J. Electrical Systems 20-7s (2024): 3386-3399

Xiangyang Xing[1*]

The Knowledge System of Composite Talents Based on the Development of Virtual Digital People

Journal of Electrical Systems

Abstract: - The present research analyzes how digital technology might enhance the talent process, including talent identification, selection, and retention. Talent development is the systematic process of cultivating people's talents and abilities in order to maximize their potential. It entails offering specialized training, tools, and opportunities for advancement to help individuals flourish in their professions and develop their careers. In this study, The Knowledge System of Composite Talents Based on the Development of Virtual Digital People (KS-CT-DVDP-QSANN) is proposed. Initially, the data gathered from development talent upwork dataset. Collected data are pre-processed to include filtering, normalization and improve the successive stages of talent data using Regularized bias-aware ensemble Kalman filter (RBAEKF).In general, Quantum Self-Attention Neural Networks predict composite talents. Hence, proposed utilize Red panda optimization algorithm (RPOA)enhance Quantum Self-Attention Neural Networks (QSANN)accurately predict the composite talents. Then, the KS-CT-DVDP-QSANN is implemented to Python and the performance metrics such as, Recall, mean square error, Accuracy, precision, F1-score, and error rate. Finally, the performance of KS-CT-DVDP-QSANN method provides 19.87%, 24.57% and 34.15% high accuracy, 23.17%, 25.42% and 29.28% higher Precision and 23.63%, 28.37% and 27.23% higher recall while compared with existing Intelligent talent: How to identify, select, and retain talents from around the world using artificial intelligence (IR-IS-RTF-AI), An innovative talent training mechanism for maker education in colleges and universities based on the IPSO-BP-enabled technique (ITTE-IPSO-BPNN) and Adaptive talent journey: Optimization of talents' growth path within a company via Deep Q-Learning (TGPC-DQL) respectively.

Keywords: development talent upwork dataset, RegularizedBias-Aware Ensemble Kalman Filter, Quantum Self-Attention Neural Networks, Red Panda Optimization Algorithm.

I. INTRODUCTION

During a recession and fierce competition, it's crucial to innovate to attract and retain top talent from all over the world. It has, however, also profited socially, adding value to talent, talent detection, and hiring procedures by creating more equitable and transparent talent platforms and inclusive training opportunities for all workers, regardless of gender, religion, or other considerations [1-3]. Human resource management is thus changing to embrace digital technology and increase effectiveness in human capital development and retention. Although competition for exceptional candidates is heating up, the size of talent teams stays consistent. Recruiting and retaining qualified personnel is especially challenging in social businesses. Measuring ideas and values is far more challenging than measuring knowledge and abilities [4-6]. These businesses need to be financially independent, but they also need to draw in the right personnel to meet social objectives. Artificial intelligence devices must identify certain profiles in order to provide charitable services to society and attain self-sustainability [7-9]. These methods raise awareness among potential employees about social firms that prioritize sustainability and profitability. Working in these companies requires transparency, diligence and accountability. Recruiters often employ outdate systems from the 20th century, whereas their targets use newer programs and networks [10-12]. Recruiters face technological, organizational ,cultural and financial barriers that prohibit them from utilizing current tools [13]. In order to find work, job seekers are increasingly turning to social media and specialised applications. Workers and temporary workers have the option to request electronic payment, smartphone contract signature, and remote video interviews [14–16]. Recruiters find it difficult to invest in the internet areas where young talent is hyper connected and easily accessible. The difference in technology utilized by recruiters and candidates may contribute to the challenge of matching supply and demand [17]. Being able to handle a variety of technologies is often essential, making it one of the most valued qualities. The internet economy has transformed social businesses by digitizing mobilization and social conversation [18]. Organizations must increase their digital maturity across all sectors, including HR and talent. Digital technology enables reaching out to passive persons who may be interested in changing careers. Employers often hire top

[1] [1]*Art School of Wuhan Business University, Wuhan, Hubei, 430056，China*

[*]*Corresponding author e-mail: xxy202403@126.com*

talent before they graduate, integrate them into their teams, and offer them better conditions and a more appreciative environment [19]. Because the power dynamics have shifted, recruiters must reconsider their profession. It's crucial to explain to applicants what the company has to offer in terms of a professional life and why they should consider working there, rather than asking them what they can give the organisation [20]. Recruiters need to satisfy the needs of brilliant individuals and work to increase their level of satisfaction in order to keep them on board and avoid losing them to rival recruiters.

Intelligent talent uses artificial intelligence to streamline the process of identifying, selecting, and retaining outstanding talent from around the world. Using AI-powered algorithms, recruiters can sift through large pools of individuals, matching talents, experiences, and cultural fit with organizational objectives. Companies may make data-driven judgments by leveraging machine learning, predictive analytics and natural language processing, thereby enhancing applicant evaluation accuracy and minimizing prejudice. However, one big disadvantage is the possibility of perpetuating bias in the data used to train AI algorithms. If the data contains historical prejudices, such as gender or racial biases in previous hiring decisions, the AI system may unintentionally perpetuate these biases, causing diversity and inclusion issues in the workforce. As a result, ongoing monitoring, review, and refining of AI systems is critical for mitigating such risks and ensuring fair and equal talent processes.

Intelligent talent uses artificial intelligence (AI) to identify talent around the world by sifting through massive amounts of candidate data, resumes, and online profiles. AI-powered systems can precisely evaluate talents, experiences, and cultural fit, allowing firms to swiftly select the best applicants. Furthermore, AI-driven predictive analytics can project candidate performance and retention probability, assisting with strategic talent acquisition and retention decisions. Companies that use AI may not only streamline their talent procedures, but also attract and retain top personnel from a variety of backgrounds, eventually stimulating creativity and driving organizational success. Quantum self-attention neural networks apply quantum computing concepts to classical self-attention processes, promising faster processing and better performance in applications that require complicated pattern identification and analysis. This method tries to solve computing limitations in large-scale data processing and optimization tasks by leveraging quantum entanglement and superposition to handle exponentially increasing state spaces more efficiently.

Major contribution of this paper a follows;

- In this paper, The Knowledge System of Composite Talents Based on the Development of Virtual Digital People [KS-CT-DVDP-QSANN] is discussed.
- Initially, the collection of Udacity has two million members known as "Udacians." They can gather at "meetups" planned in hundreds of cities throughout the continent.
- During the pre-processing stage, Regularized bias-aware ensemble Kalman filter would be used to improve the successive stages of talent.
- The QSANN is used to predicting composite talents.
- The algorithm for Red panda optimization algorithm, which improves the performance of the QSANN efficacy, was significantly enhanced topredict the composite talents.

Remaining portion of this work structured follows: segment 2: literature survey, segment 3: describes proposed methodology, segment 4: illustrates results and discussion and segment 5: conclusion.

II. LITERATURE SURVEY

Among the frequent research work depends on predicting composite talents with the help of deep learning; some of the recent investigations were presented here

Allal-Chérif, et.al, [21] have presented intelligent recruitment: IR-IS-RTF-AI. It analyzes that digital technology might enhance the recruitment process, including talent identification, selection, and retention. Using chatbots to gamify the hiring process and job interviews, candidate identification on social media is the first step in the new and varied phenomena known as e-recruitment. Artificial intelligence is then used to match candidates with jobs. Social organizations can utilize these tools to recruit personnel with mission-aligned behaviors and values, not just those with technical skills. The methodology utilized grounded theory, participant observation, and qualitative data collecting. It provides high accuracy and it provides low recall.

