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Construction of Knowledge Mapping for Vocational and Technical Education Programs and Its Application in Students' Academic Assessment

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Abstract: - Knowledge mapping for vocational and technical education programs are the academic assessment represent a significant advancement in educational methodologies. The process of constructing knowledge maps tailored to vocational and technical education, emphasizing their utility in enhancing students' learning experiences and academic evaluations. In this manuscript proposes a Construction of Knowledge Mapping for Vocational and Technical Education Programs and Its Application in Students Academic Assessment (CKMV-TEP-ASAS). Initially, the data is collected from the Holland Code (RIASEC) Test Responses data set. Then, the collected data is fed to Pre-processing segment. In pre-processing stage, Disentangled Contrastive Collaborative Filtering (DCCF) is used to clean the data. The pre-processed data are fed to feature selection. Clouded Leopard Optimization Algorithm (CLOA) is used for selecting 6 features. Then features selection output is given to spiking Early-Exit Neural Networks (SEENN) used to predict vocational personality type. The weight parameters of SEENN are optimized utilizing Horse Herd Optimization Algorithm. The CKMV-TEP-ASAS-SEENN method is implemented and the metrics such as Accuracy, Computation time, Error rate, F1-score, precision, recall, Sensitivity specificity. By then, the proficiency of the proposed approach is executed in the python platform. Proposed CKMV-TEP-ASAS-SEENN method attains 23.5%, 22.5% and 24% higher accuracy, 24.06%, 23.33% and 22.98% higher Precision, 24.12%, 22.33% and 23.98% higher sensitivity compared to other existing methods, such as Chinese Traditional Culture Teaching Application in Higher Vocational Education (RAC-TCT-HVE-RNN), Transformative Technologies in the Evaluation of a Vocational Education System (TTE-VES-CNN), and BP Neural Network Application in Teaching Quality Evaluation of Higher Vocational Education (ABPNN-TQE-HVE-BPNN) correspondingly.

Keywords: Vocational interests, Machine learning, Socio-demographic features, RIASEC, Predictive modeling, Career counseling Social network analysis. Knowledge mapping.

I. INTRODUCTION

(a) Background

For programs in vocational and technical education, knowledge mapping entails methodically classifying and illustrating the essential ideas, abilities, and proficiencies covered in the curriculum [1-3]. This mapping facilitates effective teaching and learning practices by helping to grasp the hierarchical structure of knowledge and its connections. Additionally, teachers can evaluate students' growth of practical skills and problem-solving abilities in addition to their acquisition of factual knowledge by integrating knowledge mapping into their academic assessments [4-6]. By using this method, teachers may assess students' development in a thorough way, which helps them to customize their training to each student's unique needs and improve learning outcomes as a whole [7, 8]. Furthermore, knowledge mapping clarifies expectations for students and encourages greater transparency in evaluation standards, all of which contribute to a more significant and effective learning experience in vocational and technical education programs [9, 10].

(b) Literature Review

Various research works have previously existed in the literatures which were based on application of Knowledge Mapping for Vocational and Technical Education Programs based on deep learning. Some of them reviewed were follows,

Bogacheva et al. [11] have presented machine learning methods to one area of study in psychology: career aspirations. Socio demographic characteristics were thought to be highly predictive of career interests, which may have profoundly useful ramifications for social network analysis and professional counseling. A set of responses to the psychological test known as the RIASEC (Holland Codes) served as the dataset for this investigation. Using socio demographic characteristics, various machine learning structures were applied to forecast RIASEC scales. The issues were approached as a multiclass, multi label, multi output regression challenge. Regression chains, inferring label relations, three-letter code categorization, and independent regression were the models that were employed. A comparison of models revealed that the models that take advantage of the inter correlations between RIASEC scales produced the best outcomes.

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Jiang, [12] have presented a unique hybridized LSTM-RNN to forecast vocational education students' abilities. In order to remove undesirable errors, the obtained datasets are first normalized using the normalization approach during the pre-processing stage. Then, the CTC teaching application makes use of artificial intelligence (AI) technology. The suggested method used during the forecast phase. To acquire the most effective research, the performance measures of this approach are analyzed and compared with several established techniques. The Origin tools were utilized to achieve the research findings. Students and teachers confront a number of educational challenges issues as a result of the use of CTC in the classroom.

