J. Electrical Systems 20- 9s (2024): 2804-2813

[1]Xiaoxiao Gong

[2]Dong HE

[3]Fushou Wu

Research on the Quality Development of Ideological and Political Teaching Based on Artificial Intelligence

Journal of Electrical Systems

Abstract: - Ideologies in education encompass the beliefs, customs, values, and ideologies that shape education in the areas of politics, economics, morality, faith, knowledge and reality, aesthetics, and artistic pursuits. Political and ideological education is seen to be influenced by a variety of factors, including trade relations, policy changes, protection from political dangers, and different forms of spending. This research propose novel ideology model in political teaching based on artificial intelligence techniques. Here the students politics interest based analysis has been carried out for enhancing the quality of their ideology. Then using this analysed data the quality modelling is carried out using recursive kernel component feature analysis with Gaussian adversarial encoder neural networks. Experimental analysis has been carried out in terms of training accuracy, average precision, recall, F-1 score, NSE. Based on the experiment's findings, educational activities as well as instruction became more successful, an educational intervention plan was described, the brain's plasticity was maximised, effectiveness of ideological and political education enhanced. Proposed technique attained Training accuracy of 97%, NSE of 63%, average precision of 89%, recall of 88%, F-1 score of 93%.

Keywords: Education ideology, political teaching, artificial intelligence, quality modelling, component feature analysis

1. Introduction:

Global discussions on political involvement and discourse have been sparked in the past few years by a number of noteworthy political occurrences. The 2016 US Presidential Election, Brexit, and the 2017 French Presidential Election, to mention a few, have all sparked debate about the influence of digital platforms on citizenship and authority. These questions, while highly relevant now, are by no means novel. Authors have studied the influence of mass media on democracy throughout the 20th century. Strandberg and Gro¨nlund point out that the study of online discussion is grounded in public sphere theory, which was first proposed by Habermas [1], who contended that at the time, new media, such as radio and television, were undermining an earlier interactive and face-to-face public sphere. Today's online deliberation researchers contend that social media can help with these issues because it gives citizens access to a wide range of multi-way platforms for continuous self-instruction, communication, and debate. The mass media is no longer in an oligopoly, and being a part of a traditional media outlet is no longer a prerequisite for influencing public opinion. The term "education" refers to the ideas, customs, values, and comparative and historical aesthetic knowledge that inform and shape the study of economics, politics, morals, religions, information, and reality. Lack of knowledge exchange, user interaction, and the fact that incentives have become crucial components are among the difficult aspects of political education. Engaging and meaningful educational experiences are essential for supporting students in reaching DL objectives [2]. Whether it is the app's layout or the way an election "bulletin" representative is set up, deeper learning objectives emphasise investigative learning and make sure that students are actively as well as effectively collaborating in groups to create goods or find solutions to issues together [3]. An innovative method for classifying missing values and irrelevant datasets by taking learning and RFBN optimisation into account. By focusing on principles and concepts, deep learning can be promoted rather than the acquisition of facts [4]. The integration of fundamental needs of socialist core values, goal and responsibility of attaining national rejuvenation, fundamental requirements of being a person and doing things are the three spirits of the course teaching process. This is the fundamental design principle that unites political and ideological elements with machine learning. There are differences between the political and ideological courses offered in the curriculum. Machine learning, the fundamental technology of artificial intelligence, has been

[1] [1]College of Marxism ,An Hui Medical College , AnHui 230601, China

[2]College of Marxism ,Inner Mongolia Electronic Information vocational Technology College，NeiMengGu 010070, China, E-mail: hedong84@163.com

[3]College of Marxism ,An Hui Sanlian University , AnHui 230601, China

E-mail: wfs2010@126.com

Corresponding Author Xiaoxiao Gong

actively involved in a number of application domains in recent years, including national security and defence, social and human livelihood, and technological advancement [5].

The major objectives for this proposed research as follows:

- To introduce assessment theory and machine learning techniques together, analyse evaluation indicators' rationality using collected evaluation data, and optimise the evaluation system.
- To proposed novel ideology model based political teaching quality enhancement with students interest based data analysis using artificial intelligence techniques.
- The ideology analysis with quality modelling is carried out using recursive kernel component feature analysis with Gaussian adversarial encoder neural networks
- Commitment to fostering in students a spirit of craftsmanship: investigating the theoretical foundation, derivation process, relevant scenarios, optimisation direction, and other aspects of each machine learning algorithm is essential.

