significant advancement in the way public education is provided [17]. Since the beginning of the data-intensive era, data sharing has become essential for promoting the creativity of scientific research by providing a theoretical framework for reanalysis and by minimizing the amount of repetitive work that researchers must perform [18, 19]. An intelligent platform called the IPE data resource sharing platform gathers and distributes large data for college students' educational purposes. With the help of this platform, users can look for and find the instructional materials required to satisfy the goals of online learning and communication while also enhancing scientific decision-making. High-quality educational resources are available for users to search and share from anywhere at any time [20].

Major input to the work that is compiled here;

- The IPE dataset is used to collect the data initially.
- In the pre-processing stage, the noise from IPE dataset is removed by using a modified Hamilton filter.
- After that, the pre-processed data are sent to DAGCN, which categorize student participation, performance in the classroom, and top-notch course videos.
- The neural network's weight parameter is optimized using the LEA to raise the DAGCN.
- Performance metrics such as ROC, computing time, specificity, recall, F-score, accuracy, precision, and sensitivity are examined when the suggested DAGNN-LEA approach is implemented.

The remaining portions of this manuscript are organized as follows: segment 2 examines a survey of the literature; segment 3 explains the suggested approach; segment 4 presents the results and discussion; and segment 5 conclusions

II. LITERATURE REVIEW

Numerous research studies on the platform for exchanging educational resources for students, depending on different approaches and aspects are accessible in the literature. A few of them are reviews that go like this:

Qiu et al. [21] have suggested that a platform in 2022 for exchanging information resources related to college students' political and ideological education through deep learning. The contradiction of universities having influence over students' IPE systems is demonstrated by the illogical distribution of IPE resources. In light of the features and problems associated with educational big data at the moment, this work addresses the development of a DL based platform for college students in the IPE sector to share data resources. The objective is to increase resource consumption, encourage resource sharing, and make educational big data genuinely helpful to us. In order to achieve incremental mining of dynamic data, DL was used to parameterize the collected data, compute the conjunctive normal form, produce the discernibility matrix and logical analytical formula, determine the parameters of the matching algorithm, incrementally reduce the dynamic data sample subset, and introduce the kernel attribute into each conjunction.

Du [22] have suggested that a platform for teaching English to college students online that shares resources knowledge based on deep learning. A network is now a daily necessity for every college student due to the quick progress of technology of information. For the college English teaching platform to be created, using network tools was both advantageous and required. Numerous Chinese institutions use a variety of domestically designed online English learning platforms. This research study offers a design strategy for a platform for teaching English at universities to Chinese colleges and universities, based on the ideas of communicative learning, research, and analysis. The first part of the essay provides an overview of the significance and the scientific basis of the online college English teaching platform. Next, an evaluation is conducted regarding the condition of the online college English teaching platform and a particular platform for a particular teaching network is given as an example.

Zhang [23] have suggested that a popular learning resource sharing network that makes it easier for English majors to share their teaching resources. The creation of excellent course materials and other teaching aids requires a significant time and energy investment from teachers in the traditional English education system. However, inadequate resource sharing had a detrimental effect on the school's overall teaching effectiveness due to the network's strong capacity for sharing not being completely leveraged. Using a neural network and a well-known learning resource sharing website, the way English majors share educational resources is examined. The BP neural network technology can find and predict data when exchanging educational materials with English majors because it has superior categorization and prediction functions.

Cai and Peng [24] suggested in 2022 that a deep learning-based approach to sharing online resources for teaching spoken English. Using a fixed task priority scheduling approach, this work explores resource sharing in a mixed criticality among tasks framework to improve the exchange of resources for teaching spoken English online. In addition, this research expands upon the traditional PCP protocol and provides an appropriate resource-sharing plan for the AMC scheduling model within a dynamic hybrid criticality system.Deep learning is also used in this work to assess the worst reaction time and worst blocking time for each task level.In summary, this work develops a similar intelligent teaching resource sharing system by examining the sharing behaviors of online spoken English teaching materials in conjunction with deep learning technologies.

Cheng [25] have suggested that a platform for data resource exchange based on constraint clustering for college students' political and ideological education. The conventional "silo" learning structure found in online education has been replaced by online learning communities, providing a productive setting for information exchange and collaborative growth. One of the biggest issues academics in the field of online learning are dealing with is building a vibrant online learning community. A limited clustering approach is used to formulate the process of building an online learning community, and an intelligent construction method is created. Among these three principles in particular are the sharing platform's combination of standardization and openness, the coupling of paid and public elements of data resources, and the combination of ongoing iterative development and limited freedom of choice.