Zhang et al. [13] have presented a brand-new framework for using cutting-edge technology to efficiently manage the professional growth of vocational college instructors. To evaluate a teacher's performance and potential, the system analyzes a variety of data points, such as professional activities, teaching experience, student feedback, and academic achievements, using deep learning technology. The system assesses the pros and cons, provides personalized training plans, and improves the way that education were delivered by leveraging a generative language model. A case study that shows improvements in personnel management, professional development, teaching quality, and student satisfaction attests to the system's efficacy. So the purpose of the hybrid model architecture were to efficiently extract meaningful patterns and correlations from the collected data by utilizing the unique advantages of CNNs and RNNs and limitations of different algorithms within the domain of talent management for vocational college educators.

Hasanah et al. [14] have presented map the industry classification based on electrical field work competency. Regional Model Competency Standards, which include task skills, task management skills, contingency management skills, job/role environment skills were taken into account in the competency mapping work. The study employs a survey methodology, utilizing the DACUM approach for task analysis. To determine the different industry kinds, a survey were carried out in multiple industries. The research subject were major industrial, specifically Factory PT. The disadvantages of lacks a comprehensive survey across industries and potentially hindering the assessment of identified competencies.

Long, et al. [15] have presented Using Cite Space to examine the literature on the incorporation of vocational education on China Knowledge Infrastructure at 2001 to 2023, , the study aims to clarify the development context of the topic. Furthermore, throughout the past ten years, "integration of general and vocational education" and "have consistently garnered attention." But the terms "labor education" and "secondary vocational schools" are still circulating, while the term "comprehensive high school" has stopped appearing. When the Timeline view is examined more closely, it becomes clear that themes such as vocational education, high school stage, horizontal integration are driving the growing interest in this field of study about school operating modes. The disadvantages of include a lack of methodology clarity, limited timeframe, and overlooking regional variations.

Ai1 and Feng [16] has presented in the context of classroom instruction, teaching quality evaluation were a crucial component of teaching management. An HVE quality evaluation index system was created after 16 assessment indicators were chosen based on the notion of teaching quality from the four areas of teaching attitude, teaching content, teaching process, and teaching results. BP neural network algorithm establishes the evaluation mode. The advantages of comprehensive evaluation were acknowledgment of the potential for improvement.

OZER and Suna ,[17] has presented The current study examines specific actions that can be taken to improve VET in seven areas within a year of the publication of Turkey's Education Vision 2023. Themes related to improvements towards VET include enhancing applied training with qualifications, fostering social integration through VET, establishing a quality assurance system for VET, supporting diversity in VET, fortifying cooperation with stakeholders, developing teachers' professional and pedagogical skills, and enhancing applied training and qualifications. There are recommendations made for maintaining the advancements made in VET in Turkey. The advantages of addressing the future of vocational education and training for the enhance VET quality and structure.

(c) Research Gap and Motivation

Although there has been a noticeable progress in research in vocational and technical education recently, there is still a vacuum in the application of knowledge mapping to academic evaluation procedures. The controlling the complex interplay of weights in neural connections, the necessity of hidden layers for proper RNN function, and the limitations in visualizing the intermediate layers in artificial neural networks. But conventional evaluation techniques frequently fail to adequately capture the depth and breadth of students' competencies. Researchers and educators can close this gap by using knowledge mapping tools, which provide students' knowledge, abilities, and learning paths a visual representation [18]. This method allows for more thorough assessment as well as customized learning as well as ensuring seamless integration of CNN and RNN capabilities for concurrent processing of structured and sequential data experiences based on the requirements of each individual student. The goal of this research is to increase the overall superiority of vocational and technical education programs, well prepare pupils for the workforce, and match educational assessment with real-world demands. Researchers can examine the BPNN include potential limitations in scalability, interpretability, and computational complexity when applied to large-scale datasets or complex tasks effectiveness of knowledge mapping in evaluating students' academic performance and fostering their achievement in vocational and technical domains through empirical study and methodological improvement.

