International Journal of Robotics and Automation, Vol. 39, No. 10, 2024
An Open Access Paper

CHINESE VOCATIONAL SKILLS EDUCATION QUALITY ASSESSMENT USING ATTENTIVE DUAL RESIDUAL GENERATIVE ADVERSARIAL NETWORK OPTIMISED WITH GAZELLE OPTIMISATION ALGORITHM

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Abstract

Vocational training holds significant importance in the Chinese educational system, with a deliberate emphasis on reform and innovation. Enhancing teaching quality is a priority, and conducting a comprehensive assessment of it is essential. Artificial intelligence, particularly deep learning technology, emerges as a promising solution due to its ability to effectively handle the complex and diverse aspects involved in evaluating teaching quality in vocational education. In this manuscript Chinese vocational skills education quality assessment using attentive dual residual generative adversarial network optimised with gazelle optimisation algorithm (CVSE-ADRGAN-GOA) is proposed. Initially, the input data is amassed from Chinese vocational skills education real time data. The acquired data is preprocessed using the colour Wiener filtering method for normalising the input data. Then, the preprocessed data is given to attentive dual residual generative adversarial network (ADRGAN) for the quality assessment of Chinese vocational skills education. The gazelle optimisation algorithm (GOA) is used to optimise the input weight parameters of the ADRGAN. The proposed CVSE-ADRGAN-GOA technique is activated in MATLAB and its efficacy is evaluated utilising some performance metrics, like accuracy, precision, sensitivity, F1-score, specificity, error rate, receiver operating characteristic (ROC), computational time. The proposed CVSE-ADRGAN-GOA method provides 22.43%, 21.76%, 25.65% higher accuracy, 25.67%, 22.66%, 27.92% higher precision while compared to the existing models, like Internet environment and machine learning espoused innovation way of secretarial education in higher vocational schools (CVSE-LRPM), deep learning based vocational education teaching reform quality assessment (CVSE-BPNN), and machine learning and improved support vector machine (SVM)-based teaching reform of undergraduate courses in colleges and universities (CVSE-SVM) methods, respectively.

Key Words

Attentive dual residual generative adversarial network, colour Wiener filtering method, gazelle optimisation algorithm, vocational skills education, quality assessment

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Recommended by Howard Li
(DOI: 10.2316/J.2024.206-1100)

1. Introduction

Vocational education serves as a crucial means to equip learners with professional knowledge, skills, and ethical values to contribute to societal production [1]. As such, it is intrinsically connected to a country's economic development and plays a vital role in supporting the workforce [2]. Over time, vocational education has evolved alongside the changing economy, adapting its essence and offerings [3]. Being an integral part of national education, vocational education is primarily driven by vocational colleges, where the key to enhancing overall quality lies in constructing a rational teaching system. The most direct and important factor in accomplishing teaching goals and ensuring teaching excellence in vocational education is the development of teaching activities [4].

Hence, teaching innovation stands as the crucial factor for successfully reforming vocational instruction to adapt for new economic landscape and nurture higher quality human capital for emerging economy [5]–[8]. The overall superiority of vocational schools straight impact the vocational education development, with direction, education excellence, and success of education reforms contingent on the competence and proficiency of the teaching staff [9], [10].

To implement higher quality educator team, comprehensive understanding and accurate evaluations are paramount. This fosters a sense of awareness among teachers about their achievements and shortcomings, encouraging self-improvement and progress towards higher goals [11]. Furthermore, it also allows school leaders to recognise the significance of enhancing teacher quality and teaching standards, enabling them to take targeted and strategic events to reinforce the teaching staff's capabilities [12]. To get an in-depth grasp of school's educational initiatives and improve the standard of instruction generally, school leaders and managers must assess the effectiveness of teachers' classroom coaching [13], [14]. The level of teaching directly influences the caliber of trained talents, making the assessment of school teaching quality a vital component of education administration. As such, school education quality assessment is a multifaceted and intricate process [15].

It is critical to have a scientific and reliable approach for assessing teaching quality that can evaluate teachers' performance impartially and objectively, given the intricate and multifaceted connection between teachers and students in the classroom, along with the influence of various variables on lesson delivery [16], [17]. Quality remains a highly significant subject, and with the advent of artificial intelligence concept, its continuous evolution takes paralleled the advancements in computer technology [18].

1.1 Problem Statement and Motivation

Deep learning uses multilayer nonlinear information processing and abstraction to operate on neural networks to enable supervised or unsupervised feature learning, representation, categorisation, pattern identification. However, the incorporation of teaching quality assessment as well as deep learning remains somewhat imperfect. To address this gap, this manuscript presents a novel approach for evaluating teaching quality in vocational education using deep learning.

Leveraging the benefits of neural networks in solving non-linear difficulties, the attentive dual residual generative adversarial network (ADRGAN) is proposed. This method achieves efficient, network-based, and intelligent evaluation of Chinese vocational skills education, ushering in promising advancements in the field. But the existing technique [19]–[26] does not offer the enough accuracy and increases the computation time while performing the quality assessment of Chinese vocational skills education. These drawbacks in the existing approaches motivated to do this work.

1.2 Contribution

The key contributions of this manuscript are discussed below:

- The proposed Chinese vocational skills education quality assessment using attentive dual residual generative adversarial network optimised with gazelle optimisation algorithm (CVSE-ADRGAN-GOA) method provides a novel and effective approach to evaluating the quality of vocational skills education in China.
- Initially the input data are taken from the Chinese vocational skills education real time data are preprocessed using the proposed colour Wiener filtering method [27] for normalising the input data for removing noise and inconsistencies, ensuring that the subsequent analysis and modelling are based on clean and reliable information.
- The utilisation of ADRGAN [28] enables the synthetic data generation that closely mirrors the distribution of real data, expanding the available data for assessment purposes.
- The employment of the gazelle optimisation algorithm (GOA) [29] enhances the optimisation of ADRGAN parameters, leading to improved model performance and reduced errors.
- The method incorporates performance metrics specifically tailored for assessing the quality of vocational skills education, providing a comprehensive evaluation of training programs.

Remaining manuscript is structured as: segment 2 depicts the survey of literature, segment 3 describes about the proposed technique; segment 4 shows the result, and segment 5 concludes this study.

2. Literature Review

Amongst many studies on Chinese vocational skills education quality assessment based on deep learning; some recent works are revised here.