Hou et al. [26] have suggested that a platform for exchanging educational content based on a blockchain network. A key component of raising educational standards is always the sharing of educational resources throughout higher education institutions. With the expansion of digital and network development among colleges and universities, the sharing and exploitation of excellent instructional resources can progress to a new degree. This study offered a method for utilizing blockchain technology to establish an international platform for the exchange of educational materials. By means of this platform, students globally can more conveniently obtain top-notch instruction, thereby enhancing educational parity. Meanwhile, the credit recognition system can efficiently maintain personal privacy and break down obstacles to trust between higher education and social media platforms.

Wang [27] have suggested is a cloud computing platform for the sharing of resources for teaching college English. In other nations, intelligent computing has long been utilized in the sphere of teaching and education. China was doing research on education clouds, but universities haven't yet used them to distribute course materials. Sharing instructional resources of the highest caliber was necessary to improve The unequal distribution of educational resources in China's higher education system will be somewhat mitigated by an intelligent computing-based university instructional resource sharing network. The advancement of communication networks and information technology development have ushered in the information era. Amidst digitization, the influence of educational materials on English schools was increasing daily. If intelligent computing offers the required technical support, the platform for sharing educational resources could effectively address the issues of low consumption of educational resources and unnecessary infrastructure expenditure. Promoting collaboration, resource sharing, and interregional exchanges for postsecondary education was made possible by it.

A. Motivation

According to a general assessment of recent research, deep learning-based educational resource sharing platforms for colleges and universities are crucial for student education.The internet has created hitherto unheard-of obstacles for the ideological education system. CNN, STM, C-Mean, k-mean, BPNN, Naive Bayesian data classification algorithm, and DL are examples of adaptive data fusion methods are just a few of the technologies that many researchers are working on and have been discussed in the literature.To fulfill the demands of daily instruction and learning, deep learning (DL) technology processes and combines a variety of resources to create tailored resources. Convective neural networks (CNNs) are the basis of the adaptive data fusion technique, which addresses the challenge of data fusion in the diagnosis of multisource data fusion faults.

The tree's simple matching (STM) technique can be used to determine the maximum number of nodes in two trees that match. The C-Mean Algorithm has a straightforward concept, is simple to implement, converges quickly, operates swiftly, uses minimal memory, and can handle big data sets with ease. Use the PSO algorithm to optimize the coefficient.The educational resource platform is affected by the aforementioned technologies, which have poor usage and sharing. Very few approach-based works have been provided in the literature to address this issue; these shortcomings and issues are what have inspired this study effort.

III. PROPOSED METHODOLOGY

The IPE data resource sharing platform gathers information from numerous sources and formats for college students. Using a Modified Hamilton filter, the noise is removed during the pre-processing phase. The dual attention graph convolutional networks classify the student data's excellent course videos, classroom performance, and interactions once the pre-processing step's output is provided to the classification stage. The neural network's weight parameter is optimized using the Lotus Effect Optimization Algorithm to enhance the DAGNN. Proposed methodology is illustrated in Fig 1.

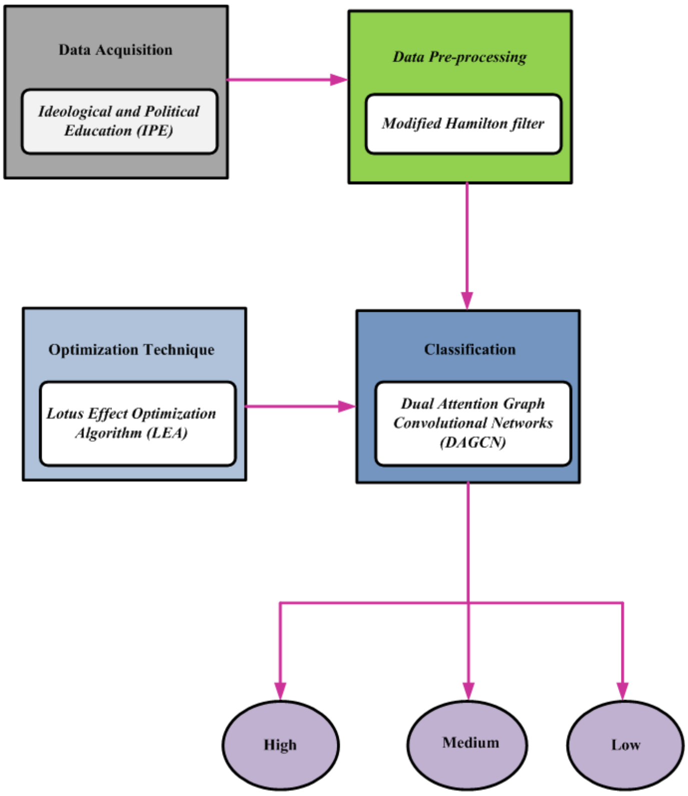

Fig 1: Proposed Methodology

A. Data Acquisition

There are many different sources and formats for the data that is gathered by the college student IPE data resource sharing platform [28].Thus, strong technological support is needed for every step of the process, from collecting data to displaying and distributing the finished product. Throughout the teaching process, collect dynamic behaviour data from instructors and students, like participation, performance in the classroom, and excellent course videos. You can then expand this data to include information about government resources, social hotspots, network hotspots, and university precision instruments and equipment. By utilizing data mining and analytic technologies, users' behaviors, habits, age ranges, and other relevant information are deduced, resulting in more intelligent and relevant search results and recommendations for them on the site.