2. Existing artificial intelligence model in political teaching quality analysis:

As part of their general educational goal, colleges and universities must teach courses on politics and ideology. The goal is to teach IAP morality courses in a methodical way using Marxism and the Chinese theoretical outcomes. It is an important way to acquire theoretical information as well as a major way to acquire political and ideological understanding. Its goal is to develop students' socialist personalities through instructional activities that the school arranges. Develop through education those who will uphold the fundamental principles of socialism and serve as its defenders, architects, and successors. Teaching IAP (ideology and politics) courses is a crucial component of teaching mission of colleges and universities. Teaching process consists of two parts: teaching and learning. Evaluating the IPE of teachers is significantly more challenging than evaluating the quality of the products. In order to acquire a thorough assessment of the quality of instruction, [6] addressed each index grade provided by the assessment subject using fuzzy mathematics theory and methodology. During the course of his research, Author [7] said that only a limited amount of general data could be gathered when evaluating education blindly using qualitative or quantitative methodologies. By utilising Internet's high speed, quickness, convenience, Work [8] can gather pertinent evaluation data in shortest period of time, process data more quickly, produce a more thorough calculation result. To develop a more methodical as well as thorough evaluation system, author [9] will analyse and research the conventional evaluation model to pinpoint its shortcomings. The ultimate goal is to find more reasonable indicators and give them scientific weights through a variety of computations. As China moves into a new phase of actively pushing socialist modernization, top-notch higher education is rising to the difficulties of the twenty-first century. Work [10] successfully solved four common natural speech processing challenges, including word segmentation and part-of-speech tagging, by using a word embedding method as well as multilayer one-dimensional convolution structure. In order to address the issue of dimension disaster, author [11] suggested using a multilayer neural network to train high-dimensional features into low-dimensional features. He also suggested using a layer-by-layer training strategy to address issue of training in deep learning being challenging to accomplish optimally. Work [12] used DL technology to analyse sentiment in sentence text, constructed a recursive neural network to create a sentence grammar analysis tree, and contributed the phrase's entire grammatical structure as a feature to the model's training.

3. Proposed political teaching ideology model:

Given the success of courses on ideological and political theory, role of ideological as well as political teaching reform of specialised courses in colleges to achieve collaborative education is suggested; Fundamentally, the pressing necessity of the primary duty of fostering morality and human development in colleges coexists with the complexity of ideological labour in the modern period. It is also a significant accomplishment in the process of enhancing and strengthening the course on political and ideological theory.

Ideological and Political Lessons

One particular kind of course that college students can take to complete their political as wekk as ideological education is an ideological and political lessons course. It serves as the primary driving force and direction behind the political and ideological establishment of schools and universities. The theoretical knowledge grounded in the essential ideas of Marxism serves as the foundation for ideological as well as political education that students get, demonstrating that these courses are the cornerstone of university-level ideological education as well as political training. Professional education courses have a big influence on the content of the curriculum as well as its ideological and political formulation. It is a related field of professional knowledge in professional curricula education that teaches ideologies and politics. The "two skins" issue between ideological and political courses at universities and other majors can be lessened by developing an ideological and political construction based on professional education courses. Additionally, in order to effectively provide ideological and political education to college students, it is imperative to expand scope of this major's educational role as well as deepen instructional reform and improve the application of knowledge gained in this field.

Osmosis's unique ideological and political education makes it challenging to attribute students' growth to specific work effects when it comes to ideological and political literacy; however, this does not preclude evaluation, as each course has its own unique ideological and political education, which primarily focuses on 3D of emotion, attitude, values. Superposition of efforts of academic tutors, university counsellors, instructors of specialised courses, and instructors of ideological as well as political theory results in an increase in students' ideological and political literacy. In order to ensure objective, thorough, and scientific evaluation results, the ideological and political teaching reform in colleges can be evaluated from the three perspectives of emotion, attitude, and values as well as from the four main bodies of ideological and political theory teachers, specialised course teachers, college counsellors, and academic tutors.

4. Political education interest based quality development using recursive kernel component (RKC) feature analysis:

The foundation of socialist advanced culture is socialist core value system, which is constructed in large part through ideological and political education. A comprehensive theoretical framework is socialist core value system. Marxism as guiding ideology, common ideal of socialism with Chinese characteristics, spirit of times with reform and opening up at its core, the national spirit with patriotism at its core, socialist concept of honour and disgrace with main content of "Eight Honours and Eight Disgraces" are among its essential contents. Due to the rich, logical, and systematic nature of socialist core value system's content, a strong carrier is required to instill principles in public's consciousness through national education. Political and intellectual education is one means of putting the socialist core value system's teachings into practice. The educated can actively participate in China's socialist modernization as a great practice through ideological as wekk as political education, which also serves to strengthen the belief of the younger educatees in Chinese-style socialism. They can also intentionally examine, analyse, and address issues using Marxist stances, perspectives, and techniques. In order to limit the influence of multi-noise data, preparing historical data is necessary to enhance accuracy of evaluating self-confidence history of ideological as well as political education culture. This will increase examination of historical development of ideological as well as political education culture's self-confidence more accurately. The system design for IPE (ideological political education) is depicted in Figure 1. Students are taught about ideological situations in IPE. In order to participate in socialist modernization, the students will promote a balanced outlook, meaning, and conception of life.