(d) Challenge

To guarantee the quality of the dataset, carry out comprehensive data pretreatment procedures such data cleansing, addressing missing values, and outlier detection. Additionally, to increase the dataset's representativeness and completeness, think about adding information from other sources [19]. The study's challenges include implementing CTC in the classroom, moving to online learning due to the COVID-19 pandemic, integrating AI into CTC instruction, addressing graduate unemployment and skill gaps, and improving the general quality of vocational education. Ensuring the availability and quality of data necessary for assessing teacher effectiveness, professional development, and student feedback is one of the main concerns. To obtain quantitative data on a range of topics, including teaching experience, course completion rates, student assessment results, and participation in professional development events, a strong data collection approach is required [20]. Creating a methodical plan for gathering, organizing, and analyzing this data is essential to a successful assessment.

(e) Contribution

- The main contribution of this research is to propose Knowledge Mapping for Vocational and Technical Education Programs using HOA-SEENN approach.

- The proposed approach is the combined operation of Horse Herd Optimization Algorithm (HOA) and spiking Early-Exit Neural Networks (SEENN).

- The CKMV-TEP-ASAS method is implemented in the MATLAB and assessed its efficacy with existing methods.

- The proposed method shows the better results compared with other existing methods

(f) Organization

Section 1 describe the introduction is explain the literature review and background of the research work, Section 2 includes the proposed methodology, Section 3 exemplifies the results, Section 4 clarifies the Conclusion.

II. PROPOSED METHODOLOGY

In this section application of Knowledge Mapping for Vocational and Technical Education Programs using HOA-SEENN approach. Block diagram of proposed CKMV-TEP-ASAS-SEENN is presented in Fig 1. It comprises dataset preparation, pre-processing, feature selection, neural network, optimization. The comprehensive explanation of all the steps are depicted below,

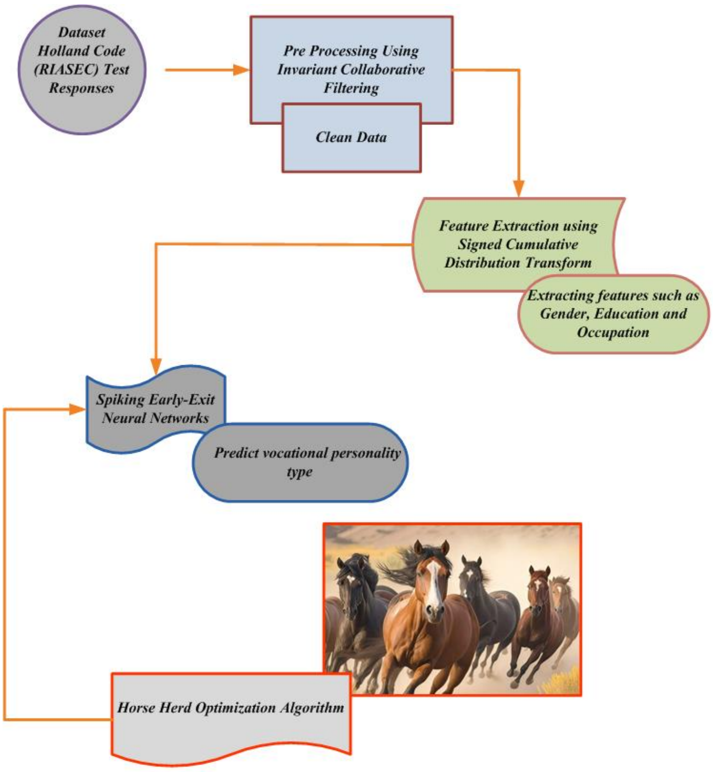

Fig 1: Block diagram for CKMV-TEP-ASAS-SEENN method

A. Data Acquisition

The data is collected from Holland Code (RIASEC) Test Responses [21]. The American psychologist John L. Holland first created the notion of vocations and occupational choice based on personality types, which is known as the Holland Codes or the Holland Occupational Themes (RIASEC). Originally developed in the late 1990s, the RIASEC model has been expanded and updated by the US Department of Labor's Employment and Training Administration and used in the "Interests" area of O*NET (Occupational Information Network), a free online database. This model categorizes six personality types: Realistic, Investigative, Artistic, Social, Enterprising, Conventional (RIASEC). These classifications help individuals understand their strengths and preferences, guiding them towards suitable career paths.