Guarino, et.al, [22] have presented TGPC-DQL. Sectors are continuously looking to optimize their human resources and add new ones. Employees, also known as talents, must acquire new skills in order for the organization to remain competitive in the marketplace. The ability of employees to grow productively was an important aspect in a company's success. Offer Adaptive Talent Journey, a revolutionary strategy for maximizing talent development within a firm. The ultimate purpose of Adaptive Talent Journey was to keep talent within the firm. It uses the concept of a "digital twin" to define a digital representation of a talent, known as the Talent Digital Twin, which was based on skill level and personal characteristics. It provides high recall and it provides low accuracy.

Liu,et.al, [23] have presented ITTE-IPSO-BPNN. Based on studies on students' basic literacy and the fundamentals of maker education, a new system for instruction and learning was created to improve their educational experience. The back propagation (BP) neural network was enhanced with the addition of the improved particle swarm optimisation (IPSO) method to improve the speed and accuracy of assessing the innovative potential of college students. It provides high recall and it provides low precision

Arroyo-Bote, et.al, [24] have presented a digital process for creating 3D resin models tailored to the Aesthetic Dentistry course. A 3-shape intraoral scanner was used to obtain stereolithography (STL) files of a real patient. Modifications were made to dental prosthesis designs using Exocad, including incisor rotation, surface adjustments to mimic dysplasias or erosions, diastemas, and tooth size variations. The virtual model was produced in resin so that students could utilize it. After the practices, students and teachers assessed the effectiveness of the 3D printed models. It provides high precision and it provides low F1score.

Llanes-Jurado, et.al, [25] have presented developing conversational Virtual Humans for social emotion elicitation based on large language models. demonstrates a Virtual Human (VH) that is built on a Large Language Model and has a realistic-looking avatar and conversational capability. This architecture integrates speech synthesis, lip synchronisation, emotive facial expressions, and psychological notions like personality, mood, and attitudes. Our modular, cognitively-inspired system was tailored for real-time, voice-based, semi-guided emotional discussions.It provides high F1score and it provides high error rate.

Yang, et.al, [26] have presented assessing the Impact of Digital Technologies on Energy Efficiency: Virtual Agglomeration and its Function. divided the efficiency of energy use into two groups: single factor and overall energy use. To examine the effects of digital technology represented by industrial robots on energy efficiency and path mechanism, the standard error test was modified using the Driscol-Kraay technique and the two-way fixed-effect model. Studies show that despite decreasing energy intensity per unit of GDP, digital technology may significantly increase total factor energy efficiency. The finding holds up to a robustness test using fixed effect space Durbin models, time-varying difference in difference, and feasible generalised least squares. It provides high mean square error and it provides low error rate.

Wahyudi, et.al, [27] have presented “Developing Instruments for Digital Talent Competence Using Partial Least Square-Based Models”. The research initiative aims to close this gap by creating a reliable and valid digital talent measurement tool. It was used for calculation and quality assessment. The measuring methodology was evaluated from both reflective and formative perspectives, with responses from 600 participants gathered using Google Forms. The 60 questionnaire items had strong validity and reliability, as demonstrated by loading factors and composite reliability more than 0.70. Direct effects were found in a variety of competencies: adaptability and flexibility had a 0.744 effect on learning dexterity, achievement orientation had a 0.782 effect on innovative creation skills, customer service orientation had a 0.810 effect on digital networking, and digital communication skills had a 0.824 effect on continuous improvement. It provides low mean square error and it provides low precision.

III. PROPOSED METHODOLOGY

In this section, The Knowledge System of Composite Talents Based on the Development of Virtual Digital People (KS-CT-DVDP-QSANN) is deliberated. Block diagram of proposed KS-CT-DVDP-QSANN presented in Figure 1. The proposed methodology uses cutting-edge digital technology to transform the talent process. It starts with talent techniques that use social media to identify candidates and progresses to more innovative approaches like gamification and chatbot-enabled interviews. The key contribution is the creation of the Knowledge System of Composite Talents Based on the Development of Virtual Digital People (KS-CT-DVDP-QSANN), which uses Regularized bias-aware ensemble Kalman filtering for data preprocessing and QSANN for talent prediction. QSANN's accuracy is improved by using the Red Panda Optimization Algorithm (RPOA). The entire process is written in Python, and performance is measured using metrics such as mean square error, , precision, recall, F1-score, accuracy ,and error rate.

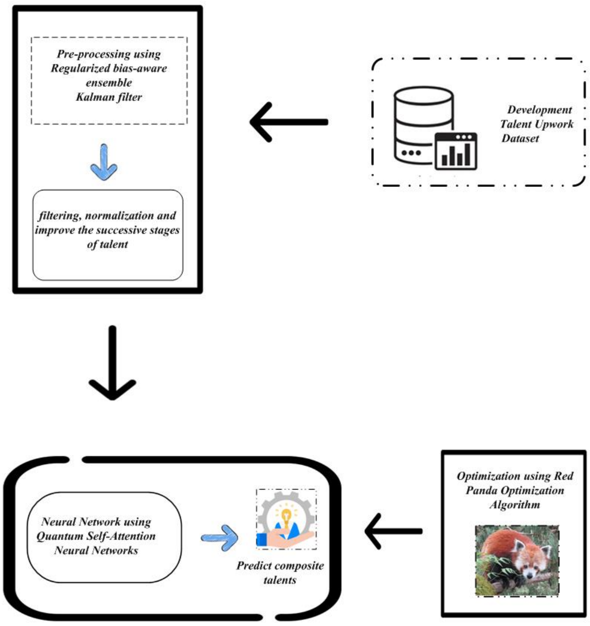

Figure 1: Block diagram proposed of KS-CT-DVDP-QSANN

A. Data Collection

Initially, the input image is collected from Development Talent Upwork dataset [28]. Data collection and analysis involves observing recruiters' use of various technologies, identifying factors that impact the talent process, identifying common themes and concerns, and reviewing academic literature. The collection of information includes participant observations as recruiters, a survey of scholarly literature, and an examination of talent specific publications and forums. Combining primary and secondary data improves reliability and enables for more precise and nuanced analysis. Data collection and analysis are done concurrently in each case inquiry, following the systematic technique of grounded theory.