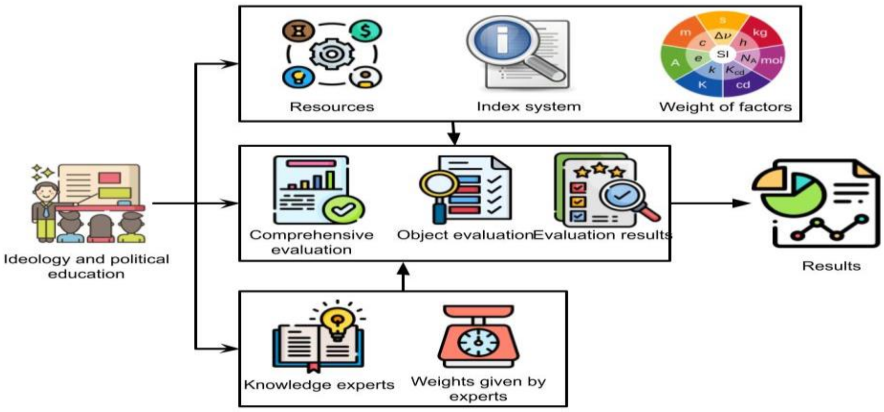

Figure- 1 proposed model in Political education interest based quality development

Let n represent number of observations and p represent number of characteristics. An n p matrix X is our data matrix. For each i = 1, 2,..., n, Xi represents i-th sample observation (Xi = (xi1, xi2,..., xip) T); Xj represents j-th feature (j = 1, 2,..., p). X exhibits the properties of a tiny sample in high-dimensional space when n << p. Let X represent the initial feature space, which is {X1, X2,..., Xp }. Assumed to exist are an ideal feature subset, X(U) X, a redundant feature subset by eqn (1)

$$feature\ space: \Omega \begin{cases} relevant\ feature\ subset \begin{cases} optimal\ feature\ subset: XU \\ redundant\ feature\ subset: XR \end{cases} \\ Irrelevant\ feature\ subset: XJ \end{cases} \quad (1)$$

For every t in Z, let Xt = [X1t,..., Xkt] 0 be a k-dimensional linear process as described by eqn (2)

$$X_t = \mu + \sum_{j=0}^{\infty} \Psi_{jt-j} \quad (2)$$

where εt = [ε1t,..., εkt] and ε ∈ R k E(εt) = 0 and 0 is a vector white noise process by eqn (3)

$$\Gamma_c(h) = \mathrm{Cov}\,(\varepsilon_t, \varepsilon_{t+h}) = \mathrm{E}(\varepsilon_t \varepsilon'_{t+h}) = \begin{cases} \Sigma_\varepsilon & \text{if } h = 0 \\ 0 & \text{if } h \neq 0 \end{cases} \quad (3)$$

The nonsingular matrix Σε is accompanied by k×k matrices of real coefficients called Ψj's. These matrices meet the following formulas: P∞ j=0 tr(ΨjΣεΨ0 j) < ∞, where tr(A) is the trace of a square matrix A. eqn (4) imply that Xt is a second-order stationary process with a covariance matrix and mean µ.

$$\Gamma_X(h) = \mathrm{Cov}\,(X_t, X_{t+h}) = \mathrm{E}\big((X_t - \mu)(X_{t+h} - \mu)'\big) = \sum_{j=0}^{\infty} \Psi_j \Sigma_\varepsilon \Psi'_{j+h} \quad (4)$$

for every h ≥ 0. Without sacrificing generality, it is assumed that ε = 0 in the following. PCA searches for linear combinations of components that capture largest percentage of variation in data while analysing a multivariate data collection. Characteristic roots and vectors of ΓX(0) are computed by PCA. Assume that non-necessarily different eigenvalues of ΓX(0) with corresponding orthonormal values are λ1 ≥... ≥ λk ≥ 0. Then, for each i = 1,..., k, ΓX(0)pi = λipi, and P 0ΓX(0)P = Ÿ, where P is k × k matrix with pi as its ith column and Λ is the k × k diagonal matrix with λi as its ith diagonal element, or Ÿ = diag(λ1,..., λk). According to constraint (i), B's columns all have norm one by eqn (5)

$$F(\boldsymbol{A}, \boldsymbol{B}) = \|\boldsymbol{X} - \boldsymbol{A}\boldsymbol{B}^\top\|^2 = \| \boldsymbol{E} \|^2 \quad (5)$$

that is equivalent to the residual squares sum. Next, the optimisation problem is presented as eqn (6)

$$\begin{cases} \min F(\boldsymbol{A}, \boldsymbol{B}) = \|\boldsymbol{X} - \boldsymbol{A}\boldsymbol{B}^\top\|^2 \\ \text{subject to } \boldsymbol{A}, \boldsymbol{B} \text{ as described above. .} \end{cases} \quad (6)$$