B. Pre- Processing Using Disentangled Contrastive Collaborative Filtering

In this section Disentangled Contrastive Collaborative Filtering (DCCF) technique is used [22]. It is used to clean the data. The ICF method, coupled with knowledge mapping, offers significant advantages for vocational and technical education programs. The dataset collected from Holland Code (RIASEC) Test Responses. According to the "invariance" principle, an ideal CF increase the invariant preference information Formally speaking, this idea is:

$$Y \perp Z_{pop} \,\big|\, Z_{pref} \tag{1}$$

Where, $\perp$ indicates the likelihood of independence. It outlines that Z_{pref} shields Y due to the impact of Z_{pop}, creating the forecasting procedure from Z_{pref} to Y steady across various Z_{pop}. Using the suggestion of movies as an example, the invariance principle can be used as a lever to examine viewers' consistent incentives to watch a film, as opposed to the erroneous correlation brought about by popular factors (such as box office). Disentanglement principle: To allow changes in popularity to have no bearing on a user's preference for an item's qualities, preference and popularity data should be independent and decomposable from one another. This idea can be expressed as follows:

$$Z_{pop} \perp Z_{pref} \tag{2}$$

It states that the acquisition of Z_{pref} is not prone to Z_{pop}. When it comes to movie recommendations, the disentanglement principle ensures that user interest in a director or celebrity will not be significantly swayed by the success of the film. Only the previous user-item interactions are provided during the training phase; the ground truth of oracle (ideal) preference and popularity information is unknown. The motivation to estimate them in the modeling arises due to this absence. In particular, based on the past exchanges, the utilize a CF back bone mode to enhance the details about preferences Z_{pref} as depictions;

$$u_r, i_r = f_r(u, i) \tag{3}$$

Where, f_r is the CF so-called preference encoder backbone. It requires ID of the user u and object i implies input, after which it produces the d -dimensional representations of preferences $u_r \in R^d$ and $i_r \in R^d$, correspondingly. In addition to the preference encoder f_r, employ an additional popularity encoder f_p , this shares the same architectural design as f_r yet seeks to accept the knowledge about popularity Z_{pop} as the illustrations:

$$u_p, i_p = f_p(u, i) \tag{4}$$

Where, f_p uses the popularity statistical measures refers input (quantity of exchanges that person has u, item i engaged in historical), also generates d - representations of dimension preferences $u_p \in R^d$ and $i_p \in R^d$. These popularity figures are interpreted as categoric attributes such as ID. Finally, the data is cleaned by using Disentangled Contrastive Collaborative Filtering. The pre-processing data is fed to feature selection phase.

C. Feature Selection Clouded Leopard Optimization Algorithm

The features selection depends on Clouded Leopard Optimization Algorithm (CLOA) [23]. This study outlines the characteristics of a medium-size clouded leopard. Stated differently, it is neither large nor little. Such magnificent animal are living in Southeast Asia rainforests. The fur of clouded leopards often exhibits a blotched pattern of black and dark dusky-grey on a backdrop of dark grey or ochreous. The ears are black, its head contains black patches. The corners of the lips to neck, nape to t shoulders, and the corners of the eyes to the face are all covered in partially linked or divided stripes. This is a lonely, timid cat. Two natural behaviors which are more notable than the animal's other actions have been observed in person. These animals sleep on the trees throughout the day. They come down from the trees at night, when they are at their busiest. The fundamental concept for the suggested CLO design came from modeling these two notable acts in clouded leopards.

Step 1: Initialization

The CLO population, which is made up of all clouded leopards, can be represented numerically by a matrix in accordance with (5).

In a matrix, the input parameter is produced at random.

$$K = \begin{bmatrix} M_1 \\ \\ M_i \\ \\ M_N \end{bmatrix}_{N \times m} = \begin{bmatrix} M_{1,1} & M_{1,j} & M_{1,m} \\ \\ M_{i,1} & M_{i,j} & M_{i,m} \\ \\ M_{N,1} & M_{N,j} & M_{N,m} \end{bmatrix}_{N \times m} \tag{5}$$

Here K indicates walruses' populace, M_i epitomizes i th walrus, $M_{i,j}$ symbolizes j th decision variable from i th walrus, N represents No.of walruses, m represents count of decision variables.