B. Data Preprocessing Using Modified Hamilton filter

Pre-processing of the data set is required when it comprises non-existent data that is inconsistent, noisy (external), and incomplete (missing). Elements of theft, abduction, robbery, and murder were mentioned in this [29]. By using a modified Hamilton filter, the data is preprocessed.

Hamilton proposes utilizing a projection based on AR (4) and its 8-quarter forecast inaccuracy. The portion of the macroeconomic time series that is repeated the selection of the 8-quarter horizon was based on its cyclical characteristics. The simple auto regression and macroeconomic time series y_t can be computed as follows:

$$y_t = \beta_0 + \beta_{1y_t-8} + \beta_{2y_t-9} + \beta_{3y_t-10} + \beta_{4y_t-11} + \mu_t \tag{1}$$

The residual μ_t provides the cyclical component.

$$\hat{\lambda}_t = y_t - \hat{\beta}_0 - \beta_1 \hat{y}_{t-8} - \hat{\beta}_2\, y_{t-9} - \hat{\beta}_3\, y_{t-10} - \hat{\beta}_4\, y_{t-11}. \tag{2}$$

Employ log quarterly real GDP; it's easy to mistake this $\hat{\lambda}_t$ for an output gap. When it comes to the difference filter, cycles of 8, 4, 8/3, and 2 quarters are negligible, if not entirely avoided, as noted by Hamilton and Scheduler. To assess the output gap $\tilde{y}_t$, a proposal based on 4–12 quarter head projections and a forecast error average that is equally weighted:

$$\tilde{y}_t = 1/9 \sum_{i=4}^{12} \hat{\lambda}_{t,j}, \tag{3}$$

$$\hat{\lambda}_{t,j} = y_t - \hat{\beta}_{0,j} - \beta_{1,j} \hat{y}_{t-j} - \hat{\beta}_2\, y_{t-j-1} - \hat{\beta}_{3,j}\, y_{t-j-2} - \hat{\beta}_4\, y_{t-j-3} \tag{4}$$

The Hamilton filter's cyclical features are changed as follows in light of frequency domain analysis: making it appropriate for evaluating output gaps. It can be used to estimate output gaps thanks to the Hamilton filter. Stationary process with covariance $\tilde{y}_t$ at frequency $\gamma \in [0, \pi]$ is provided via the auto covariance function's Fourier transform.

$$sd_y(\gamma) = \frac{1}{2\pi} \sum_{\tau=-\infty}^{\infty} acf(\tau) e^{-j\omega t} \tag{5}$$

Here $j = \sqrt{-1}$ and γ is determined using radians. Furthermore, a two-sided moving average can be used to represent a time-invariant filter with precise addable weights:

$$x_t = \sum_{k=\infty}^{\infty} B_k X_{t-k} \tag{6}$$

For a linear filter like that, its squared gain is computed using the PTF $|b(\gamma)|^2 = |B(e^{-j\gamma})|^2$ calculation.

$$sd_x(\gamma) = |b(\gamma)^2| sd_x(\gamma) \tag{7}$$

Dealing cycle frequencies, or cycles with a length of 6 to 32 quarters, or radians, are what the PTF for filtered business cycles should have a value of 1, from $\gamma = 2\pi/6$ to $\gamma = 2\pi/32$, and for every other frequency, a value of zero.

Following the process of noise reduction, for categorization, the data are imported into DAGCN.

C. Classification using Dual Attention Graph Convolutional Networks (DAGCN)

This article discusses DAGCN [30]. Equation (8) can be used to compute the dynamics of the system.

$$l^{k+1} = \varphi(\tilde{b}\tilde{c}^{-1} l^k w) \tag{8}$$

Where, $\tilde{b} = b + I_n$ is each node's adjacency matrix with self-connection, $\tilde{c}$ is represents $\tilde{b}$'s diagonal node degree matrix, w is denoted as the parameter of the model to be trained, and $\tilde{b}\tilde{c}^{-1}$ is the normalized graph structure. l^k becomes a vector of node properties with k-hop local structure information in it, after this operation is applied k times. It should be noted that the results of each step in the iteration of equation 8 except for l^k, can only be used to produce the following convolution result. Our AGC layer's main goal is to improve the model so that it may take useful information from each hop in addition to relying just on the result of the k-hop convolution. As a result, a hierarchical representation that includes the most important data from several hop convolution procedures will be the convolution output. The following is the formation of a hierarchical node representation λ_{v_n} using the exhibit attention behavior and equation 9:

$$\lambda_{v_n} = \sum_{i=1}^{k} \alpha_i l_{v_n}^k \tag{9}$$

$l_{v_n}^k$ denotes the node v_n local structure in $k-hops$, and α is the attention weight. The aggregation result for each hop is, in short, analyzed using vanilla attention to determine its significance. The information about the hierarchical structure is contained in the final node representation. Each layer has a variable number of neurons, and there may be variations in the excitation function employed.