Wu [19] presented Internet environment and machine learning espoused innovation way of teaching in higher vocational schools. The presented method introduces a machine learning-based teaching management system for the Internet. The system consists of various interfaces like file access, message, task acquisition, and debugging. Its core components encompass state server, routing server, push message server, and middleware for instant messaging, which interact with each other. The presented method uses linear regression prediction mode (LRPM) for the Chinese vocational skills education quality assessment. The presented method provides high accuracy, but it gives higher computation time.

Ni and Wang [20] presented deep learning-based vocational education teaching reform quality assessment. The use of artificial intelligence, especially deep learning technology, proves highly effective in addressing the complexities of assessing teaching superiority. The presented method uses the deep leaning method called back-propagation neural network (BPNN) for the Chinese vocational skills education quality assessment. The research confirms that the approach objectively and impartially evaluates teaching quality, enhances teachers' enthusiasm for teaching, improves their teaching standards, and fosters exceptional abilities. The presented method provides high precision, but it gives higher error rate.

Zhou [21] presented machine learning and improved support vector machine (SVM) algorithm-based teaching reform of undergraduate courses in colleges with universities. Its primary objective was to enhance the quality of professional teaching by conducting examination into the teaching status. The particle swarm optimisation algorithm optimises SVM's weight parameter. The presented method provides high sensitivity, but it gives lower specificity.

Zhang *et al.* [22] presented an estimation of variations in information-base teaching to enhance the learning accomplishments of Chinese higher vocational college pupils. The focus was on analysing the impact of information-base teaching on student learning outcomes in vocational colleges. SVM-based teaching approach was used to enhance the Chinese higher vocational college students learning achievements. The presented method provides lower computation time, but it gives lower specificity.

Huang *et al.* [23] presented the teaching quality estimation of Chinese-Foreign cooperation in running schools (CFCRS) for sustainable development (ESD) from the perspective education. The study devises a comprehensive teaching quality estimation model comprising resource input, faculty environ, teaching procedure, and teaching output. Utilising decision-making trial with evaluation laboratory-basis analytic network process, the research investigates the interrelationships among teaching quality aspects in CFCRS. The presented method provides lower error rate, but it gives lower F1-score.

Mei and Symaco [24] have presented university-wide entrepreneurship education (EE) in China's higher education institutions: Issues and challenges. The presented method examines the obstacles and complexities involved in implementing a university-wide EE program in China, focusing on Zhejiang province. The study identifies four primary challenges, including the quest for legitimacy, diverse models of EE development, scarcity of qualified entrepreneurship faculty and experts, and insufficient collaboration among stakeholders. The presented method provides higher accuracy, but it gives lower sensitivity.

Jin *et al.* [25] presented Novice teachers' appraisal of expert feedback in a teacher professional development program in Chinese vocational education. This research study investigates how novice teachers perceive expert feedback in a vocational schoolteachers' professional development program. The most prevalent appraisal categories and the distinctions betwixt Chinese language teachers and vocational subject teachers were examined. The suggested method provides higher precision, but it gives lower specificity.

Wang [26] presented 'A cultured man is not a tool': the influence of Confucian legacies on the standing of vocational teaching in China. The presented method delves into the historical and philosophical origins of the academic/vocational divide in China. It examines how confucian values and the imperial examination system contributed to the establishment of a hierarchy between intellectual and manual labour. By utilising institutional logics theory, the suggested approach examines the lingering effects of this legacy on the perception of occupations as well as vocational education in modern Chinese culture. The suggested method provides higher specificity, but it gives lower accuracy.

3. Proposed Methodology

In this research work, CVSE-ADRGAN-GOA is proposed. Chinese vocational skills education refers to the system of education in China that focuses on providing practical skills and training to students, preparing them for specific occupations or trades. It is designed to equip students with the necessary knowledge, technical expertise, and hands-on experience required to enter the workforce and pursue careers in various industries. The block diagram of CVSE-ADRGAN-GOA is represented in Fig. 1. The detailed description of proposed CVSE-ADRGAN-GOA method is expressed below.

3.1 Input Data Acquisition

The data acquisition phase includes the acquisition of input data from the Chinese vocational skills education real time data. This data encompasses administrative records, survey responses, observational insights, and performance metrics, providing a holistic perspective on the quality of vocational skills education in China. The data acquisition process involves data extraction from existing databases, survey administration, field observations, and data aggregation. Rigorous data quality assurance measures ensure the accuracy, completeness, and consistency of the collected information, laying a solid foundation for the subsequent stages of analysis and modelling. In China, education and training for jobs are available at four distinct levels: lower secondary schools, upper secondary vocational schools, tertiary education, and adult education and on-the-job training. The categorisation of Chinese vocational schools into public and private institutions based on their funding sources is as follows. As of 2009, there were a total of 1,181 vocational institutions, with approximately 23 percent (272 schools) being private colleges. The remaining 77 percent were state colleges, divided into 635 public institutions owned by central or local governments, 84 public institutions affiliated with state-owned enterprises, 173 public institutions associated with industry associations, and 17 public institutions belonging to other public agencies. Then, the acquired data are preprocessed using the filtering approach.

3.2 Data Preprocessing

The preprocessing step is crucial in minimising the impact of noise, ensuring that the vocational skills education data is more accurate and trustworthy. The effectiveness of this colour Wiener filtering method [27] plays a vital role in refining the input data and improving its suitability for analysis, contributing to the overall robustness of the CVSE-ADRGAN-GOA method in assessing the vocational skills education quality in China. This involves a series of steps to ensure that the subsequent analysis and modelling are built on clean and reliable information. The colour