Given that X is data matrix, it is a given matrix, as such, remains constant during the optimisation process, by eqn (7)

$$\frac{\|\boldsymbol{X} - \boldsymbol{A}\boldsymbol{B}^\top\|^2}{\|\boldsymbol{X}\|^2} \quad (7)$$

To reducing $\|\boldsymbol{X}-\boldsymbol{A}\boldsymbol{B}^{\top}\|^{2}$ as in eqn (8)

$$F(\boldsymbol{A},\boldsymbol{B})=\frac{\|\boldsymbol{X}-\boldsymbol{A}\boldsymbol{B}^{\top}\|^{2}}{\|\boldsymbol{X}\|^{2}} \tag{8}$$

Consequently, the goal function is represented by F, which is redefined in (4) and stands for the squared relative error. F represents low-range approximation's degree of fit. Because minimising objective function is same as minimising relative error, smaller values of the objective function indicate a better match.

5. Gaussian adversarial encoder neural networks (GAdEnNN):

Maximum likelihood estimation approach is used to solve the method specifications of a data matrix X = {x 1,x 2,...,x m }. Objective formulation is shown as follows by eqn (9)

$$\max_{\boldsymbol{\alpha},\boldsymbol{\mu},\boldsymbol{\Sigma}} \sum_{j=1}^{n} \ln\left(\sum_{i=1}^{k} \alpha_i \frac{1}{2\pi^{n/2}|\boldsymbol{\Sigma}_i|^{1/2}} e^{-\frac{1}{2}(\boldsymbol{x}_j-\boldsymbol{\mu}_i)^{T}\boldsymbol{\Sigma}_i^{-1}(\boldsymbol{x}_j-\boldsymbol{\mu}_i)}\right) \tag{9}$$

where αi is relevant mixture coefficient and μi and Σi are parameters of ith Gaussian mixture component. In many real-world situations, absence of incomplete features in samples prevents previously discussed methods from effectively managing the missing features in the data. There are numerous approaches to solving the partial data clustering problem. These methods employ standard GMM clustering methods to these imputed data matrices after preprocessing data to minimise the negative effects of missing data. The observable features, xj (oj), missing features, x j (mj), make up each sample x j (1 ≤ j ≤ n). We suggest optimising missing portions of data x j (mj) while maintaining the observable characteristics x j (oj) unaltered when we optimise the prior of k components, the mean μ k, and the covariance Σk for the kth Gaussian basis. As a result, we configured our clustering with partial data Gaussian mixture model as follows by eqn (10)

$$\max_{\boldsymbol{\alpha},\boldsymbol{\mu},\boldsymbol{x}} \sum_{j=1}^{n} \ln\left(\sum_{i=1}^{k} \alpha_i p\left(\boldsymbol{x}_j \mid \boldsymbol{\mu}_i,\boldsymbol{\Sigma}_i\right)\right) \text{ s.t. } \boldsymbol{x}_j\left(o_j\right)=\boldsymbol{x}_j^{o} \tag{10}$$

Observable elements of jth sample, x j, are represented by x j (oj), a symmetric positive definite matrix Σi, and probability density of jth sample value corresponding to ith Gaussian component, p(x j | μi, Σi), can be stated as follows as in eqn (11)

$$p\left(\boldsymbol{x}_j \mid \boldsymbol{\mu}_i,\boldsymbol{\Sigma}_i\right)=\frac{1}{2\pi^{n/2}|\boldsymbol{\Sigma}_i|^{1/2}} e^{-\frac{1}{2}(\boldsymbol{x}_j-\boldsymbol{\mu}_i)^{\top}\boldsymbol{\Sigma}_i^{-1}(\boldsymbol{x}_j-\boldsymbol{\mu}_i)} \tag{11}$$

To guarantee that the values of the observable component of data matrix x j (oj) remain constant throughout the optimisation process, we also set restrictions on it. Additionally, throughout the clustering process, we can use the EM algorithm to continually optimise missing portion of data matrix x j (mj).