B. Preprocessing using RegularizedBias-Aware Ensemble Kalman Filter

In this section, RBAEKF [29] using this to improve the successive stages of talent. A regularized bias-aware ensemble combined with a Kalman filter is a potent tool for data fusion and prediction. This hybrid methodology offers various advantages by combining the capabilities of ensemble learning, which uses several models to improve accuracy and resilience, and the Kalman filter's capacity to dynamically update predictions depending on incoming data. To begin, the regularized bias-aware ensemble reduces overfitting by penalizing complex models, assuring generalizability to previously unknown data. Second, the Kalman filter optimally estimates system states by recursively updating predictions with fresh measurements, which is especially useful in dynamic systems with noisy inputs. Furthermore, the bias-aware component corrects systematic flaws in ensemble models, improving overall performance and dependability. This data assimilation object seeks to minimize estimating uncertainty and distance to observables while reducing estimator bias. In math, can pose the problem by given equation (1).

$$\mathrm{N}(\psi_i) = \left\|\psi_i - \psi_i^e\right\|^2_{B^{e-1}_{\psi\psi}} + \left\|x_i - c_i\right\|^2_{B^{-1}_{aa}} + \gamma\left\|a_i\right\|^2_{B^{-1}_{aa}} \qquad (1)$$

Here, $\left\|x_i - c_i\right\|$ is represented the model captures the main physical mechanisms, $\left\|\psi_i - \psi_i^e\right\|$ is represent the semi-positive definite matrix weighted by the k_2 norm. $\mathrm{N}(\psi_i)$ is represented a set of model parameters that minimizes the model bias's norm.It additionally minimizes the estimator's bias, but also its distance from the observables. Mathematically, pose the problem by regularizing is given equation (2)

$$\frac{1}{2}\frac{c\mathrm{N}}{c\psi_i}\bigg|_{\psi_i^z} = B_{\psi\psi}^{e-1}\left(\psi_i^z - \psi_i^e\right) + \frac{c\,x_i}{c\psi_i}\bigg|_{\psi_i^z}^{\mathrm{T}} B_{cc}^{-1}\left(x_i^z - c_j\right) + \gamma\frac{c\,a_i}{c\psi_i}\bigg|_{\psi_i^z}^{\mathrm{T}} \tag{2}$$

Here, γ is represented the impacts the gradient on the left-hand side, $B_{\psi\psi}^{e-}$ is represent the evolution slowly with the bias norm. ψ_i^z is represent the minimizes the regularized bias- aware cost function. The analysis state must be sufficiently close to the prediction in order to linearize the analysis bias as supplied equation in order to be solved mathematically. (3)

$$a_i^z \approx a_i^e \mathrm{H}^e L\left(\psi_i^z - \psi_i^e\right) \tag{3}$$

Here, H^e is represent the jacobian; a_i^e is represent the forecast bias; ψ_i^z is represent the grouping the terms; L is represent the measurement operator. Adding the Woodbury matrix inversion formula is given equation (4)

$$\psi_i^z = \psi_i^e + J\left[\left(\mathrm{I} + \mathrm{H}^e\right)\left(c_i - x_i^e\right) - \gamma B_{cc} B_{aa}^{-1} \mathrm{H}^e a_i^f\right] \tag{4}$$

Here, J is represent the regularized Kalman gain matrix; a_i^f is represent the Instead of generating an ensemble of biases; ψ_i^z is represent the grouping the terms. Generate a qualitatively accurate model with a simulation time that matches the timescale of experimental measurements in given equation (5)

$$J = B_{\psi\psi}^e L^S \left[B_{cc} + \left(\mathrm{I} + \mathrm{H}^e\right) L_{\psi\psi}^e L^S \left(\mathrm{I} + \mathrm{H}^e\right)^S + \gamma B_{cc} B_{aa}^{-1} \mathrm{H}^e L B_{\psi\psi}^e L^S \mathrm{H}^{e^S} \right]^{-} \tag{5}$$

Here, B_{cc} is represent the covariance matrix; $B_{\psi\psi}^e$ is represent the error covariance matrix; B^{-1} is represent the precision matrices. Finally, the RBAEKF improves the successive stages of talent. Then, the pre-processed output is fed to QSANN for predict the talents.

C. Prediction using Quantum Self-Attention Neural Networks

In this section, QSANN [30]is discussed. QSANN is used for predicting the composite talents. Quantum self-attention neural networks use quantum computing principles with self-attention processes to provide unparalleled performance in processing complicated data structures, particularly in natural language processing and picture recognition. By using quantum systems' entanglement and superposition features, these networks may manage large-scale, high-dimensional data with less computational complexity than classical counterparts. Furthermore, their ability to capture complicated interactions between data items using self-attention mechanisms enables more subtle feature extraction and context understanding, resulting in improved model performance and generalization capabilities. As quantum computing capabilities evolve, QSANN hold enormous promise for pushing the boundaries of machine learning and AI research. The traditional self-attention method consists of three components:, values mkeys, and queries. Queries and keys are weighted and assigned to corresponding values to produce final results in given equation (6)

$$\left|\psi_r\right\rangle = T_{enc}\left(x_r^{(k-2)}\right) G^{\otimes m}\left|0^m\right\rangle \tag{6}$$

Here, $\left(x_r^{(k-2)}\right)$ is represent the classical input data; T_{enc} is represent the quantum ansatz; G is represent the Hadamard gate; $\left|\psi_r\right\rangle$ is represent the input state. Query quantum devices can include hundreds of physical qubits. Noise, both coherent and incoherent, hinders practical implementation of quantum algorithms. Query and key parts, respectively in given equation (7)

$$\left\langle A_p \right\rangle_R := \left\langle \psi_R \right| T_J^{\varepsilon}\left(\theta_p\right) \left|\psi_R\right\rangle \tag{7}$$

Here, $\left\langle A_p \right\rangle_R$ is a representation measurement output of the query part; $\left|\psi_r\right\rangle$ is represent the input state; T_J^{ε} is represent the unitary nature of quantum circuits They evaluate our model's performance through numerical text classification experiments with various data sources. A d-dimensional vector represents the value part's measurement outputs is given equation (8)

$$o_R := \left[\left\langle S_1 \right\rangle_R \;\left\langle S_2 \right\rangle_R \cdots \left\langle S_c \right\rangle_R\right]^{\mathrm{T}} \tag{8}$$

Here, o_R the sigmoid activation functions; $\lfloor \langle S_1 \rangle_R \ \langle S_2 \rangle_R \cdots \langle S_c \rangle_R \rfloor$ is represent the Pauli observable; c is represent the dimensional. As has been discussed, the inner-product self-attention model may not be appropriate for dealing with quantum data.

$$x_R^{(k)} = x_R^{(k-2)} + \sum \overline{\alpha}_{R,i} \cdot o_i \tag{9}$$

Here, $x_R^{(k)}$ is represent the small colored squares; Between the R-th and i-th input vectors, $\overline{\alpha}_{R,i}$ stands for the normalised quantum self-attention coefficient; o_i the sigmoid activation vector. $x_R^{(k-2)}$ is represent the classical inputs.

$$\alpha_{R,i} := d^{-\left(\langle A_p \rangle_R - \langle A_j \rangle_i\right)^2} \tag{10}$$

Here, $\alpha_{R,i}$ represent the quantum self-attention coefficients; $\langle A_j \rangle_i$ is represent the Quantum measurements on one-dimensional classical space. Finally QSANN is predicted the aid in reducing recruiting costs, time-to-hire and employee turnover is provided. In this work, Red panda optimization algorithm (RPOA) is assigned to enhance QSANN. RPOA assigned for tuning weight V^m *and* $t(s)$ parameterising.