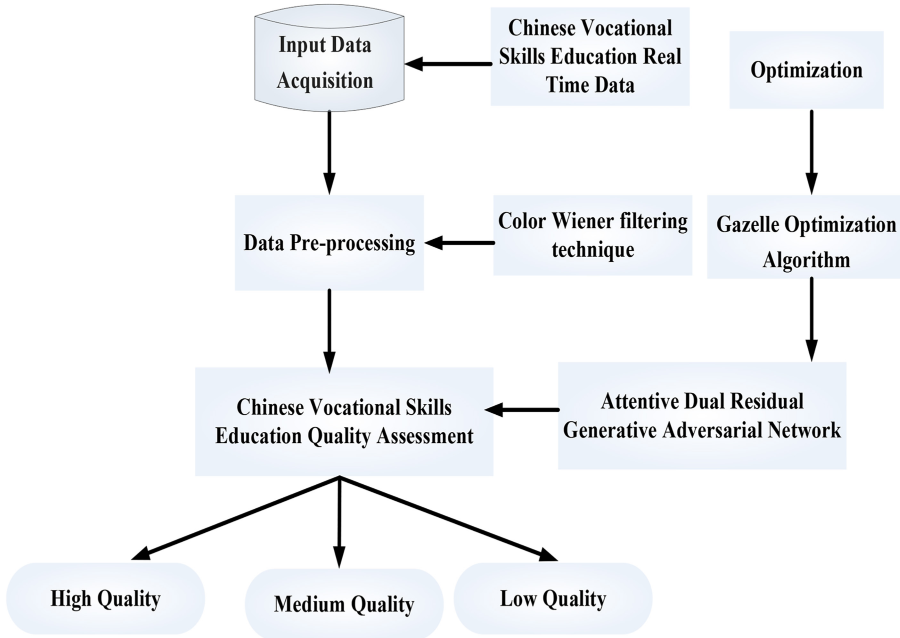

Figure 1. Block diagram of proposed CVSE-ADRGAN-GOA approach.

Wiener filtering process typically includes the estimation of power spectral densities of the true signal and noise. This information is then utilised to calculate the Wiener filter coefficients, which are applied to the input data in the frequency domain. By doing so, the method effectively suppresses noise and inconsistencies, contributing to the normalisation of the data. The inverse Fourier transform is subsequently applied to bring the filtered data back to the time domain. The colour Wiener filter for preprocessing considering normalisation of the data can be represented using (1)

$$G(f) = \frac{Z(f)\,H^*(f)}{|H(f)|^2 + \frac{1}{\mathrm{SNR}(f)}} \tag{1}$$

where $G(f)$ implies frequency response of colour Wiener filter, $Z(f)$ represents the normalised data, $H(f)$ is the frequency response of the system (including any distortions or noise), $*$ denotes the complex conjugate, $\mathrm{SNR}(f)$ is the signal-to-noise ratio at frequency f. Subsequently, the normalised data is calculated using the discrete Fourier transform $\hat{Z}(f)$ is expressed in (2)

$$\hat{Z}(f) = I \circ Z(f) \tag{2}$$

here '$\circ$' represents the element-wise multiplication operation, I means the transfer function of the colour Wiener filter, $Z(f)$ represents the normalised data. The normalised value is acquired using the (3)

$$Z(f) = (O - M)/\mu \tag{3}$$

here O means the original value of the data to normalise; M represents the mean, μ expresses the standard deviation. Then, transform the filtered data back to the time domain using the inverse Fourier transform F^{-1}. Thus, preprocessed data is obtained using (4)

$$z(t) = F^{-1}[Z(f)] \tag{4}$$

here $z(t)$ is the final preprocessed data. Thus, each data point in dataset is scaled up so that it has mean 0 and a standard deviation 1. After completing the preprocessing process, the preprocessed data goes to the neural network for the quality assessment of Chinese vocational skills education.

3.3 Quality Assessment of Chinese Vocational Skills Education Using Attentive Dual Residual Generative Adversarial Network

The Chinese vocational skills education quality assessment is obtained using the proposed deep leaning approach called ADRGAN [28]. The presented method focuses on assessing the quality of Chinese vocational skills education through the implementation of an innovative technique known as ADRGAN. The ADRGAN is a powerful deep learning method that has two neural networks, they are generator and discriminator, which work in tandem to make realistic with high-quality data. In ADRGAN model, the generator generates synthetic data that resembles the real data distribution. It takes preprocessed data as input and transforms it into simulated vocational skill learning scenarios. The generator architecture includes an attention mechanism that focuses on relevant features in the input preprocessed data, improving the superiority and realism of the generated synthetic data. The discriminator is another neural network that aims to distinguish between real and synthetic data. It takes both real and synthetic data as input and outputs a probability indicating whether the input data is real or synthetic. The discriminator architecture includes dual residual blocks that enhance its discriminative power and enable it to effectively identify synthetic data that closely resembles real data. The training process of ADRGAN involves an adversarial game between the generator and the discriminator. While the discriminator attempts to correctly categorise real and synthetic data, the generator aims to create synthetic data that is undifferentiated from the real data. This adversarial relationship drives the improvement of both networks, leading to the creation of high-quality synthetic data for vocational skills education assessment.

In this context, the GAN is specifically designed to evaluate the effectiveness and performance of vocational skills education in China. By leveraging the power of GAN, the model can generate synthetic data that simulates the superiority of vocational education in various scenarios. The "Attentive" aspect of the model implies that it incorporates an attention mechanism, enabling it to focus on crucial features and regions in the data during the assessment process, thereby enhancing the accuracy of the evaluation. The proposed ADRGAN adversarial loss function $C(G, D)$ captures the adversarial training procedure between the generator and discriminator modules of the network is specified in (5),

$$C(G, D) = E[\log(D(R))] + E[\log(1 - D(G(I)))] \quad (5)$$

here G means the generator and D refers the discriminator, E represents the expectation of the log-probability that the discriminator assigns to real data, I means the generator input, R means the preprocessed data given to ADRGAN. The aim of generator is to generate quality assessment of Chinese vocational skills education to deceive the discriminator, while the discriminator finds the difference between generated data and real data. The generator function is expressed in (6)

$$gen = \arg \min_{\text{gen}} \max_{\text{dis}} \mathrm{C}(G, D) \quad (6)$$

Then, the discriminator function is expressed in (7)

$$dis = \arg \max_{\text{dis}} \mathrm{C}(D, G) \quad (7)$$

here G stands for the generator and D stands for discriminator. The generator is aided *via* loss values, performs the local details, and makes use of the global features to validate that the created data is not deformed in addition to creating quality assessment of Chinese vocational skills education to deceive the discriminator. The loss value is derived using (8)

$$L_{\text{total}} = \frac{1}{2} * L_M + \frac{1}{2} * L_O \quad (8)$$

here L_{total} indicates the total loss value, L_M means the loss value of quality assessment, and $L_O$denotes loss value of entire preprocessed data. The loss value of vocational education quality assessment is derived using (9)