Encoder portion translates the input, x ∈ R d, to z, also known as a latent variable. Moreover, the decoder attempts to piece together the input data from z. Autoencoders are trained with the goal of minimising reconstruction error. The encoder and the decoder can be defined formally as transitions τ1 and τ2, by eqn (12)

$$\tau_1(X)\rightarrow Z$$

$$\tau_2(Z)\rightarrow \hat{X}$$

$$\tau_1,\tau_2=\underset{\tau_2,\tau_2}{\operatorname{argmin}} \parallel X-\hat{X}\parallel^{2} \tag{12}$$

The framework of the VAEs model is the same as that of the autoencoders; however, it is predicated on the idea that the latent variables have a uniform or Gaussian distribution. It learns the latent variables by variational inference. The premise behind VAEs is that a directed graphical model p(x|z) generates data, encoder's job is to learn an approximation qφ(z|x) to posterior distribution p□(z|x). VAEs are trained with goal of minimising the loss function by eqn (13)

$$\mathfrak{L}=D_{KL}\left(q_{\phi}(\mathbf{z}\mid\mathbf{x}) \parallel p_{\theta}(\mathbf{z})\right)-\mathbb{E}_{q_{\theta}}(\log p_{\theta}(\mathbf{x}\mid\mathbf{z})) \tag{13}$$

Objective function that vanilla GAN employs is "minimising Jensen-Shannon divergence between fake and real distributions." By eqn (14)

$$\min_{G}\max_{D} V(D,G) = \mathbb{E}_{x\sim\mathbb{P}_r}[\log\ D(x)]\ + \mathbb{E}_{\tilde{x}\sim\mathbb{P}_g}[\log\left(1 - D(\tilde{x})\right)] \quad (14)$$

And the created bogus data is x˜ = G(z). A random noise point sampled from distribution p(z) is denoted by z. To compute cross-entropy reconstruction loss, original training data (x, y) is input into trained VAE. Pr and Pg represent distribution of actual and false data. The following is the definition of the sample (xi, yi)'s binary cross-entropy reconstruction loss by eqn (15)

$$L(x_i, y_i) = -\sum_{k=1}^{d}\ \left[x_{i,k}\log\ \hat{x}_{i,k} + \left(1 - x_{i,k}\right)\log\left(1 - \hat{x}_{i,k}\right)\right] \quad (15)$$

where d is the number of features and xi,k is k-th feature value of sample xi; xˆi = Decoder(Encoder(xi), yi). For every "y_i∈" class "j}, maximum class reconstruction loss (maxLj) of class j is defined as maxL_j=k*max{L(x_i,y_i)", where k is the scaling factor, which is often set at 1.0. We compress RGB input dimensions to half of original image's dimensions by using an encoder with a convolutional layer and stride of 2. Our observations indicate that this is the encoder's ideal configuration. Since our goal is to find underlying latent variables of data to feed into GAN, we do not use the decoder in our architecture. As a result, we require an architecture that reduces the data's size significantly. Because adding a decoder would cause the data to be reconstructed to its original dimensions, we only use the encoder for this.

6. Performance analysis:

This paper's technique is tested against both BP neural networks and conventional artificial neural networks in a specific experimental environment for data categorization research. Table 1 depicts the experimental setting.

Table-1 simulation parameters

Projects	Introduction
Memory	64GB
Development language	C++
Main frequency	3.8GHz
Processor	Core i7
Running platform	windows
Language interface	Python, C/C++

This paper's approach is utilised to classify the original data when the experimental environment is set up, and it is then compared and analysed with two other neural network algorithms. The reason for the low accuracy rate during the first training phase of the system's recognition performance was that not enough samples were obtained to enable accurate recognition. The sample type increases along with the amount of samples in training set, system's capacity for self-adaptation causes the accuracy of data categorization to rise quickly. the relationship between each network's accuracy in detecting samples and the quantity of samples in training set. We can observe that the accuracy of deep neural networks rises fastest with the number of training sets by looking at the link between recognition accuracy and number of samples in training set.

Dataset description- B2FIND: Student political participation, political consciousness at college, and opinions on occupation and learning environment in Cologne. Topics: Social background, career aspiration, description of ideal career, parents' wealth and financial status, connection to parents and their political involvement, fields of study and degree sought; assessment of the university of Cologne's study environment; weekly study schedule structured around attendance at seminars and lectures; contentment with academics; social network; political socialisation; evaluation of college professors and students; interaction with professors and assistants; assessment of the practical applicability of studies; issues at the university; the role of a college; interest in college politics; involvement in personal political activities on campus; affiliation with a college group or fraternity; perspective on political remarks made by professors; perspective on student parliament; and perspective on the social system, social disputes and conflicts.