The best member of the CLO population is defined as the one who provides the highest value for the objective function. The best member of the population must be changed since the population's position in the search space is modified and new values are computed for the target function.

Step 2: *Random Generation*

After initialization process, features selected randomly using aid of CLOA algorithm approaches.

Step 3: Fitness function estimation

Initialized evaluations utilized to generate a random result. It evaluated to select features. This given in equation (6),

$$fitness\ function = [selecting\ multiple\ features] \tag{6}$$

Step 5: Night Activities for Hunting

At night, the clouded leopard emerges from its hiding spot and goes hunting. The clouded leopard's nocturnal activity prompts them to shift places as they hunt. This clouded leopard approach uses metaheuristic algorithms to represent the ideas of exploration and global search, enabling population members to precisely and globally scan various regions of the search space. To mathematically depict this behavior, the positions of other members of the population in the search space are considered as prey locations for each clouded leopard. The target prey is randomly selected to be in one spot. Using (9), a new scenario depending on the anticipated prey's position is created for the corresponding clouded leopard. If this new location has a superior value for the objective function, it replaces the corresponding clouded leopard, according to (10):

$$x_{i,j}^{P1} = \begin{cases} xi,j + ri,j \cdot (pi,j - Ii,j \cdot xi,j), & F_i^P < Fi; \\ xi,j + ri,j \cdot (xi,j - Ii,j \cdot pi,j), & else \end{cases} \tag{7}$$

$$Xi = \begin{cases} X_i^{P1}, & F_i^{P1} < Fi; \\ Xi, & else \end{cases} \tag{8}$$

Where X_i^{P1} O indicates new positioning for i th clouded leopard depending on 1st phase of CLO, $x_{i,j}^{P1}$ refers j th dimension, F_i^{P1} refers objective function, ri,j implicates random count at $[0,1]$, pi epitomizes selected prey position for i th clouded leopard that chose randomly through set $\{X_1, X_2, \ldots\ldots, X_{i-1}, X_{i+1}, \ldots\ldots, X_N\}$, $p_{i,j}$ specifies j th prey pi dimension, $I_{i,j}$ epitomizes objective functioning of the prey pi, F_i^P specifies random count chosen through set $\{1,2\}$

Step 6: Daily Rest on the Trees

After hunting and devouring their victim, clouded leopard go towards the woods to relax and digest their food. They consequently rest on trees for the majority of the day. The clouded leopard's behavior causes a shift in position in the vicinity of their current location. In metaheuristic algorithms, this tactic embodies exploitation and local search, whereby the algorithm seeks out better solutions in the vicinity of those it has already found. To replicate the behavior of clouded leopards, a random place is produced using (11) close to each clouded leopard's location. According to (12), the new position replaces the old one if the goal function's value increases there.

$$X_{i,j}^{P2} = x_{i,j} + \frac{l_j + r_{i,j} \cdot (u_j - l_j)}{t} \cdot (2r_{i,j} - 1) \tag{9}$$

$$X_i = \begin{cases} X_i^{P2}, \ F_i^{P2} < F_i; \\ X_i \quad else \end{cases} \tag{10}$$

where X_i^{P2} represents new positioning for i th clouded leopard with respect to the 2nd phase of CLO, $x_{i,j}^{P2}$ refers j th dimension, F_i^{P2} implicates objective function, $r_{i,j}$ implicates randomly chosen count at $[0,1]$.

Step 7: Termination Criteria

In this step, CLOA completes, best solution obtained through each process iterations returned as output. CLOA selected 6 features from Holland Code (RIASEC) Test Responses dataset. Then the selected features are given to Spiking Early-Exit Neural Networks. Selected features from Holland Code (RIASEC) Test Responses shown in table 1.