$$\begin{aligned} L_{\text{CO}} = {} & E[-0.5 * \text{quality}(G(I), R) - 0.5 * \text{quality} \\ & (G(I) \circ M, R \circ M)] \end{aligned} \quad (9)$$

here $\circ$ means the element wise multiplication, gen stands for the generator network, M means matrix related to data in quality assessment, loss$_{\text{CO}}$ quality assessment loss, R represents the available resources. The loss function during the quality assessment is represented in (10)

$$L_F(x, x') = \sum_{j=0}^{n} \left| x^{(j)} - x'^{(j)} \right| \quad (10)$$

here $x^{(j)}$ means each value on the available tasks, and $x'^{(j)}$ indicates that on the allocated tasks. Then, L_F loss functioning in proposed ADRGAN generator is represented in (11),

$$\begin{aligned} L_{L_F}(G) = {} & E[0.5^* \|R - G(I)\|_1 \\ & +0.5^* \|R \circ M - G(I) \circ M\|_1] \end{aligned} \quad (11)$$

here $\|.\|$ means L_F norm, R represents the preprocessed data and M represents matrix related to data in quality assessment. Since the objective function of the generative adversarial network is combined to other losses and the prediction outcomes are scaled, thus improves the operating presentation. The final generator loss function based on fusion strategy is given in (12)

$$G = \arg \min_{\text{gen}} \max_{\text{dis}} \mathrm{C}(G, D) + (s_1 \cdot L_{L_F} + s_2 \cdot L_{\text{CO}}) \quad (12)$$

here s_1 is set to 0.75, s_2 is set to 1.5. While doing quality assessment of Chinese vocational skills education, the generator recognises lower frequency loss together with loss of perception, then the retrieval effect of higher frequency pseudo flaws not optimal. To differentiate the authenticity of quality assessment discriminator makes the training of entire ADRGAN steady with quick convergence speed is expressed in (13)

$$x_j = \left\{ \begin{array}{cc} y_j & j = 1 \\ K_j(y_j) & j = 2 \\ K_j(y_j + x_{j-1}) 2 < j \leq s \end{array} \right\} \quad (13)$$

here x_j denotes output of $K_j(.)$ for quality assessment. The receptive fields of each network layer are gradually raised by this discriminator using multi-scale characteristics at granular level. Input feature map is separated as four blocks after the convolution and each part is denoted asy_j, $j \in \{1, 2, 3, 4\}$, with the format of Convolution-Batch Norm-Relu as related components specified by $K_j(.)$. Thus, the quality assessment decisions are obtained effectively using the proposed ADRGAN deep leaning approach for Chinese vocational skills education. Then, the proposed method uses the optimisation algorithm for optimal quality assessment Chinese vocational skills education. The integration of an attention mechanism in the proposed model points towards the capability of focusing on relevant parts of the input data, which can be particularly useful for analysing complex educational data, such as student performance, skill development, and teaching effectiveness. The interpretable assessment of proposed CVSE-ADRGAN-GOA method could offer insights into the factors that contribute most to vocational skills education quality which classifies the Chinese vocational skills education as high quality, medium quality, and low quality. This could be helpful for educators and policymakers in making data-driven decisions. Then, the ADRGAN does not disclose any acceptance of optimisation methods for calculating the ideal parameters for confirming exact quality assessment. Hence, the proposed ADRGAN neural network is optimised using the optimisation algorithm.

3.4 Optimization of Attentive Dual Residual Generative Adversarial Network Using Proposed Gazelle Optimisation Algorithm

Gazelle optimisation algorithm (GOA) [29] is a novel and effective optimisation technique employed to optimise the parameters of ADRGAN model for examining the quality of vocational skills education in China. Inspired by the social foraging behaviour of gazelles, the GOA algorithm mimics the natural exploration and exploitation strategies of gazelles, enabling it to efficiently navigate the search space of ADRGAN parameters and identify the optimal configuration that maximises synthetic data quality. By iteratively updating the position of each gazelle based on its own experiences, the position of the leader (the gazelle with the best fitness value), and the sensory awareness of food sources (regions of high synthetic data quality), the GOA algorithm effectively guides the search towards high-quality parameter configurations, leading to the creation of synthetic data that resembles the real data distribution closely and offers valuable insights into the assessment of vocational skills education in China. The GOA imitates the grazing and running from predators characteristics of the gazelle. The flowchart of GOA is specified in Fig. 2. The stepwise process is deliberated below.

Step 1: Initialisation

The populace of gazelle is determined by (14),

$$Z = \begin{bmatrix} z_{1,1} & z_{1,2} & \cdots & z_{1,g} \\ z_{2,1} & z_{2,2} & \cdots & z_{2,g} \\ \vdots & \vdots & \vdots & \vdots \\ z_{n,1} & z_{n,2} & \cdots & z_{n,g} \end{bmatrix} \tag{14}$$

here Z specifies set of current candidate populace of gazelle.

Step 2: Random generation

Afterward the initialisation process, the input weight parameters are created at random through GOA method.

Step 3: Fitness function

It generates random solution from the initialised values. This is computed by (15),

$$Fitness\ Function = optimize\ \left[x^{(j)}\right] \tag{15}$$

Step 4: Foraging strategy for exploitation

The exploitation phase concentrates that the gazelles are pasturing calmly without the presence of carnivore or the carnivore is going after gazelles. The efficiently neighbourhood regions are covered by the Brownian motion indicated through uniform and managed phases. It is considered that the gazelles move with Brownian motion.

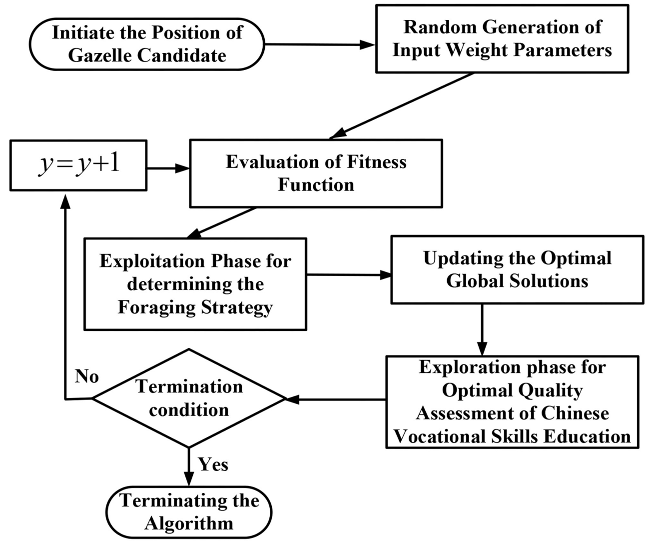

Figure 2. Flowchart of GOA for optimising attentive dual residual generative adversarial network.