Along with surveys for students, teachers, and school principals, IEA Civic Education Study, 2016 (ICCS 2016) featured a test of civic knowledge as well as understanding for students. Regional models for Europe and Latin America were added to the comprehensive core assessment. These modules looked into related areas of civic as well as citizenship education and were made to adaptably identify regional interests. The national research centres of the participating nations acquired information about national contexts for civic and citizenship education, which was included to the survey results. Under the direction of Amsterdam-based International Association for Evaluation of Educational Achievement (IEA), data were gathered in 2015 and 2016. Over 94,000 eighth graders from about 3,800 schools across 24 nations provided data to ICCS. More than 37,000 instructors' data from those schools, as well as additional contextual data gathered from national research centres and school principals, were added to the student data.

Table-2 Comparative for B2FIND dataset

Technique	Training accuracy	NSE	Average precision	Recall	F-1 score
ANN	75	74	70	76	72
BPNN	80	70	87	89	76
RKC_ GAdEnNN	89	65	93	94	91

Table-3 Comparative for CIVED dataset

Technique	Training accuracy	NSE	Average precision	Recall	F-1 score
ANN	70	77	74	76	71
BPNN	78	68	80	79	76
RKC_ GAdEnNN	97	63	89	88	93

The above table-2-3 shows Comparative based on various smart grid security dataset. The dataset analysed are B2FIND, CIVED dataset in terms of Training accuracy, NSE, average precision, recall, F-1 score. 100 data records are randomly picked as test set and 200 data records are randomly selected as training set from evaluation database. Debugging experiments reveal that following experimental parameter settings yielded the best results: Activation function is tanh(),learning rate is 0.005, there are 5000 cycles total—all of which depend on how many characteristics there are. The nodes of the input, hidden, and output layers are configured as 8, 6, and 1, respectively.

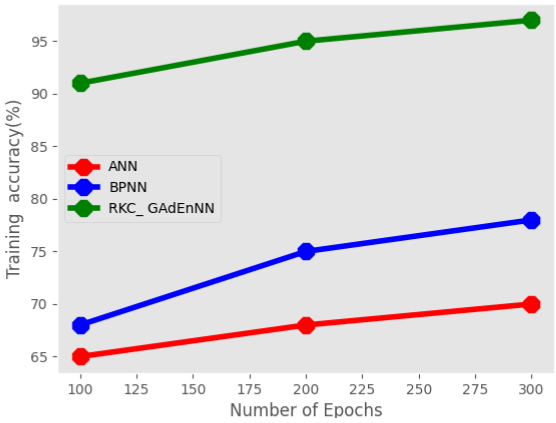

Figure-2 comparison of Training accuracy

The analysis for training accuracy is displayed in Figure 2. Here, the proposed technique achieved 89% training accuracy, 75% existing ANN, and 80% BPNN for the B2FINDdataset; for the CIVED Dataset, the proposed technique achieved 97% training accuracy, 70% existing ANN, and 78% BPNN. This is because there is insufficient low-dimensional sample feature available in first-level label classification procedure to maintain high accuracy classification results. From standpoint of convolution filters as well as image features, network model finds it challenging to learn stable image features when there are an excessive number of convolution filters and not enough training sample data. Experimental results indicate that when amount of training sample data is restricted, the network becomes more challenging to achieve since there are more weight parameters to learn when the network model has more convolution filters. During training, recognition impact is diminished in steady state.

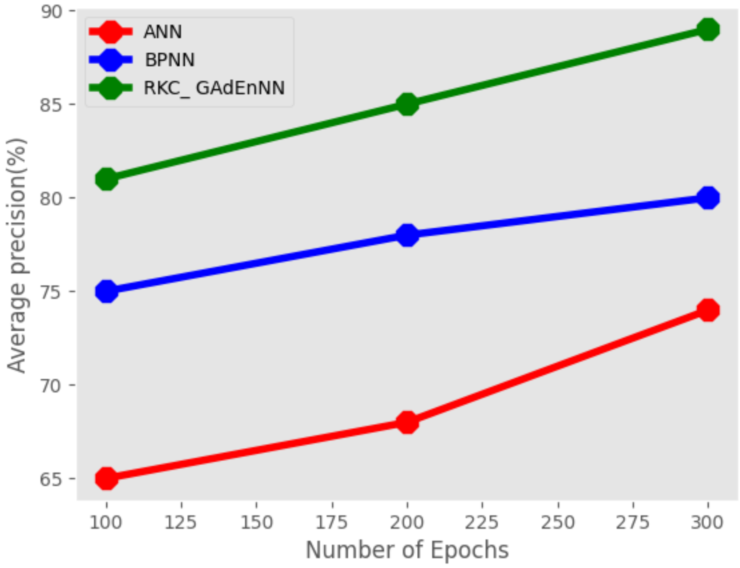

Figure-3 comparison of Average precision

It is evident that each sample group's evaluation value rises as original score does, which is consistent with people's perceptions of qualitative relationship between evaluation value as well as original score and demonstrates the plausibility of the model presented in this paper. Sample 2's evaluation value needs to be greater than sample 1's and smaller than sample 1's when initial scores are the same for all three groups of samples. This upward trend in evaluation values is inevitable. Figure 3 shows analysis in Average precision. Here proposed technique Average precision 93%, existing ANN 70%, BPNN 87% for B2FINDdataset; for CIVED Dataset proposed technique Average precision 89%, existing ANN 74%, BPNN 80%.