D. Optimization of PHNN using Red Panda Optimization Algorithm

In this segment, RPOA [31] is described. The RPO improved the QSANN weight parameters o_R *and* T_{enc} in order to improve the suggested KS-CT-DVDP-QSANN technique's ability to predicting the composite talents. RPOA is efficient in finding optimal or near-optimal solutions to optimization issues. It effectively explores the search space by replicating red pandas' foraging behavior, allowing it to quickly narrow down to potential places. The algorithm's simplicity makes it straightforward to implement and comprehend. It does not require complex mathematical formulas or advanced parameter adjustment, which decreases the computational cost and makes it easier to apply in practice.The RPOA is a metaheuristic algorithm inspired by the behavior of red pandas, an endangered species that lives in the eastern Himalayas and southwestern China.

Step 1: Initialization Phase

Red pandas make up the population-based metaheuristic algorithm known as the RPOA technique. Each red panda in the RPOA design symbolises a possible fix for the issue, offering particular values for the issue variables based on where it is located in the search space.

$$Y = \begin{bmatrix} Y_1 \\ \vdots \\ Y_p \\ \vdots \\ Y_N \end{bmatrix}_{N\times m} = \begin{bmatrix} y_{1,1} & \cdots & y_{1,q} & \cdots & y_{1,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ y_{p,1} & \cdots & y_{p,q} & \cdots & y_{p,m} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ y_{N,1} & \cdots & y_{N,q} & \cdots & y_{N,m} \end{bmatrix}_{N\times m} \tag{11}$$

Where, Y denotes the population matrix of red pandas; Y_p denotes the p^{th} red pandas; $y_{p,q}$ denotes the q^{th} dimension; N denotes the number of red pandas and m denotes the number of problem variables.

Step 2: Random Generation

After initialization, weight parameters are formed randomly generated. Best fitness values are chosen based on a conditional explicit hyperparameter scenario.

Step 3: Fitness Function

First, a solution candidate matrix representing the starlings starting positional vectors is identified. This matrix is first assigned to random values inside a search space; the fitness function selecting the optimal features.

$$\text{Fitness function} = \mathrm{F} = \text{Optimizing}\left(o_R \ \textit{and} \ \mathrm{T}_{enc}\right) \tag{12}$$

Where, o_R increasing the accuracy, T_{enc} is represent decreasing the error.

Step 4: The Strategy of Red Panda in Foraging o_R

In the first process that RPOA; red pandas' position is modelled based on their natural foraging behavior. Red pandas have remarkable recognition and movement skills.. They use their superior scent, hearing, and eyesight abilities to locate food sources. In RPOA design, food resources for each red panda are determined by the location of other red pandas with higher objective function values.

$$T_i^{Q1} : r_{i,q}^{Q1} = r_{i,q} + m \cdot Z_t^{idf} (SFS_{i,q} - J \cdot r_{i,q} \times o_R) \qquad (13)$$

Where, R_i^{Q1} denotes the new position of the i^{th} red panda; $r_{i,q}^{Q1}$ denotes the q^{th} dimension; m denotes the random numbers; Z_t^{idf} denotes the updated feature at time t; $SFS_{i,q}$ denotes the q^{th} dimension; o_R the sigmoid activation functions ; J denotes a randomly selected number and $r_{i,q}$ denotes the q^{th} dimension. Figure 2 shows flow chart of RPOA for optimizing QSANN,

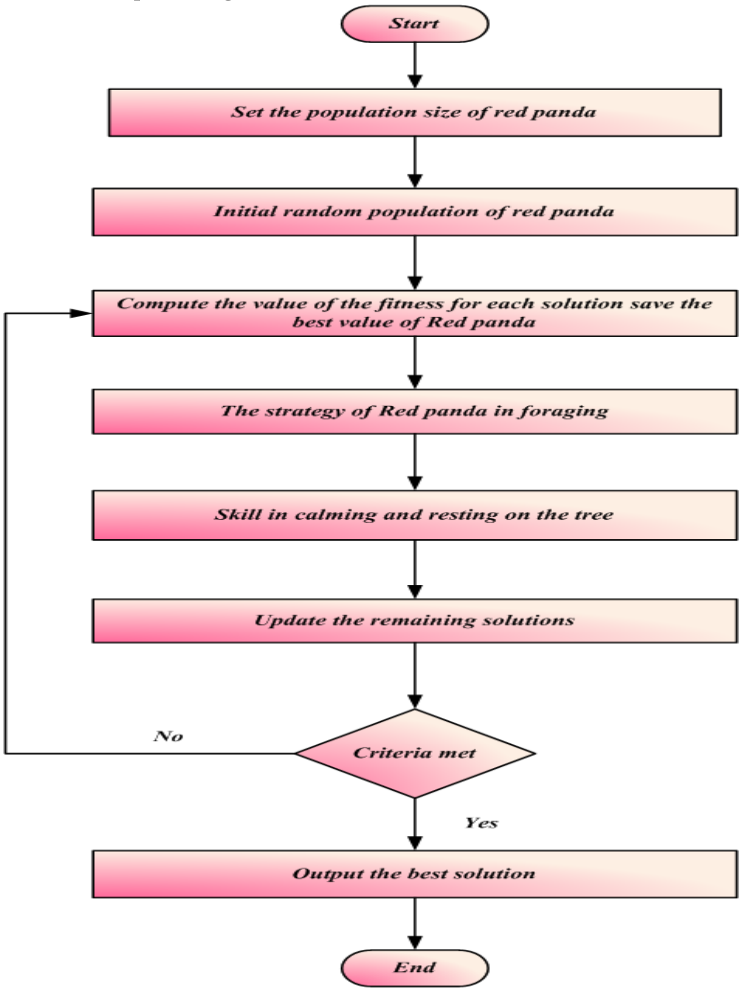

Figure2: Flow Chart of RPOA

Step 5: Skill in Climbing and Resting on the tree T_{enc}

Red pandas' position in the 2nd phase of the RPOA is determined on their ability to climb and rest on trees. The majority of red pandas' time is spent lounging on trees. The animal first feeds on the ground before scaling nearby trees. Red pandas' positions slightly alter as they approach and ascend the tree, improving the suggested RPOA algorithm for local search and exploitation in attractive areas.

$$T_{p,q}^{Q1} = r_{p,q} + \frac{bf_q + M_s \cdot (Z_t^{adt} + \mathrm{T}_{enc}(uf_q - bf_q))}{t} \qquad (14)$$

Where, $R_{p,q}^{Q1}$ denotes the q^{th} dimension; $r_{p,q}$ indicates the q^{th} dimension; bf_q denotes the lower bound of the q^{th} problem variables; M_s denotes the random numbers; Z_t^{adt} denotes the updated feature at time t; T_{enc} is represent the quantum ansatz; uf_q denotes the upper bound of the q^{th} problem variable and t denotes the iteration counter.

Step 6: Termination

The o_R *and* T_{enc} predict weight parameter value from Quantum Self-Attention Neural Networks is enhanced by using the RPOA; and it Continue with step 3 until the halting requirement is met. The KS-CT-DVDP-QSANN algorithm efficiently predicts the composite talents.

IV. RESULT AND DISCUSSION

The actual outcomes of the proposed method are presented in this sector. The proposed KS-CT-DVDP-QSANN method is implemented Python platform on computer with 12 GB RAM, Intel ®core (7M) i3-6100CPU @ 3[U1] .70 GHz processor Under some performance metrics, the number of iterations corresponds to the number of batches required to complete one epoch. Assessed by utilizing several performance, Recall, precision, Accuracy ,F1-score, mean square error and error rate. The result of KS-CT-DVDP-QSANN approach was compared with existing IR-IS-RTF-AI, TGPC-DQL and ITTE-IPSO-BPNN techniques.