It is expressed at (16),

$$h_{\text{bro}}(z,\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(y-\mu)^2}{2\sigma^2}\right) \tag{16}$$

here z expresses the point using Gaussian probability distribution function of zero mean μ and unit variance σ.The exploitation phase can be mathematically depicted using the (17)

$$\vec{C}_{m+1} = \vec{C}_m + t.\vec{U} * .\vec{U}_B * .\left(E_m - \vec{\vec{U}}_B * .\vec{C}_m\right) \tag{17}$$

here $\vec{C}_{m+1}$ represents the next iteration's solution, $\vec{C}_m$ expresses the current iteration's solution, t means gazelles grazing speed, $\vec{U}_B$ random number vectors of the Brownian motion, $\vec{U}$ uniform random numbers vector in [0,1].

Step 5: Exploration phase for optimising $x^{(j)}$

Exploration phase is used to improve the searching ability in optimisation problem. When the gazelle spotted the predator the gazelle runs, and predator chases it. Two runs are denoted through sudden direction change, this can be denoted as ϕ. The character of gazelle when it spots predator is mathematically expressed (18)

$$\vec{C}_{m+1} = \vec{C}_m + T.\mu\vec{U} * .\vec{U}_L * .\left(E_m - \vec{\vec{U}}_L * .\vec{C}_m\right) \tag{18}$$

here $\vec{U}_L$ represents random numbers vector depended on Levy distributions, T represents the top speed of the gazelle. Levy distribution $L(z_j)$ is denoted in (19)

$$L(z_j) = |z_j|^{1-\beta} \tag{19}$$

where z_j denotes the flight length and $1 < \beta \leq 2$ represent the power-law exponent. The character of the predator chasing the gazelle is mathematically expressed (20)

$$\vec{C}_{m+1} = \vec{C}_m + T.\mu\text{d} * .\vec{U}_B * .\left(E_m - \vec{\vec{U}}_L * .\vec{C}_m\right) \quad (20)$$

Here d means the variable that controls the predator's movement. The predator success rates that affects the escaping ability of the gazelle thus being trapped in a local minimum is avoided by the GOA algorithm. The predator success rate is mathematically expressed (21)

$$\vec{C}_{m+1} = \begin{cases} \vec{C}_m + d\left[\vec{l} + U * .\vec{(u-l)}\right] * .\vec{V} & if\ s \leq psr \\ \vec{C}_m + [\text{psr}(1-s)+s]\left(\vec{C}_{s1} - \vec{C}_{s2}\right) & \text{else} \end{cases} \quad (21)$$

here $\vec{V}$ means a binary vector formed by developing a random number s in $[0, 1]$. s_1 and s_2 are the gazelle matrix's random indexes; $\vec{C}_{s1}$ represents the gazelle's position for s_1; $\vec{C}_{s_2}$ represents the gazelle's position for s_2.

Step 6: Termination

The factor $x^{(j)}$ optimises through gazelle optimising approach; Step 3 will repeat until satisfy the halting criteria $y = y + 1$. ADRGAN is optimised with GOA for quality assessment of Chinese vocational skills education with better accuracy. Thus, the proposed CVSE-ADRGAN-GOA method effectively assesses the quality of Chinese vocational skills education.

4. Result and Discussions

The simulation results of proposed CVSE-ADRGAN-GOA are discussed. The proposed technique is implemented in MATLAB. The model was implemented in Intel® Core TM i3 processor, Microsoft's Windows 10 operating scheme and RAM of 4.00 GB. The performance metrics is estimated. The efficiency of the proposed technique is analysed to the existing CVSE-LRPM [19], CVSE-BPNN [20], and CVSE-SVM [**??**] methods.

- True positive(TP): assessment correctly detects a positive outcome related to vocational skills education.
- True negative(TN): assessment accurately recognizes the absence of a positive outcome related to vocational skills education.
- False positive(FP): assessment wrongly detects a positive or successful outcome related to vocational skills education when it is not actually present
- False negative(FN): the assessment wrongly detects a positive or successful outcome related to vocational skills education when it is not actually present

4.1 Precision

It measures the predictive capability of the samples by evaluating their predictive value, which can be either positive or negative depending on the class for which it is computed, and is expressed in (22),

$$\text{precision} = \frac{\text{TP}}{TP + FN} \quad (22)$$

4.1.1 Accuracy

The ratio of the number of samples correctly classified per scheme to the total number of samples is used to calculate the accuracy value that is exhibited in (23),

$$\text{accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \quad (23)$$

4.1.2 F-Score

A composite metric known as the F-score favors methods with higher sensitivity and presents challenges to methods with more specificity expressed in (24),

$$F - \text{score} = \frac{\text{TP}}{TN + \frac{1}{2}[FN + FP]} \quad (24)$$

4.1.3 Sensitivity

Sensitivity approximates the probability that the positive (negative) sample is true to assess the effectiveness of the method on a single class and is depicted in (25),

$$\text{sensitivity} = \frac{\text{TP}}{TP + FN} \quad (25)$$

4.1.4 Specificity

By estimating the probability that the positive sample is real, it assesses the effectiveness of the strategy on a single class, and is specified in (26),

$$\text{specificity} = \frac{\text{TN}}{FP + TN} \quad (26)$$

4.1.5 AUC

This is computed through (27),

$$AUC = 0.5 \times \left(\frac{\text{TP}}{TP + FN} + \frac{\text{TN}}{TN + FP}\right) \quad (27)$$

4.2 Simulation Result

The simulation outcomes of CVSE-ADRGAN-GOA are shown in Figs. 3–10. The performance is analysed to the existing CVSE-LRPM, CVSE-BPNN, and CVSE-SVM models.