Deep learning can be optimized to reveal deeper latent features by building an attention graph convolutional module using several attention convolution layers stacked together at the residual learning technique, ultimately leading to a superior final representation of a node λ_{vn} . The total of the previous layer's output plus the initial y value makes up each AGC layer's input.

$$\lambda_{v_n}^{rn+1} = \sum \alpha_i l_{v_n}^k \qquad l_{v_n}^0 = \lambda_{v_n}^{rn} + y \tag{10}$$

$$\lambda_{v_n} = Dense(\{\lambda_{vn}^0, \lambda_{vn}^1, ..., \lambda_{vn}^m\}, \theta) \tag{11}$$

Where each attention graph convolution layer's output is combined by the dense layer $Dense()$. To keep things simple, we can represent the graph as an *n*-by-*c* matrix *g*,here each row represents a node. $v \in g$ is the node representation of a λ for every vertex.

$$g = (\gamma_{v1.}\gamma_{v2,}\text{.........}\ \gamma_{vn}) \tag{12}$$

From the node's representation, the graph-level representation is the first step in the task of classifying graphs. The majority of earlier studies aggregate all node representation vectors to create a network representation vector employing sort pooling or mean/max pooling. In place of standard max and mean pooling they propose a self-attention pooling layer because they think those methods are ineffective and needless. The objective is to maximize the information underneath the nodes' representation while encoding any given graph into a particular size embedding matrix. When creating the weights vector α, the input for the attention mechanism is the learned graph node representation from the convolution module.

$$\beta = soft\max(\ u_2 \tanh(u_1 g^T\ )) \tag{13}$$

Here r is denoted as a hyper-parameter indicating how many subspaces should be used in order to distinguish between the node representation and the graph representation, u_1 and u_2 are represent as weight matrices in the corresponding c-by-c and c-by-r shapes.

$$Y = soft\max(ZM + C) \tag{14}$$

Here, $soft\max$ function is carried out along the input's 2nd dimension.

Finally, the DAGCN processing that groups the data based on student achievement, interaction, classroom performance, and excellent course videos. Typically, DAGCN doesn't offer the optimization techniques needed to choose the best variables to confirm a precise detection. Thus, for the optimization algorithm to be effective, the weight parameter λ_{v_n} of the DAGCN must be optimized.

D. Optimization Technique using Lotus Effect Optimization Algorithm (LEA)

The lotus effect, which is the self-cleaning characteristic of water on flower leaves, is used for extraction and local search operations in a new evolutionary algorithm known as the LEA. It uses effective operators from the dragonfly algorithm for exploration, like the flying of dragonflies during flower pollination [31].

Step 1: Initialization

Put the input parameters back to their starting points. Here, the DAGCN weight parameters serve as the input parameters, which are represented as λ_{v_n} .

Step 2: Random Generation

The input parameter in a matrix described by is generated randomly.

$$e = \begin{bmatrix} y_{11} & y_{12} & y_{13} \\ y_{21} & y_{22} & y_{23} \\ y_{31} & y_{32} & y_{33} \end{bmatrix} \tag{15}$$

Here, e is denoted as the arbitrary generation and y is denoted as the system's factors.

Step 3: Calculation of Fitness Value

Initialized assessments and the random response yield the outcome. Fitness function evaluation uses the effects of weight parameter optimization λ_{v_n}. The formula (16) is used to calculate it.

$$fitness\ function = Optimizing\ [\lambda_{v_n}] \tag{16}$$

Here, γ_{vn} denotes the better node representation.

Step 4: Exploration Phase

Dragonflies in the LEA are responsible for biological global pollination, which is analogous to the recommended algorithm's exploration stage. The dragonfly algorithm takes into account two concepts of enemy and food, along with three fundamental characteristics of insect swarms: separation, alignment, and cohesiveness. This mimics the intelligent behavior of dragonflies. The act of shielding someone from encountering their neighbours is known as separation. The process via which individuals match their own speed to that of others in their immediate surroundings is known as alignment. Cohesion indicates people's tendency to congregate in the middle of the neighbourhood's population. Each swarm's primary goal is to survive. As a result, everyone needs to be drawn to food sources and kept away from adversaries. Five factors—all of which might be quantitatively modelled—are in charge of revising each person's position within the swarm in light of these two behaviors.