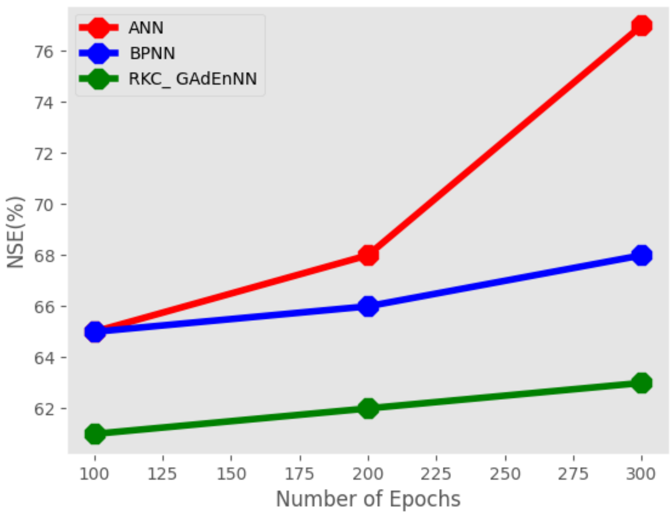

Figure-4 comparison of NSE

It is shown that neural network evaluation method is utilized in teaching evaluation model to evaluate the construction of NN evaluation judgement realised by related IP. Similarly, different disciplines need to choose the neural network for sample training that best suits them in order to more accurately calculate quality of instruction in each profession or discipline. Analysis in NSE is shown in Figure 4. In the B2FINDdataset, proposed technique obtained NSE of 65%, the existing ANN attained 74%, and BPNN attained 70%; in the CIVED dataset, the proposed technique obtained NSE of 63%, the existing ANN attained 77%, and BPNN attained 68%.

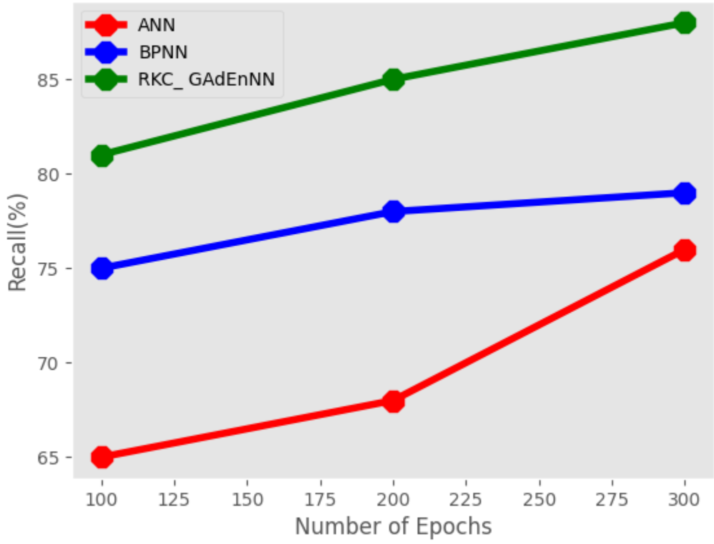

Figure-5 comparison of Recall

The findings indicate that after using this teaching strategy, 55% of students believe it to be extremely effective, 35% believe it to be effective, and 10% are unsure. In summary, the incorporation of ML into ideological as well as political course curriculum has enhanced student engagement and fostered mastery of both ML and ideological as well as political courses. As a result, this style of instruction helps students achieve better course learning objectives. The Recall analysis is displayed in Figure 5. Here, the proposed technique achieved 94% Recall, 76% existing ANN, and 89% BPNN for the B2FINDdataset; for the CIVED, the proposed technique achieved 88% Recall, 76% existing ANN, and 79% BPNN.