Figure 3 displays accuracy analysis. Accuracy analysis is vital assessing the reliability and effectiveness of the model in evaluating the quality of vocational skills education in China. It assesses the proportion of correctly classified schools among all the schools in the dataset. The analysis aims to determine the model's ability to distinguish between different quality categories, such as high quality, medium quality, and low quality. The proposed CVSE-ADRGAN-GOA method provides 29.32%, 28.53%, 27.65% higher accuracy for high quality, 28.82%, 29.43%, 27.35% higher accuracy for medium quality, 29.75%, 28.58%, 27.94% higher accuracy for low quality when comparing to the existing CVSE-LRPM, CVSE-BPNN, and CVSE-SVM methods, respectively.

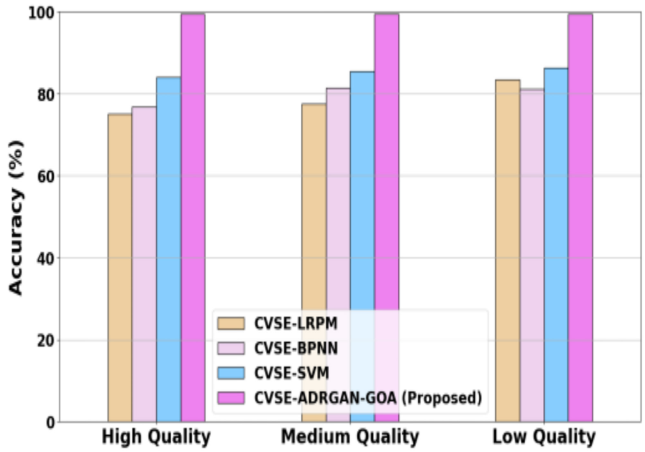

Figure 3. Performance of accuracy analysis.

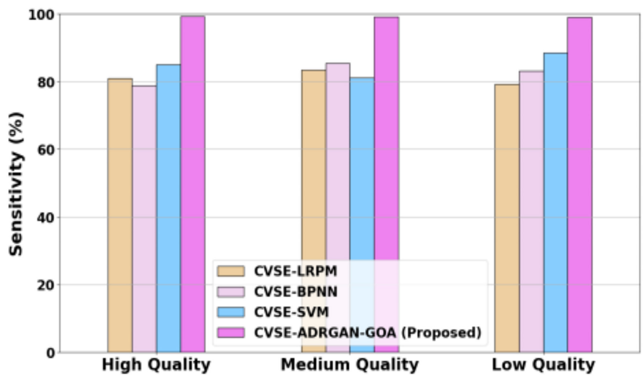

Figure 4. Performance of sensitivity analysis.

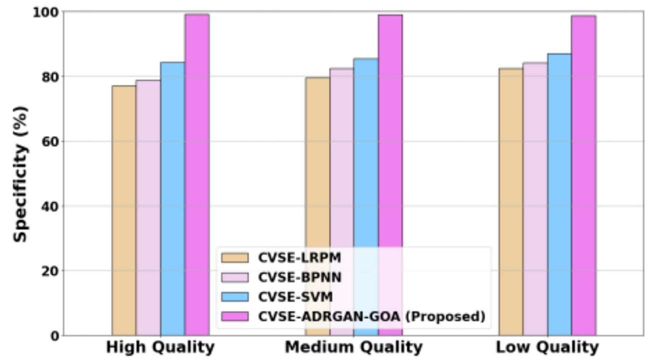

Figure 5. Performance of specificity analysis.

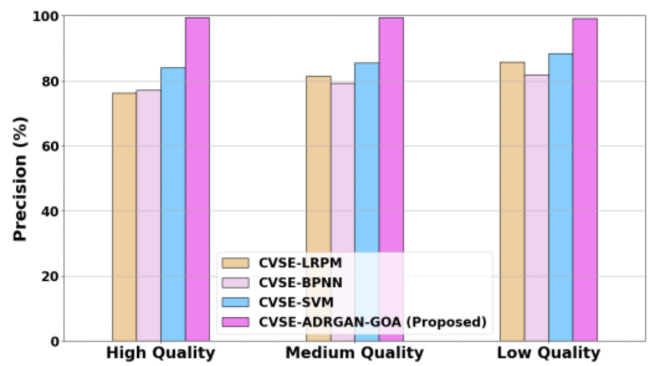

Figure 6. Performance of precision analysis.

Figure 4 displays performance of sensitivity analysis. It aims to understand how sensitive the assessment model is to changes in key factors. This information can help in refining the model, improving its robustness, and gaining insights into the relative importance of different factors in evaluating vocational skills education quality in China. The proposed CVSE-ADRGAN-GOA method provides 29.67%, 28.87%, 27.83% higher sensitivity for high quality, 29.78%, 28.32%, 27.59% higher sensitivity for medium quality, 29.87%, 28.97%, 27.13% higher sensitivity for low quality when comparing to the existing CVSE-LRPM, CVSE-BPNN, and CVSE-SVM methods, respectively.

Figure 5 displays performance of specificity analysis. Specificity analysis in Chinese vocational skills education quality assessment assesses the model's ability to accurately identify schools that truly belong to a specific quality category. This analysis helps understand the model's capability to correctly detect schools with specific qualities, reducing false positives. A high specificity score indicates the model's effectiveness in correctly identifying schools with the desired quality level. The proposed CVSE-ADRGAN-GOA method provides 28.23%, 27.88%, 26.65% higher specificity for high quality, 28.23%, 27.88%, 26.65% higher specificity for medium quality, 28.55%, 27.52%, 26.19% higher specificity for low quality when comparing to the existing CVSE-LRPM, CVSE-BPNN, and CVSE-SVM methods, respectively.

Figure 6 displays performance of precision analysis. Precision analysis in Chinese vocational skills education quality assessment evaluates the model's ability to provide accurate positive predictions. This analysis helps understand the model's precision in correctly identifying schools with the desired quality, reducing false positives and improving the reliability of positive predictions. A high precision score indicates that the model is providing more accurate and trustworthy assessments. The proposed CVSE-ADRGAN-GOA method provides 28.53%, 27.28%, 26.35% higher precision for high quality, 28.93%, 27.11%, 26.15% higher precision for medium quality, 28.28%, 27.32%, 26.49% higher precision for low quality when comparing to the existing CVSE-LRPM, CVSE-BPNN, and CVSE-SVM methods, respectively.