Table 1: Selected features using MBO

S.No	Selected Features
1	Family size
2	Education
3	Gender
4	Race
5	Country
6	Voted

D. Spiking Early-Exit Neural Networks (SEENN)

In this section, Spiking Early-Exit Neural Networks (SEENN) [24] is discussed. SEENN is used to predict vocational personality type. Empirical data supporting this assumption is provided in the Appendix. A. Let C_t be the collection of accurate anticipated input samples for each time step t, and $C_1 \subseteq C_2 \subseteq .... \subseteq C_T$. Also denote $W = \overline{C}_T$ the suggestion using the averaged earliest time step (AET) metric, which is provided by, as the incorrect prediction set [24].

$$AET = \frac{1}{N}\left(|C_1| + T|W| + \sum_{t=2}^{T} t\left(|C_t| - |C_{t-1}|\right)\right) \tag{11}$$

Where $|\cdot|$ yields the set's cardinal number, and $|C_t| - |C_{t-1}|$ yields the quantity of samples that are a part of C_t yet not to C_{t-1}. $N = |C_T| + |W|$ is the validation dataset's total sample count. The AET metric characterizes a perfect world in which accurate predictions are consistently inferred with the fewest number of time steps necessary, all the while maintaining the initial accuracy. Because it is typically impossible to ascertain whether a sample cannot be accurately classified before to inference, it is important to note that wrong samples are inferred using the greatest amount of time steps. The proposed approach can be used to predict RIASEC scales based on the user profile. The training set is large enough to accomplish this, and a small amount of fine-tuning data should be enough to improve the model's performance to the necessary degree. Features that are absent from the social network of interest is removed on the dataset, and the final step is to train the model using the generated subset of features. To ascertain the input sample confidence score's difficulty, the proxy signal. Let the network prediction probability distribution be expressed formally as $p = soft\max(f_t(x)) = [p_1, p_2, ..., p_M]$, where M is the confidence score divided by the number of objective classes (CS) is defined as

$$CS = \max(p) \tag{12}$$

Which indicates the highest likelihood of, p. The, CS is a signal used to quantify uncertainty. Should the, CS if sufficiently high (e.g., $CS = 0.99$), If not, the prediction distribution quite predictable (e.g., $CS = \frac{1}{M}$), the distribution of predictions is uniform and highly unpredictable.

In formal terms, think of an input sample x as well as a policy network f_p using parameter θ, characterize the time step candidate selection policy as an n -dim distribution in categories:

$$v = soft\max\left(f_p\left(x;\theta\right)\right), \pi_\theta\left(z|x\right) = \prod_{K=1}^{n} v_K^{z_K} \tag{13}$$

Where, v is the categorical distribution probability, which is derived by using a softmax function to estimate the policy network. Thus v_k symbolizes the likelihood of selecting t_k as the SNN's total number of time steps. An action $z \in \{0,1\}^n$ is taken into account when sampling v. Here, z is a one-hot vector because it is only possible to choose one time step. Observe that the architecture of the policy network is sufficiently compact that, in comparison to SNN, the cost of policy inference is minimal. The model being offered may be helpful since it enables the counselor to use the client's sociodemographic characteristics in addition to her answers on the RIASEC or other vocational test. Calculating Gradients in the Policy Network Our goal in training the policy network is to optimize the expected reward function in order to achieve this. Finally, SEENN predicted vocational personality type. In this research, HOA is assigned to enhance SEENN. Here, HOA is assigned for turning weight parameter of SEENN.

E. Horse herd optimization algorithm (HOA)

In this section, Optimization using HOA [25] is utilized to enhance weights parameters (v) of SEENN. Sociability (S), Hierarchy (H), and Grazing (G) are the three main behaviors for HOA. This approach was inspired by 6 common behaviors of horses that have been discussed.

Step 1: Initialization

Initialization, the random vectors produce the input parameters at random. It expressed in equation.

$$K = \begin{bmatrix} u_1 \\ u_i \\ u_N \end{bmatrix}_{N\times m} = \begin{bmatrix} u_{1,1} & u_{1,j} & u_{1,m} \\ u_{i,1} & u_{i,j} & u_{i,m} \\ u_{N,1} & u_{N,j} & u_{N,m} \end{bmatrix}_{N\times m} \tag{14}$$

Let k specifies walruses' populace, u_i specifies i th walrus, $u_{i,j}$ implies j th decision variable through i th walrus, N denotes count of walruses, m epitomizes decision variables.

Step 2: Random Generation

After initialization, weight parameters are formed random wise generated.