The formula for separation is as follows:

$$B_i^t = -\sum_{j=1}^{N} y_i^t - y_j^t \tag{17}$$

In the evolution iteration t, y_i denotes the position of the current individual with index i, y_j denotes the position of the j th individual in the neighbourhood, and N denotes the total number of individuals in the neighbourhood.

The following formula is used to calculate alignment:

$$C_i^t = \frac{\sum_{j=1}^{N} y_j^t}{N} \tag{18}$$

Here, y_j indicates the neighborhood resident's velocity in evolution iteration t

The formula for cohesion is as follows:

$$D_i^t = \frac{\sum_{j=1}^{N} y_i^t - y_j^t}{N} - y_j^t \tag{19}$$

The following formula determines the attraction toward food sources:

$$E_j^t = y_+^t - y_i^t \tag{20}$$

Here y_+^t is the location, or best-found answer, of the food source that resulted from this evolutionary cycle, or t.

The formula for enemy distraction is given below:

$$G_i^t = y_-^t + y_i^t \tag{21}$$

Here, y_-^t is denotes the enemy position, or t, which is the worst-found answer and the outcome of the current evolution iteration.

The architecture of the PSO algorithm was used to create the dragonfly algorithm, and the step length—or, to put it more succinctly, step is comparable to PSO's velocity vector. The step, often known as the velocity vector, is defined as follows and indicates the direction of the dragonfies' movement:

$$\Delta y_i^{t+1} = \left(bB_i^t + cC_i^t + dD_i^t + eE_i^t + gG_i^t\right) + w\Delta y_i^t \quad (22)$$

Here a is denoted as the coefficient of separation. The i th individual's separation degree in an evolutionary iteration is known as the B_i^t. i, c stands for alignment coefficient, C_i^t for individual alignment, d for cohesion coefficient, D_i^t for i th individual cohesion, e for food factor, E_i^t for i th individual food source, g for enemy factor, G_i^t for i th individual enemy, w for inertia weight, and t for algorithm iteration counter all make up this equation.

The position vectors are computed as follows after the step vector has been determined:

$$y_i^{t+1} = y_i^t + w\Delta y_i^{t+1} \quad (23)$$

In the event that their neighborhood is devoid of solutions, the artificial dragonflies must fly with a random stride length throughout the search area in order to enhance their unpredictable/stochastic behaviors. In this instance, the following relation is used to update the dragonfly positions:

$$y_i^{t+1} = y_i^t + Levy(h) \times y_i^t \quad (24)$$

Where h represents the position vector's dimensions and t denotes the counter of the current iteration. To calculate $Levy$, the following relation is used:

$$Levy(x) = 0.01 \times \frac{r_1 \times \sigma}{|r_2|^{\frac{1}{\beta}}} \quad (25)$$

Here β is a constant number and r_1, r_2 are denoted as two arbitrary numbers in the range of 0 to 1. This relation is used to calculate α :

$$\alpha = \left(\frac{L(1+\beta \times \sin(\pi\beta))}{L\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right)^{\frac{1}{\beta}} \quad (26)$$

Here in:

$$L(x) = (x-1)! \quad (27)$$

Step 5: Exploitation Phase

In the proposed algorithm, the extraction phase is local pollination, or self-fertilization. In this type of pollination, each flower's growth region surrounding the best-found blossom is determined by a coefficient. Other solutions flow toward the best-found solution, which serves as the foundation for movement. The movement algorithm starts with longer steps and ends with shorter ones.

$$y_i^{t+1} = y_i^t + R\left(y_i^t - m^*\right) \quad (28)$$

Here m^* is indicated as the best pollen location discovered thus far among all evolution iterations, and Y_{t+1} is the pollen location in the $t+1$ th iteration. The growth area, or R , gets smaller as the algorithm iterates. As the algorithm progresses toward its conclusion and converges to the optimal value, the movement steps actually get shorter at the beginning.

$$R = 2e^{-\left(\frac{\Delta t}{N}\right)^2} \quad (29)$$

Here N is denoted as the total amount of iterations and t is represent as the algorithm's current evolution iteration.

Step 6: Update the Best Solution

The process is finished if the best result is achieved.

Step 7: Termination

If the solution is the best, the procedure will terminate; if not, until a solution is found, it will loop back to the step 3 fitness calculation and process the ensuing levels.

IV. RESULT AND DISCUSSION

The results of the experiments conducted in the development of a student-based deep learning-based educational resource sharing platform utilizing the DAGCN -LEA method. MATLAB/Simulink is used to conduct the simulations. MATLAB is used to simulate the suggested approach under various performance criteria. Results of DAGCN-LEA analyzed using the current methods, including BPNN, DCNN, and CNN.