Figure 7 displays performance of F1-score analysis. Analysing the F1-score in Chinese vocational skills education quality assessment can provide valuable insights into the efficacy of the assessment process and the overall quality of vocational skills education. The proposed CVSE-ADRGAN-GOA method provides 27.43%, 26.88%, 27.25% higher F1-score for high quality, 28.93%, 27.11%, 26.15% higher F1-score for medium quality, 28.28%, 27.32%, 26.49% higher F1-score for low quality when comparing to the existing CVSE-LRPM, CVSE-BPNN, and CVSE-SVM methods, respectively.

Figure 8 displays performance of error rate analysis. Analysing the error rate in Chinese vocational skills

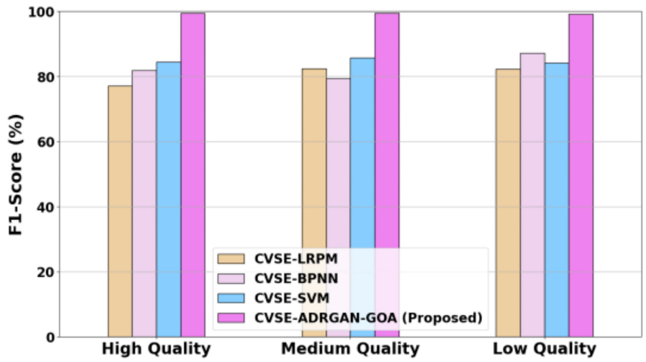

Figure 7. Performance analysis of F1-score.

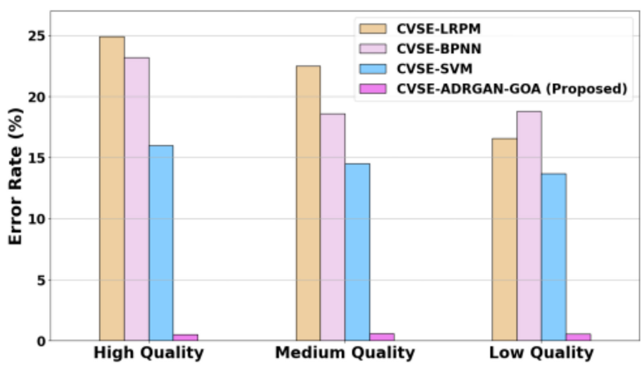

Figure 8. Performance analysis of error rate.

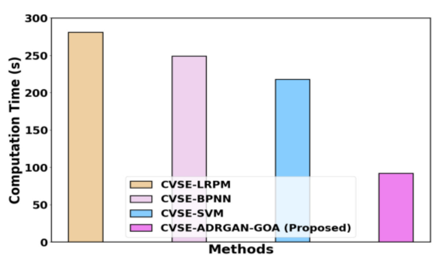

Figure 9. Performance analysis of computation time.

education quality assessment can provide insights into the overall accuracy and assessment process. The error rate scales the proportion of incorrect predictions produced by the assessment system. The proposed CVSE-ADRGAN-GOA method provides 57.13%, 56.78%, 47.25% lower error rate for high quality, 58.92%, 57.19%, 46.15% lower error rate for medium quality, 68.28%, 57.32%, 46.49% lower error rate for low quality when comparing to the existing CVSE-LRPM, CVSE-BPNN, and CVSE-SVM methods, respectively.

Figure 9 displays performance of computation time analysis. Computation time analysis in Chinese vocational skills education quality assessment focuses on understanding the time it takes to process and analyse the assessment data. This analysis is essential to evaluate the efficiency and scalability of the assessment system, particularly when dealing with a large number of students

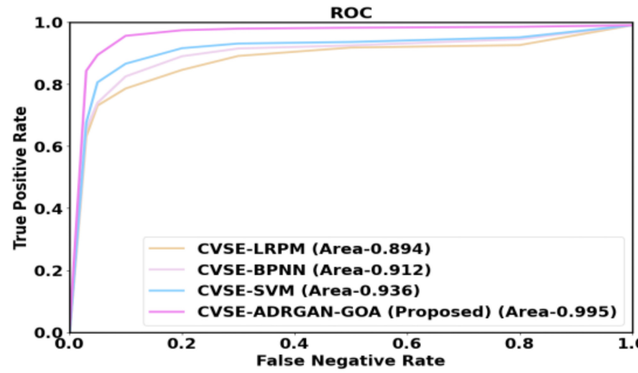

Figure 10. Performance analysis of ROC.

or complex evaluation algorithms. The proposed CVSE-ADRGAN-GOA method provides 37.93%, 39.78%, 35.65% lower computation time when comparing to the existing CVSE-LRPM, CVSE-BPNN, and CVSE-SVM methods, respectively.

Figure 10 displays performance of receiver operating characteristic (ROC) analysis. It evaluate the performance of classification models or algorithms in predicting the quality of vocational skills education. It is commonly used in binary or multi-class classification tasks, where the assessment data is categorised into different classes. The proposed CVSE-ADRGAN-GOA method provides 27.13%, 26.78%, 27.25% higher AUC value when comparing to the existing CVSE-LRPM, CVSE-BPNN, and CVSE-SVM methods, respectively.

Overall, the proposed CVSE-ADRGAN-GOA method lies in the innovative integration of multiple advanced techniques and tackles the challenging problem of vocational skills education quality assessment. This approach have significant implications for improving vocational education, identifying areas for enhancement, and facilitating better alignment between skills development and industry requirements in China.

5. Conclusion

The proposed CVSE-ADRGAN-GOA is implemented successfully. The proposed CVSE-ADRGAN-GOA method is activated in MATLAB. This research integrates ADRGAN neural networks to assess teaching quality, capitalising on their non-linear learning capacity with error tolerance. The proposed method introduces assessment scheme tailored for evaluating vocational teaching superiority, demonstrating how data collection and evaluation findings are effectively implemented. This assessment mode, leveraging neural networks, fully exploits their advantages, paving the way for a novel approach to measure vocational education quality. The performance of proposed method attains 27.13%, 26.78%, 27.25% higher AUC value, 37.93%, 39.78%, 35.65% lesser computation time analysed to the existing CVSE-LRPM, CVSE-BPNN, and CVSE-SVM methods, respectively.