A. Performance Measures

This is an important stage in determining the exploration of optimization algorithm. Performance measures to evaluate to access performance likes mean square error , , precision, Recall, F1-score, Accuracy and error rate.

1) Accuracy

Equation (15) provides the accuracy value, which is obtained by dividing the number of samples properly categorised by scheme by the total number of samples.

$$accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{15}$$

Here, TP signifies true positive, TN denotes true negative, FN means false negative and FP denotes false positive.

2) Precision

The accuracy of a machine learning model's positive prediction is one measure of the model's performance, along with precision. The concept of accuracy is given by Equation (16), which is the ratio of genuine positives to all positive forecasts.

$$precision = \frac{TN}{FP + TN} \tag{16}$$

3) Recall

Recall is intended by dividing entire count of true positive, false negative predictions by number of true positives. The model's capacity to collect all pertinent instances is measured. It is shown in equation (16),

$$\mathrm{Re}call = \frac{TP}{TP + FN} \tag{17}$$

4) F1-score

The F1-score is a measure used to assess the effectiveness of a deep learning model. Precision and recall are combined into a single score (F1-score). Thus it’s give this equation (18),

$$F1 - score = \frac{\mathrm{Pr}ecision * \mathrm{Re}call * 2}{(\mathrm{Pr}ecision + \mathrm{Re}call)} \tag{18}$$

5) Mean Squared Error

A metric for assessing a regression model's accuracy is the MSE. The average of the squares of the variations between the dependent variable's actual and expected values is computed. It is given in equation (19),

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$
(19)

Here , $\hat{y}_i$ specifies the predicted values, n specifies the number of data points, y_i specifies the observed value and MSE specifies the mean squared error.

6) Error Rate

The Error rate, also known as the classification error rate, is a metric that measures a classification model's overall accuracy. It denotes the percentage of erroneously classified cases in the dataset and it is given by the equation (20).

$$ErrorRate = \frac{FP + FN}{TP + TN + FP + FN} \tag{20}$$

B. Performance Analysis

This is a crucial step for determining the exploration of optimization algorithm. Performance measures to evaluate to access performance like mean square error ,Accuracy, , Recall, F1-score, precision , and error rate.

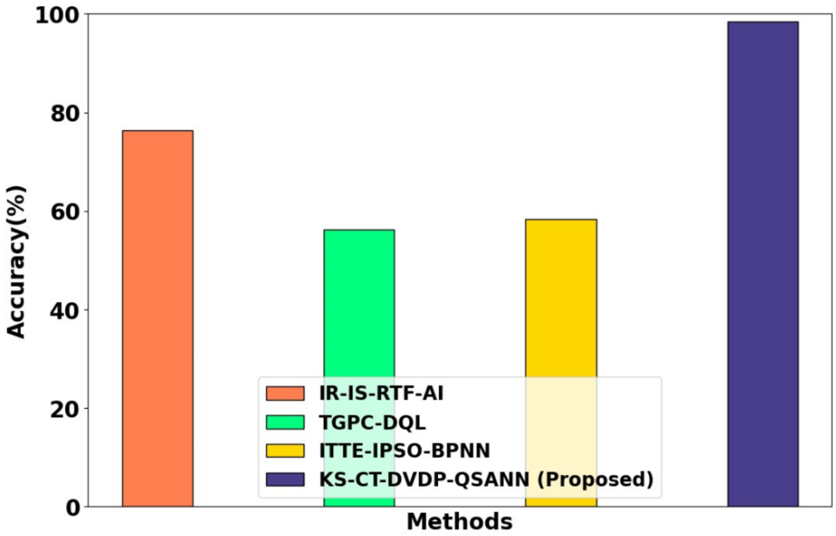

Figure3: Performance analysis of Accuracy

Figure 3 determines accuracy analysis. When compared to existing approaches such as IR-IS-RTF-AI, TGPC-DQL, and ITTE-IPSO-BPNN, the suggested KS-CT-DVDP-QSANN method achieves significant performance improvements in accuracy. This breakthrough demonstrates the efficacy of the Knowledge System of Composite Talents Based on the Development of Virtual Digital People (KS-CT-DVDP) in conjunction with the Quantitative Self-Adaptive Neural Network (QSANN) model, as it achieved 19.87%, 24.57% and 34.15%higher accuracy. The synergistic combination of these components is anticipated to provide a more nuanced and adaptable approach to data processing and decision-making, resulting in improved predictive accuracy. This highlights the ability of advanced knowledge systems and neural network techniques to considerably increase performance across a variety of domains. Here, the proposed KS-CT-DVDP-QSANN method attains19.87%, 24.57% and 34.15% higher accuracy compared with existing IR-IS-RTF-AI, TGPC-DQL and ITTE-IPSO-BPNNmethods.

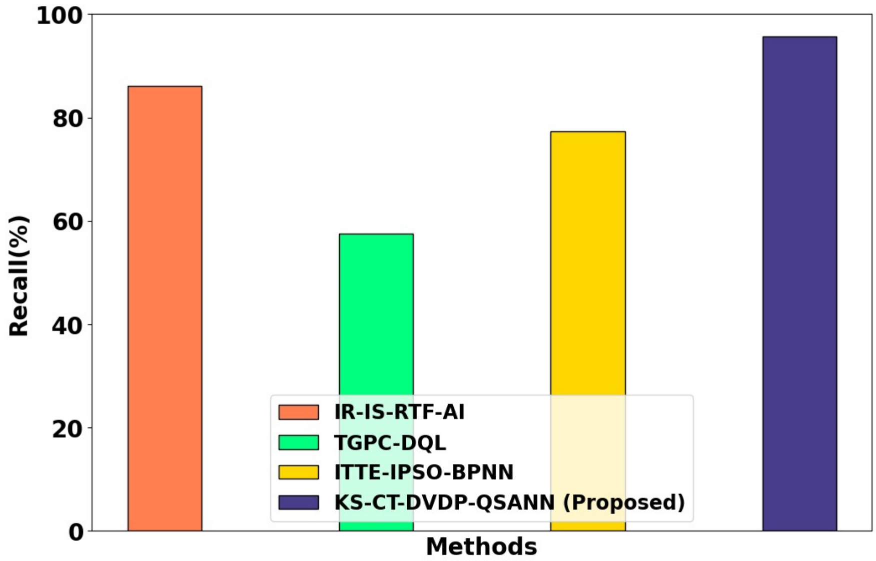

Figure4: Performance analysis of Recall

Figure 4 determines recall analysis. When compared to existing IR-IS-RTF-AI, TGPC-DQL, and ITTE-IPSO-BPNN approaches, the recall performance of the Knowledge System of Composite Talents (KS-CT-DVDP) method is significantly superior. The KS-CT-DVDP-QSANN approach produces outstanding recall rates of 23.63%, 28.37% and 27.23%, respectively. This improved performance demonstrates the effectiveness of the KS-CT-DVDP strategy for exploiting composite skills and virtual digital identities. The KS-CT-DVDP method outperforms traditional approaches by integrating diverse knowledge systems and leveraging the developmental capabilities of virtual digital individuals, demonstrating superior recall. Here, the proposed KS-CT-DVDP-QSANN method attains23.63%, 28.37% and 27.23% higher recall compared with existing IR-IS-RTF-AI, TGPC-DQL and ITTE-IPSO-BPNNmethods.