A. Performance metrics

Performance metrics like sensitivity, specificity, f1-score, and computation time are also compared. To evaluate the performance measures, it is essential to have the confusion matrix. To scale the confusion matrix, one needs comprehend the true positive (TP), true negative (TN), false positive (FP) and false negative (FN) values.

1) Accuracy

It is described as the total number of occurrences in the dataset. The outcome is a matrix that describes the model's performance for every class. Equation so establishes it eqn (30),

$$Accuracy(acc) = \frac{TP + TN}{TP + TN + FP + FN} \tag{30}$$

2) Sensitivity

Sensitivity is the word for true positive rate or recall. The equation (31) is used to compute the sensitivity.

$$Sensitivity(sen) = \frac{TP}{TP + FN} \tag{31}$$

3) Precision

True positive predictive principles, which are computed using equation (32) are the terms used to describe the precision.

$$\mathrm{Pr}ecision = \frac{TP}{TP + FP} \tag{32}$$

4) F-score

This yields the sensitivity's harmonic mean and positive predictive value.

Baye's theorem determines the positive predictive value (pv).

$$pv = \frac{sen \times p}{(sen \times p + (1 - spe) \times (1 - p))} \tag{33}$$

$$p = \frac{TP + FN}{TP + FP + FN + TN} \tag{34}$$

In equation(35), therefore, is used to get the F-score.

$$F - Scorevalue = 2 \times \frac{sen \times pv}{sen + pv} \tag{35}$$

5) Recall value

The equation (36) depicts the recall value.

$$\mathrm{Re}call = \frac{pt}{(TP + FN)} \tag{36}$$

B. Performance Analysis

Fig 2 to 7 shows the simulation outcomes of DAGNN-LEA. Then the outcomes are analysed with existing CNN, BPNN, and DCNN.

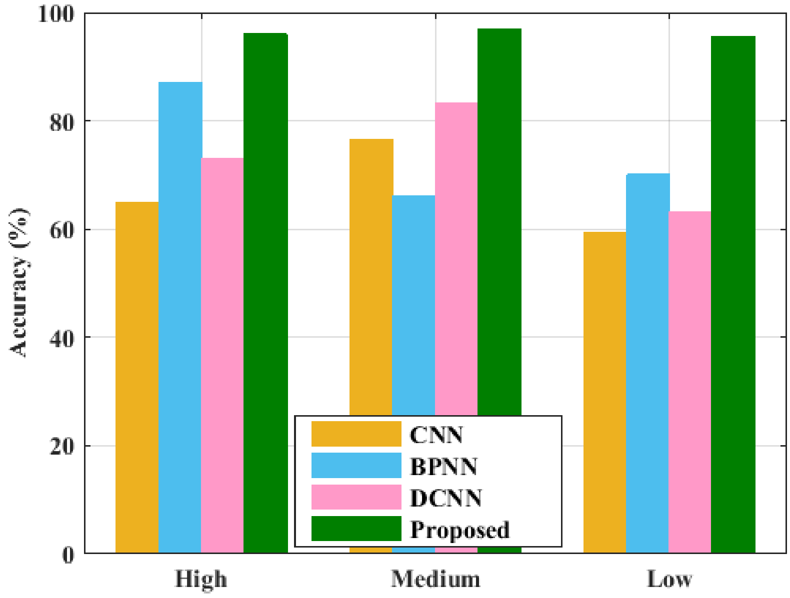

Fig 2: The accuracy value comparison between the proposed and existing systems

The accuracy value comparison between the proposed and existing systems is depicts in Fig 2. The suggested is higher than CNN, BPNN, and DCNN, respectively. The medium achieves 20.46%, 35.58%, 23.54%, the low achieves 21.45%, 30.76%, 18.43%, and the high achieves 50.56%, 20.76%, 35.97%.

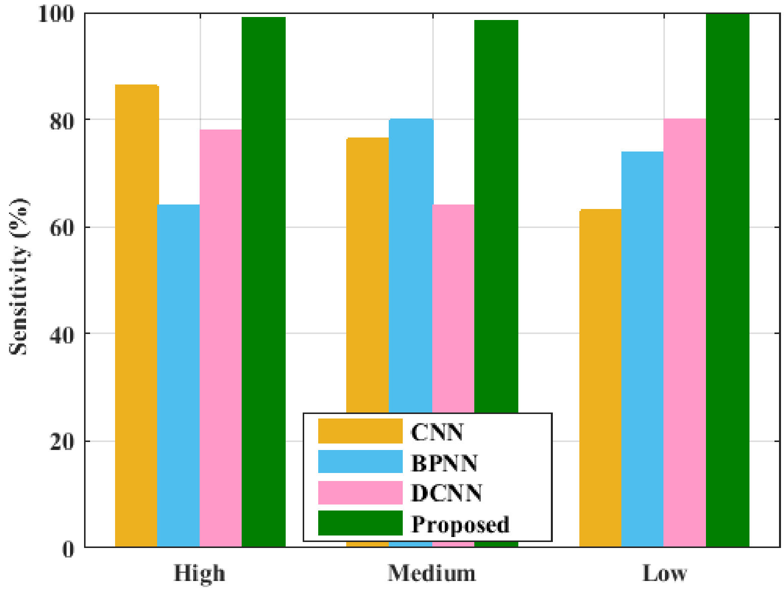

Fig 3: The sensitivity value's performance with the proposed and existing systems.