References

[1] Y. Zhou and H. Zhou, Research on the quality evaluation of innovation and entrepreneurship education of college students based on extenics, *Procedia Computer Science*, *199*, 2022, 605–612.

[2] B. Jiang, Research on the application of Chinese traditional culture teaching in higher vocational education, *Educational Sciences: Theory and Practice*, *22*(2), 2022, 1–14.

[3] J. Zhang, H. Yin, andT. Wang, Exploring the effects of professional learning communities on teacher's self-efficacy and job satisfaction in Shanghai, China, *Educational Studies, 49*(1), 2023, 17–34.

[4] L. Darling-Hammond, Defining teaching quality around the world, *European Journal of Teacher Education, 44*(3), 2021, 295–308.

[5] Q. Haiyan and W. Allan, Creating conditions for professional learning communities (PLCs) in schools in China: The role of school principals, *Professional Development in Education*, *47*(4), 2021, 586–598.

[6] X. Zhang, W. Admiraal, and N. Saab, Teachers' motivation to participate in continuous professional development: Relationship with factors at the personal and school level, *Journal of Education for Teaching, 47*(5), 2021, 714–731.

[7] X. Zheng, H. Yin, and Y. Liu, Are professional learning communities beneficial for teachers? A multilevel analysis of teacher self-efficacy and commitment in China, *School Effectiveness and School Improvement*, *32*(2), 2021, 197–217.

[8] X. Eryong and J. Li, What is the ultimate education task in China? Exploring "strengthen moral education for cultivating people"("Li De ShuRen"), *Educational Philosophy and Theory*, *53*(2), 2021, 128–139.

[9] L.M. Thien, S. Liu, L.Q. Yee, and D. Adams, Investigating a multiple mediated-effects model of instructional leadership and teacher professional learning in the Malaysian school context: A partial least squares analysis, *Educational Management Administration and Leadership*, *51*(4), 2023, 809–830.

[10] L. Bao and P. Yu, Evaluation method of online and offline hybrid teaching quality of physical education based on mobile edge computing, *Mobile Networks and Applications*, *26*(5), 2021, 2188–2198.

[11] S. Xu, J. Ren, F. Li, L. Wang, and S. Wang, School bullying among vocational school students in China: Prevalence and associations with personal, relational, and school factors, *Journal of Interpersonal Violence*, *37*(1–2), 2022, NP104–NP124.

[12] S.M. Talebizadeh, R. Hosseingholizadeh, and M.Ş. Bellibaş, Analyzing the relationship between principals' learning-centered leadership and teacher professional learning: The mediation role of trust and knowledge sharing behavior, *Studies in Educational Evaluation, 68*, 2021, 100970.

[13] M. Pilz and K. Wiemann, Does dual training make the world go round? Training models in German companies in China, India and Mexico, *Vocations and Learning, 14*(1), 2021, 95–114.

[14] A.O. Kingsley, U.G. Inyang, O. Msugh, F.T. Mughal, and A. Usoro, Recognizing facial emotions for educational learning settings, *IAES International Journal of Robotics and Automation, 11*(1), 2022, 21.

[15] K.H. Erian, P.H. Regalado, and J.M. Conrad, Missing data handling for machine learning models, *IJRA,* 2021, 123–132.

[16] K.E. Manjunath, Y.S. Honnavar, R. Pritmani, and K. Sethuraman, Detection of duplicate and non-face images in the eRecruitment applications using machine learning techniques, *IAES International Journal of Robotics and Automation, 10*(2), 2021,114.

[17] K.L., Flores-Rodriguez, F. Trujillo-Romero, and J.J. Gonzalez-Barbosa, Active object search using a pyramid approach to determine the next-best-view, *IAES International Journal of Robotics and Automation, 11*(1), 2022, 70.

[18] M. Leung, R. Ortiz, and B.W. Jo, Semi-automated mid-turbinate swab sampling using a six degrees of freedom collaborative robot and cameras, *IAES International Journal of Robotics and Automation (IJRA), 12*(3), 2023, 240.

[19] Y. Wu, Innovation path of secretarial education in higher vocational schools based on internet environment and machine learning, *Soft Computing*, 2023, 1–11.

[20] Z. Ni and F. Wang, Quality assessment of vocational education teaching reform based on deep learning, *Computational and mathematical methods in medicine*, *(2022)*. 2022.

[21] Y. Zhou, Teaching reform of undergraduate courses in colleges and universities based on machine learning and improved SVM algorithm, *Security and Communication Networks*, *(2022)*. 2022.

[22] H. Zhang, W. Dai, and J. He, An analysis of the differences in information-based teaching to improve the learning achievements of Chinese higher vocational college students, *Asia Pacific Education.* 2023, 1–13.

[23] L. Huang, W. Zhang, H. Jiang, and J.L. Wang, The teaching quality evaluation of Chinese-Foreign cooperation in running schools from the perspective of education for sustainable development, *Sustainability*, *15*(3), 2023, 1975.

[24] W. Mei, and L. Symaco, University-wide entrepreneurship education in China's higher education institutions: Issues and challenges, *Studies in Higher Education*, *47*(1), 2022, 177–193.

[25] X. Jin, D. Tigelaar, A. Van der Want, and W. Admiraal, Novice teachers' appraisal of expert feedback in a teacher professional development programme in Chinese vocational education, *Teaching and Teacher Education, 112*, 2022, 103652.

[26] G. Wang, A cultured man is not a tool: The impact of confucian legacies on the standing of vocational education in China, *Journal of Vocational Education and Training*, 2022, 1–18.

[27] J. Xing, H. Yuan, C. Chen, and W. Gao, Wiener filter-based color attribute quality enhancement for geometry-based point cloud compression, *Proc. 2022 Asia-Pacific Signal and Information Processing Association Annual Summit and Conf. (APSIPA ASC),* Chiang Mai, 2022, 1208–1212.

[28] Q. Luo, H. He, K. Liu, C. Yang, O. Silven, and L. Liu, Rain-like layer removal from hot-rolled steel strip based on attentive dual residual generative adversarial network, *IEEE Transactions on Instrumentation and Measurement*, 2023.

[29] J.O. Agushaka, A.E. Ezugwu, and L. Abualigah, Gazelle optimization algorithm: A novel nature-inspired metaheuristic optimizer, *Neural Computing and Applications*, *35*(5), 2023, 4099–4131.

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