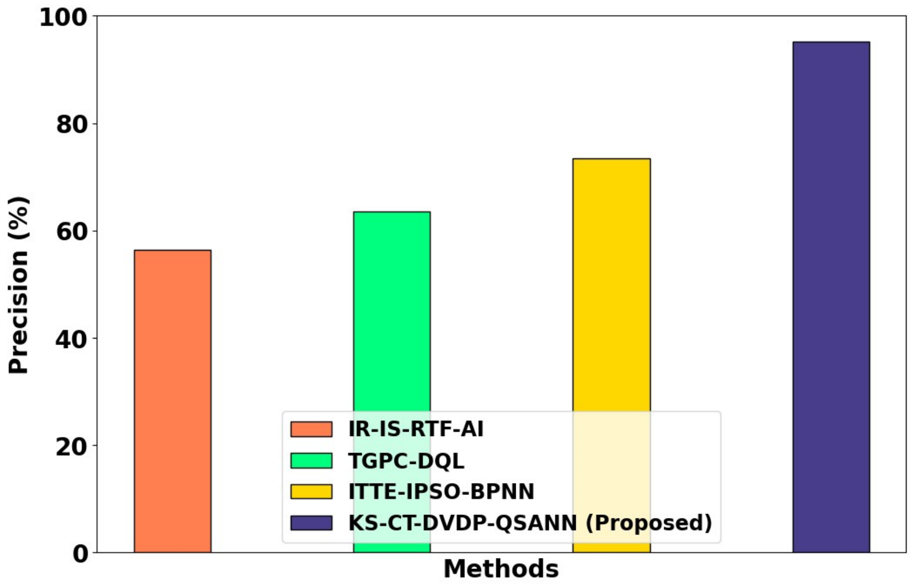

Figure 5: Performance analysis of Precision

Figure 5 determines precision analysis. Precision performance analysis using the Knowledge System of Composite Talents (KS-CT) method indicates considerable advances over previous methodologies such as IR-IS-RTF-AI, TGPC-DQL, and ITTE-IPSO-BPNN. In comparison to these methods, the KS-CT-DVDP-QSANN method improves precision by 23.17%, 25.42% and 29.28%, respectively. This improvement is due to numerous features inherent in the KS-CT strategy, including its capacity to harness the collective wisdom of composite talents, employ virtual digital persons for extensive data analysis, and deploy a highly efficient and adaptive QSANN algorithm. These advantages allow the KS-CT-DVDP-QSANN technique to not only outperform existing methods in terms of precision, but also to demonstrate its potential as a robust solution for complicated problems in a variety of fields. Here, the proposed KS-CT-DVDP-QSANN method attains23.17%, 25.42% and 29.28% higher precision compared with existing IR-IS-RTF-AI, TGPC-DQL and ITTE-IPSO-BPNNmethods.

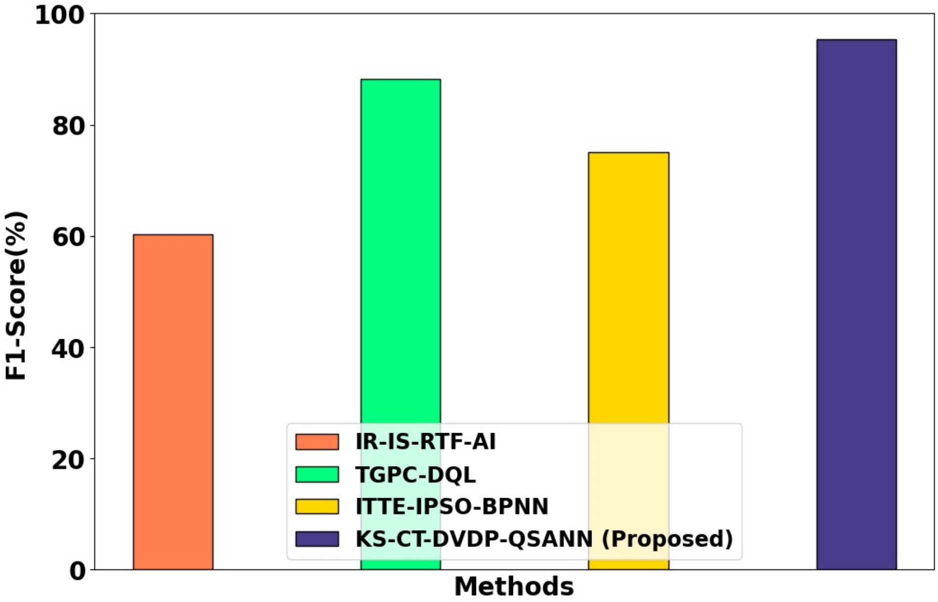

Figure 6: Performance analysis of F1 Score

Figure 6 determines F1 Score analysis. The KS-CT-DVDP-QSANN method outperforms previous methods by achieving F1 Scores that are 18.47%, 23.65%, and 30.98% higher than the IR-IS-RTF-AI, TGPC-DQL, and ITTE-IPSO-BPNN approaches, respectively. This considerable improvement demonstrates the effectiveness of the Knowledge System of Composite Talents Based on the Development of Virtual Digital People (KS-CT-DVDP) in improving predictive accuracy. This strategy is likely to achieve a more sophisticated understanding of the underlying data by employing a combination of skills contained within a virtual digital framework, resulting in more accurate predictions and classifications. Furthermore, the use of the QSANN (Quantum Simulated Annealing Neural Network) technique is likely to contribute to its improved performance, indicating the effectiveness of using sophisticated computational paradigms in predictive modeling tasks. Here, the proposed KS-CT-DVDP-QSANN method attains 18.47%, 23.65%, and 30.98% higher F1 Score compared with existing IR-IS-RTF-AI, TGPC-DQL and ITTE-IPSO-BPNNmethods.