The sensitivity value's performance with the proposed and existing systems is depicts in Fig 3. The suggested is higher than CNN, BPNN, and DCNN, respectively. The medium achieves 21.46%, 33.58%, 23.54%, the low achieves 21.45%, 30.76%, 18.43%, and the high achieves 30.56%, 21.76%, 35.97%.

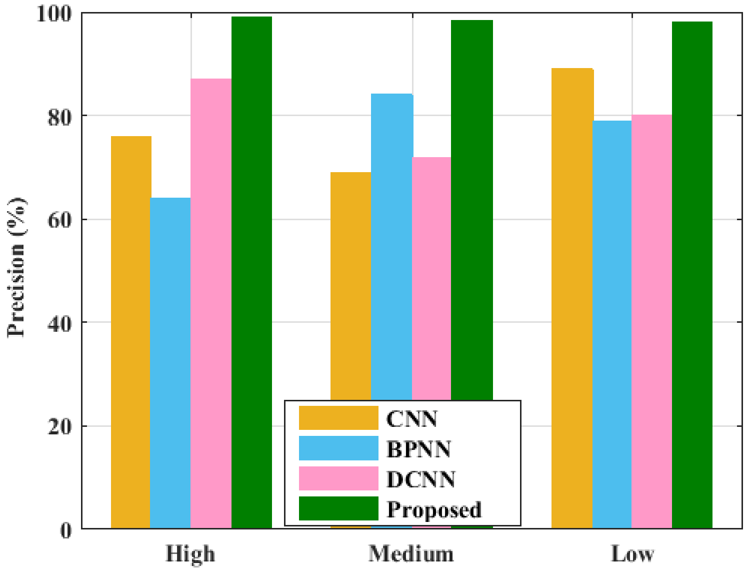

Fig 4: The precision value analysis using proposed and existing systems.

The precision value analysis using proposed and existing systems is depicts in Fig 4. Comparing the suggested to CNN, BPNN, and DCNN, respectively, the medium achieves 21.46%, 33.58%, and 23.54%, the low achieves 21.45%, 30.76%, and 18.43%, and the high achieves 30.56%, 21.76%, and 34.97%.

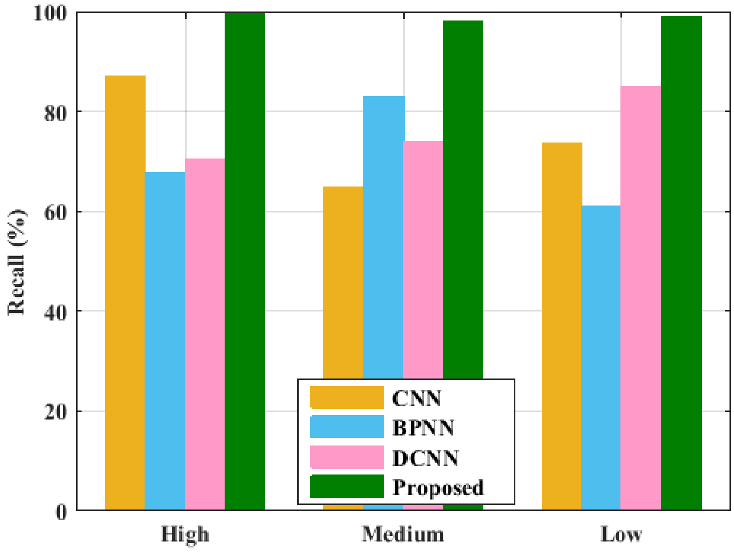

Fig 5: The recall value's performance with the proposed and existing systems.

The recall value's performance with the proposed and existing systems is depicts in Fig 5. The suggested is higher than CNN, BPNN, and DCNN, respectively. The medium achieves 22.46%, 31.58%, and 22.54%, the low achieves 22.45%, 29.76%, and 17.43%, and the high achieves 23.56%, 22.76%, and 31.97%.