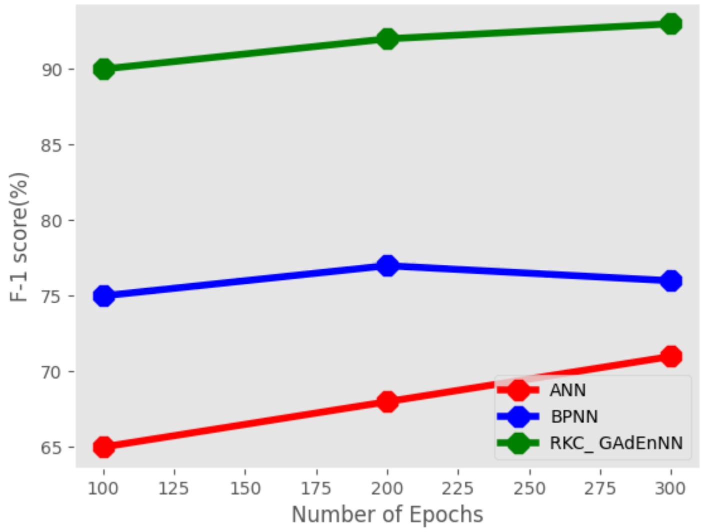

Figure-6 Comparison of F-1 score

Figure 6 presents the F-1 score analysis. On the B2FIND dataset, the suggested technique yielded 91% F-1 score, 72% existing ANN, and 76% BPNN; on the CIVED dataset, it produced 93% F-1 score, 71% existing

ANN, and 76% BPNN. A set of feature vectors to be chosen as destination output vector, reference source vector, parametric architecture method configuration is automatically set with a range of structural properties in self-learning.

7. Conclusion:

Based on artificial intelligence approaches, this research proposes a fresh ideology model for political education. Here, an interest-based political analysis of the pupils has been conducted to improve the calibre of their ideology. Next, recursive kernel component feature analysis using Gaussian adversarial encoder neural networks is used to perform quality modelling utilising this examined data. The approach presented in this research has stable accuracy in information data classification as well as high accuracy in the analysis of historical process data. When 200 historical process texts are examined, it becomes more stable. The algorithm's efficiency is increased and processing times are shortened by continuously adjusting the model parameters in response to freshly provided sample data. We verified that the incremental learning approach can improve the evaluation model and time efficiency when the evaluation data is larger by conducting experiments and analysing the results. The inquiry-based teaching design of the smart classroom stage is only theoretically explored; no further in-depth design work is done due to various conditions' restrictions. It must therefore be further enhanced in the future.

Funding：

This work was sponsored in part by Philosophy and Social Science Research Project of Anhui Province (2023AH052572)

Reference:

[1] Yun, G., Ravi, R. V., & Jumani, A. K. (2023). Analysis of the teaching quality on deep learning-based innovative ideological political education platform. *Progress in Artificial Intelligence*, *12*(2), 175-186.

[2] Zhang, B., Velmayil, V., & Sivakumar, V. (2023). A deep learning model for innovative evaluation of ideological and political learning. *Progress in Artificial Intelligence*, *12*(2), 119-131.

[3] Zhou, Z., & Liu, Y. (2023). Political teaching application in high vocational care courses based on machine learning systems. *Soft Computing*, *27*(11), 7657-7666.

[4] Qi, F., Chang, Y., Ramesh, K., & Hemalatha, P. (2023). Online and offline teaching connection system of college ideological and political education based on deep learning. *Progress in Artificial Intelligence*, *12*(2), 163-174.

[5] Botao, L., & Yanpeng, J. (2023). Analysis of interaction mode of ideological and political flipped classroom based on deep learning algorithm and student feedback data. *Soft Computing*, 1-10.

[6] Geng, F., John, A. D., & Chinnappan, C. V. (2023). Analysis of the teaching quality using novel deep learning-based intelligent classroom teaching framework. *Progress in Artificial Intelligence*, *12*(2), 147-162.

[7] Wu, R., Huang, Z., Zhou, Z., Gayathri, R., & Premalatha, R. (2023). Feature recognition of student using heuristic political effective evaluation reinforcement learning algorithm. *Progress in Artificial Intelligence*, 1-14.

[8] Gencoglu, B., Helms-Lorenz, M., Maulana, R., Jansen, E. P., & Gencoglu, O. (2023). Machine and expert judgments of student perceptions of teaching behavior in secondary education: Added value of topic modeling with big data. *Computers & Education*, *193*, 104682.

[9] Yang, D. Transformation Research on the Teaching Mode of Ideological and Political Courses in Colleges and Universities under Big Data Environment. *Applied Mathematics and Nonlinear Sciences*, *9*(1).

[10] Feng, T. (2023). Research on the development path of internet ideological and political education based on deep learning. *Soft Computing*, 1-10.

[11] Du, G., Sun, Y., & Zhao, Y. (2023). The innovation of ideological and political education integrating artificial intelligence big data with the support of wireless network. *Applied artificial intelligence*, *37*(1), 2219943.

[12] Zhao, M., & Dong, X. (2023, October). Evaluation of Deep Clustering for Assessing Undergraduate Understanding in Ideological and Political Education: Data-Driven Analytics. In *International Conference on Genetic and Evolutionary Computing* (pp. 103-111). Singapore: Springer Nature Singapore.