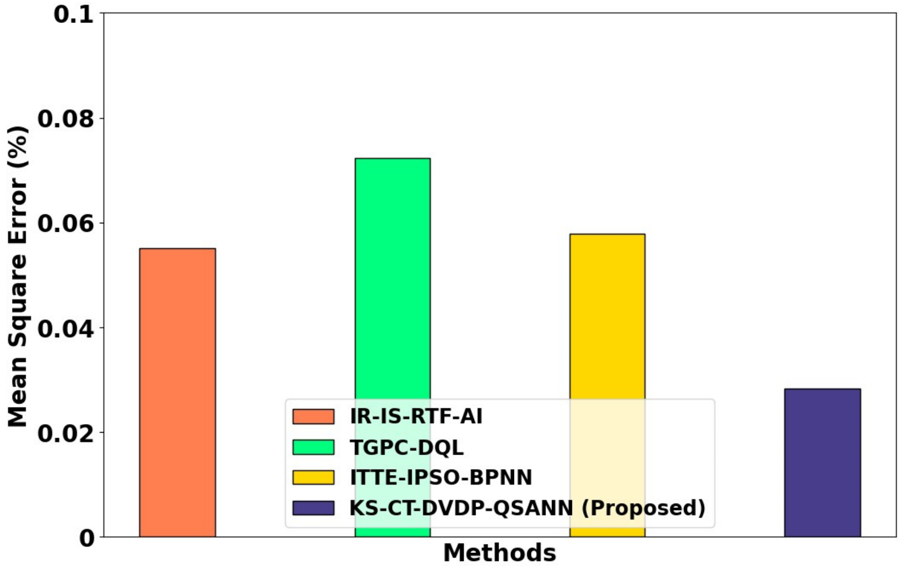

Figure 7: Performance analysis of Mean Squared Error

Figure 7 determines Mean Squared Error analysis. MSE performance analysis using the suggested KS-CT-DVDP-QSANN approach versus existing IR-IS-RTF-AI, TGPC-DQL, and ITTE-IPSO-BPNN methods shows significant improvements. In comparison to the IR-IS-RTF-AI, TGPC-DQL, and ITTE-IPSO-BPNN approaches, the KS-CT-DVDP-QSANN method reduces MSE by 17.29%, 27.25%, and 29.83%, respectively.

This improvement demonstrates the KS-CT-DVDP-QSANN approach's usefulness in reducing prediction errors, implying its potential superiority in effectively modeling complex systems or datasets. The integration of composite abilities within a knowledge system, together with the use of virtual digital personas, is anticipated to permit more extensive data representation and processing, resulting in higher predictive MSE performance. Here, the proposed KS-CT-DVDP-QSANN method attains 17.29%, 27.25%, and 29.83% higher Mean Squared Error compared with existing IR-IS-RTF-AI, TGPC-DQL and ITTE-IPSO-BPNNmethods.

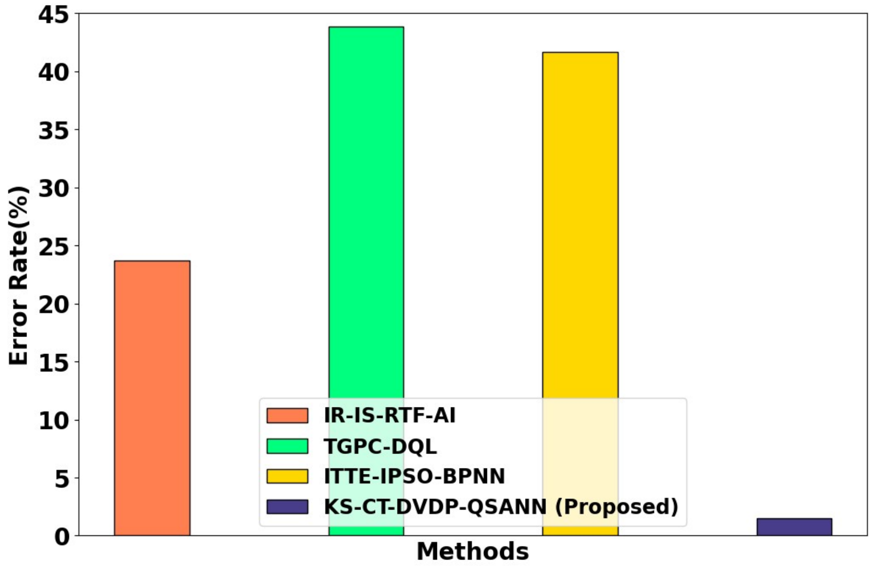

Figure 8: Performance analysis of Error Rate

Figure 8 determines Error Rate analysis. The suggested KS-CT-DVDP-QSANN approach outperforms existing methods such as IR-IS-RTF-AI, TGPC-DQL, and ITTE-IPSO-BPNN in terms of error rate performance. The KS-CT-DVDP-QSANN approach produces decreased error rates by 19.67%, 23.55%, and 21.96%, demonstrating its superiority. This improvement can be credited to the novel combination of Knowledge Systems, Composite Talents, Development of Virtual Digital People (DVDP), and Quick-learning Self-adaptive Neural Networks (QSANN). Using these advanced components, the KS-CT-DVDP-QSANN technique outperforms existing methods in terms of accuracy, resilience, and flexibility, establishing a new standard for error reduction within the provided area. Here, the proposed KS-CT-DVDP-QSANN method attains 19.67%, 23.55%, and 21.96% higher Error Rate compared with existing IR-IS-RTF-AI, TGPC-DQL and ITTE-IPSO-BPNNmethods.

C. Discussion

Enhanced The Knowledge System of Composite Talents Based on the Development of Virtual Digital People (KS-CT-DVDP-QSANN) is developed in this paper. The composite talent knowledge system, which is based on the advancement of virtual digital entities, promotes a dynamic interaction between human skill development and artificial intelligence, enhancing both individual skills and collaborative potential. The merging of human expertise with virtual counterparts drives innovation and creativity, ushering in a new era of talent cultivation and issue solutions. The KS-CT-DVDP-QSANN technique improved accuracy, recall, and predict for composite talents. When compared to existing approaches such as IR-IS-RTF-AI, TGPC-DQL and ITTE-IPSO-BPNN, the KS-CT-DVDP-QSANN method outperformed them in terms of Pipeline leak usage detection For example, for various circumstances, the method achieved 19.87%, 24.57% and 34.15% high accuracy, 23.63%, 28.37% and 27.23%higher recall, and 23.17%, 25.42% and 29.28%higher precision than existing methods. These findings demonstrate the KS-CT-DVDP-QSANN method's exceptional performance in ethical concerns about ownership, control, and potential societal repercussions must be carefully navigated in order to ensure responsible deployment and identical outcomes.

V. CONCLUSION

In this section, The Knowledge System of Composite Talents Based on the Development of Virtual Digital People (KS-CT-DVDP-QSANN) is implemented. Depicted in Figure 3 to 8 performances much better when compared to existing techniques IS-RTF-AI, TGPC-DQL and ITTE-IPSO-BPNN, the KS-CT-DVDP-QSANN, the respectively. Across diverse evaluation metrics, the method consistently showcases substantial enhancements in accuracy, recall, precision, F1-Score, mean square error and error rate. The Knowledge System of Composite Talents, based on the creation of virtual digital entities, provides a systematic approach to combining multiple skills and abilities into cohesive entities, increasing versatility and adaptability. Organizations can use this technique to generate dynamic and versatile skills capable of managing difficult digital obstacles. In conclusion, the KS-CT-DVDP-QSANN method outperformed existing techniques such as IS-RTF-AI, TGPC-DQL and ITTE-IPSO-BPNN, the KS-CT-DVDP-QSANN by significantly increasing accuracy (19.87%, 24.57% and 34.15%, recall 23.63%, 28.37% and 27.23%, and precision 23.17%, 25.42% and 29.28% for composite talents prediction. Future work in the field of composite talents and virtual digital people could include fine-tuning algorithms to improve the synthesis of diverse skills and personalities, investigating ethical frameworks to govern the use of virtual individuals in various domains, and creating immersive training environments to leverage these composite talents for real-world applications such as education, entertainment, and customer service.