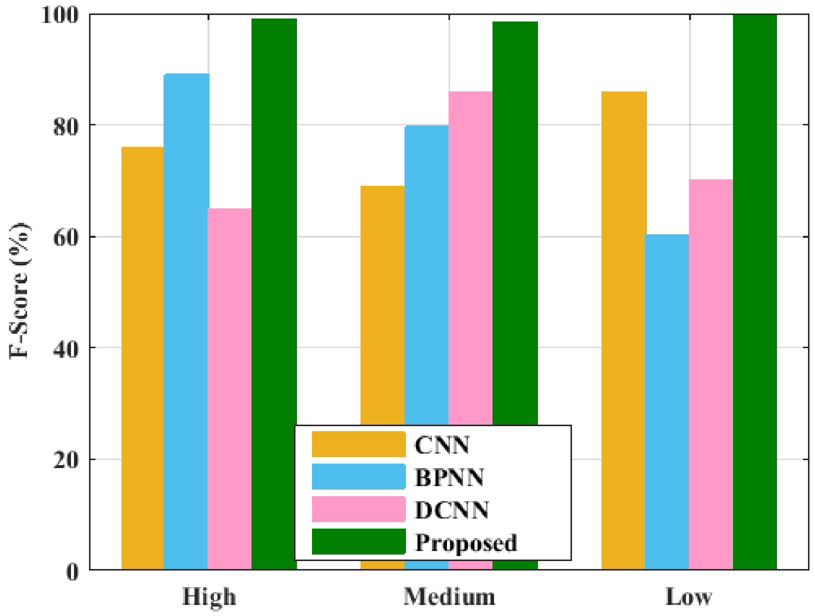

Fig 6: The F-score value comparison between the proposed and existing systems.

The F-score value comparison between the proposed and existing systems is depicts in Fig 6. The suggested is higher than CNN, BPNN, and DCNN, respectively. The medium achieves 21.46%, 33.58%, 23.54%, the low achieves 21.45%, 30.76%, 18.43%, and the high achieves 22.56%, 21.76%, 33.97%.

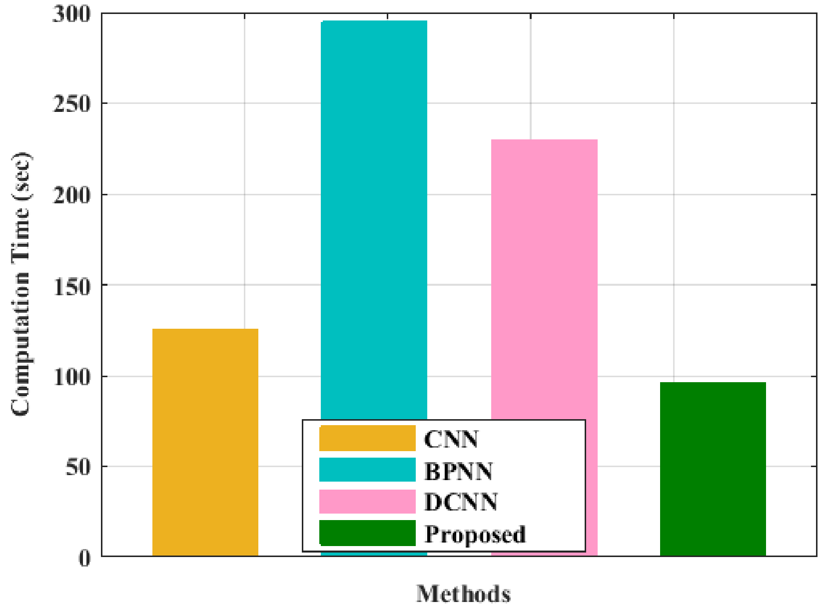

Fig 7: Computation time analysis using proposed and existing methods.

Computation time analysis using proposed and existing methods is depicts in Fig 7. The suggested DAGCN -LEA is evaluated against the current CNN, BPNN, and DCNN techniques. When compared to current methods such as CNN, BPNN, and DCNN, respectively, the suggested DAGCN -LEA method yields 5.34%, 10.11%, and 10.26% lesser computing time. As compared to the CNN, BPNN, and DCNN models that are currently in use, respectively.

V. CONCLUSION

The Political and Ideological Education is a crucial initial stage in gathering data (IPE). During pre-processing, the student data is processed using a modified Hamilton filter. The outcome of the pre-processing is sent to the classification, which use Dual Attention Graph Convolutional Networks (DAGCN) to effectively categorize student data in order to classify interaction, classroom performance, and excellent course videos. The purpose of the LEA is to enhance DAGCN, which correctly categorizes student engagement, academic achievement, and superior course videos. The MATLAB Simulink platform is used to evaluate the proposed strategy and compare it to other existing approaches. Several scenarios are investigated with the proposed method, including recall, calculation time, F-score, accuracy, precision, and sensitivity. The DAGCN classifier, at the system's conclusion, is used to identify excellent course videos, classroom performance, and student interaction. The classifier's accuracy has increased to 98% with this exact choice of the best region-expanding method.

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