Acknowledgement

2023 Ministry of Education Industry-University Cooperation Collaborative Education Project: Research on Composite Talent Cultivation Programme for Virtual Digital Human Development.（NO：230805295290205）

REFERENCE

[1] Zhang, Y. (2024, January). Design of Digital Circuit Virtual Simulation Experiment Basedon Situated Learning Theory. In *Proceedings of the 3rd International Conference on New Media Development and Modernized Education, NMDME 2023, October 13–15, 2023, Xi'an, China*.

[2] Liu, Y., Zeng, N., Papadonikolaki, E., Maritshane, K. & Chan, P.W., (2024). The future of digitalized project practices through data-savvy talent: A digital competence formation perspective. *Project Leadership and Society*, *5*, p.100120.

[3] vanDyck, M., Lüttgens, D., Piller, F.T. & Brenk, S, (2023). Interconnected digital twins and the future of digital manufacturing: Insights from a Delphi study. *Journal of Product Innovation Management*, *40*(4), 475-505.

[4] Abouelenein, Y.A.M., Selim, S.A.S. & Elmaadaway, M.A.N. (2024). Impact of a virtual chemistry lab in chemistry teaching on scientific practices and digital competence for pre-service science teachers. *Education and Information Technologies*, *29*(3), 2805-2840.

[5] Guillén-Gámez, F.D., Ruiz-Palmero, J. & Gómez-García, M. (2023). Digital competences in research: creativity and entrepreneurship as essential predictors for teacher training. *Journal of Computers in Education*, 1-20.

[6] Mu, C.X. (2023, November). Research on Talents Cultivation Model of Application-oriented Undergraduate in the Era of AI. In *ICMEIM 2023: Proceedings of the 4th International Conference on Modern Education and Information Management, ICMEIM 2023, September 8–10, 2023, Wuhan, China* (p. 190). European Alliance for Innovation.

[7] Mahdiloo, M., Andargoli, A.E., Toloo, M., Harvie, C. & Duong, T.T. (2023). Measuring the digital divide: A modified benefit-of-the-doubt approach. *Knowledge-Based Systems*, *261*, 110191.

[8] Zhang, P., Ma, S.G., Zhao, Y.N. & Cao, X.Y. (2023). Analyzing Core Competencies and Correlation Paths of Emerging Engineering Talent in the Construction Industry—An Integrated ISM–MICMAC Approach. *Sustainability*, *15*(22), 16011.

[9] Mhlanga, D. (2023). Financial Technology, Digital Transformation, and Quality Education in the Fourth Industrial Revolution. *FinTech and Artificial Intelligence for Sustainable Development: The Role of Smart Technologies in Achieving Development Goals*, 171-191.

[10] Bing, B. (2023). The impact of higher education on high quality economic development in China: A digital perspective. *PloS one*, *18*(8), e0289817.

[11] Mahmoud, A.B. (2024). Aging in the Digital Age: Public Beliefs about the Potential of Virtual Reality (VR) for the Aging Population. *Journal of Macromarketing*.

[12] Burtscher, M., Piano, S. & Welby, B. (2024). Developing skills for digital government: A review of good practices across OECD governments.

[13] Chai, Y. (2023). Application of Virtual Reality Technology in Display Design. *RevistaIbérica de Sistemas e Tecnologias de Informação*, (E55), 404-414.

[14] Verweel, L., Newman, A., Michaelchuk, W., Packham, T., Goldstein, R. & Brooks, D., (2023). The effect of digital interventions on related health literacy and skills for individuals living with chronic diseases: A systematic review and meta-analysis. *International journal of medical informatics*, 105114.

[15] Celik, I. (2023). Exploring the determinants of artificial intelligence (Ai) literacy: Digital divide, computational thinking, cognitive absorption. *Telematics and Informatics*, *83*, 102026.

[16] Wang, R., Wang, Q., Shi, R., Zhang, K. & Wang, X. (2023). How the Digital Economy Enables Regional Sustainable Development Using Big Data Analytics. *Sustainability*, *15*(18), 13610.

[17] Moneva, M.L.V. & Oropilla, C.T. (2024). Identifying Socioemotional Skills for the Digital Age: Foundations of an Early Childhood Literature-Based Program.

[18] Li, H. and Li, Y. (2023). Exploring the Cultivation of Innovative Talents in the Era of Big Data and Cloud Computing. *Adult and Higher Education*, *5*(1), 19-27.

[19] Zhang, X., Li, C. & Jiang, Z. (2023). Research on Talent Cultivating Pattern of Industrial Engineering Considering Smart Manufacturing. *Sustainability*, *15*(14), 11213.

[20] Ya, Y., Zifei, M. & Guoxian, W. (2023). Survey and Research on the Influencing Factors for the Development of Rural Digital Logistics under the Background of the Internet-Based on Observation of H County, Yunnan Province. *development*, *37*, pp.43-53.

[21] Allal-Chérif, O., Aránega, A.Y. & Sánchez, R.C. (2021). Intelligent recruitment: How to identify, select, and retain talents from around the world using artificial intelligence. *Technological Forecasting and Social Change*, *169*, p.120822.

[22] Guarino, A., Malandrino, D., Marzullo, F., Torre, A. & Zaccagnino, R. (2022). Adaptive talent journey: Optimization of talents' growth path within a company via Deep Q-Learning. *Expert Systems with Applications*, *209*, 118302.

[23] Liu, Y. (2023). An innovative talent training mechanism for maker education in colleges and universities based on the IPSO-BP-enabled technique. *Journal of Innovation & Knowledge*, *8*(4), 100424.

[24] Arroyo-Bote, S., Bennasar-Verger, C., Martínez-Jover, A., Ferragut-Pina, P., Riutot-Sbert, P., López-González, Á.A. & Barkvol, P. (2024). Development of a three-dimensional printed model from a digital impression of a real patient for aesthetic dentistry undergraduate teaching. *Journal of Dental Education*.

[25] Llanes-Jurado, J., Gómez-Zaragozá, L., Minissi, M.E., Alcañiz, M. & Marín-Morales, J. (2024). Developing conversational Virtual Humans for social emotion elicitation based on large language models. *Expert Systems with Applications*, *246*, 123261.

[26] Yang, S., Mengyu, H. & Xiuwu, Z. (2024). Assessing the Impact of Digital Technologies on Energy Efficiency: The Role of OFDI and Virtual Agglomeration. *Journal of Resources and Ecology*, *15*(1), 117-129.

[27] Wahyudi, M., Chakim, M.H.R., Si, M.V.A., Saputra, D.B. & Rahardja, R. (2023, November). Developing Instruments for Digital Talent Competence Using Partial Least Square-Based Models. In *2023 11th International Conference on Cyber and IT Service Management (CITSM)* (pp. 1-9). IEEE.

[28] https://www.kaggle.com/datasets/hanifalirsyad/development-talent-upwork

[29] Nóvoa, A., Racca, A. & Magri, L. (2024). Inferring unknown unknowns: regularized bias-aware ensemble Kalman filter. *Computer Methods in Applied Mechanics and Engineering*, *418*, 116502.

[30] Li, G., Zhao, X. & Wang, X., (2024). Quantum self-attention neural networks for text classification. *Science China Information Sciences*, *67*(4), 1-13.

[31] Givi, H., Dehghani, M. & Hubálovský, Š., 2023. Red panda optimization algorithm: An effective bio-inspired metaheuristic algorithm for solving engineering optimization problems. *IEEE Access*.