Step 3: Fitness Function

In order to calculate the fitness value utilizing

$$FitnessFunction = optimize\,(v)$$

Here v is used to increase the accuracy.

Step 4: Grazing (G)

As grazing animals, horses consume a variety of plant and grass foods. They spend 16 to 20hrs a day grazing on a pasture, with little time for rest. Continuous eating is the term for this kind of leisurely munching. It's possible that you have observed the mares grazing in the pasture with their foal. With coefficient g, the HOA algorithm simulates the grazing space surrounding each horse, allowing each horse to graze in a specific area. Horses can graze at any stage of their lives. Grazing's mathematical implementation can be found in

$$\vec{G}_m^{Iter,AGE} = gIter\left(\breve{u} + p\breve{l}\right)\left[X_m^{(Iter-1)}\right] \quad AGE = \alpha, \beta, \delta \tag{15}$$

$$g_m^{Iter,AGE} = g_m^{(Iter-1,AGE)} \times \omega_g \tag{16}$$

Here $\vec{G}_m^{Iter,AGE}$ is parameter for motion of i th horse, it displays the worried horse's grazing propensity. This element lowers linearity in ω_g according to iteration. $\breve{l}$ and $\breve{u}$ are the grazing space's lower and upper boundaries, respectively, and p is an arbitrary value that falls between 0 and 1. It is advised to think about $\breve{l}$ and $\breve{u}$ equivalent to 1.05 and 0.95 in turn, and the coefficient g is the same as 1.5 across all age groups.

Step 5: Hierarchy (H)

Equine freedom does not exist in and of itself. They follow a leader in life, which is a responsibility typically assigned to people. According to the law of hierarchy, an adult stallion or mare is also in charge of providing leadership in herds of wild horses. In this instance, the herd's inclination to follow the strongest and most knowledgeable horse is said to be represented by the coefficient h in HOA. Research has demonstrated that horses in the Middle Ages adhere to the law of hierarchy β and γ (5 and 15 ages).

$$\vec{H}_m^{Iter,AGE} = h_m^{Iter,AGE}\left[X_*^{(Iter-1)} - X_m^{(Iter-1)}\right] AGE = \alpha, \beta \, and \, \gamma \tag{17}$$

$$h_m^{Iter,AGE} = h_m^{(Iter-1)} - X_m^{(Iter-1),AGE} \times \omega_h \tag{18}$$

Where, $\vec{H}_m^{Iter,AGE}$ epitomizes how the ideal horse location affects the velocity parameter $X_*^{(Iter-1)}$ specifies where the best horse is located.

Step 6: Sociability (S) for Optimizing

Horses requisite to interact with other people and animals on occasion. Since the horses are being pursued by predators, their safety has been ensured by herd life. Pluralism facilitates escape and raises the possibility of survival. Horses can be observed fighting a lot because of their social nature, which irritates people because of their individuality. While most horses dislike being alone, some of them appear content when they are with sheep and cattle. This action, which is exhibited by factor, is thought to be a move towards the typical positioning of other horses. The horses amongst the ages of five and fifteen are drawn to the herd represented by the following equation:

$$\vec{S}_m^{Iter,AGE} = s_m^{Iter\ AGE}\left[\left(\frac{1}{N}\sum_{j=1}^{N} X_j^{(Iter-1)}\right) - X_m^{(Iter-1)}\right], AGE = \beta, \gamma \tag{19}$$

$$\vec{s}_m^{Iter,AGE} = s_m^{(Iter-1),AGE} \times v \tag{20}$$

$\vec{S}_m^{iter,AGE}$, displays the social mobility vector of i th horse, $S_m^{iter,AGE}$ represents how the worried horse is oriented with relation to the herd in $Iter^{th}$ iteration. $S_m^{iter,AGE}$, declines with an each cycle ω_s factor. N, further displays the total horses, AGE specifies range of ages for any horse. The s coefficient for β, γ in the parameter sensitivity analysis, horses are computed.

Step 7: Termination Criteria

Verify the termination criteria; if the best result is achieved, the process is over; if not, moved on to step 3. Fig.2 illustrates the flowchart of Horse herd optimization algorithm for Optimizing SEENN Weight Parameter. Then finally, CKMV-TEP-ASAS-SEENN classified the vocational personality type with high accuracy.

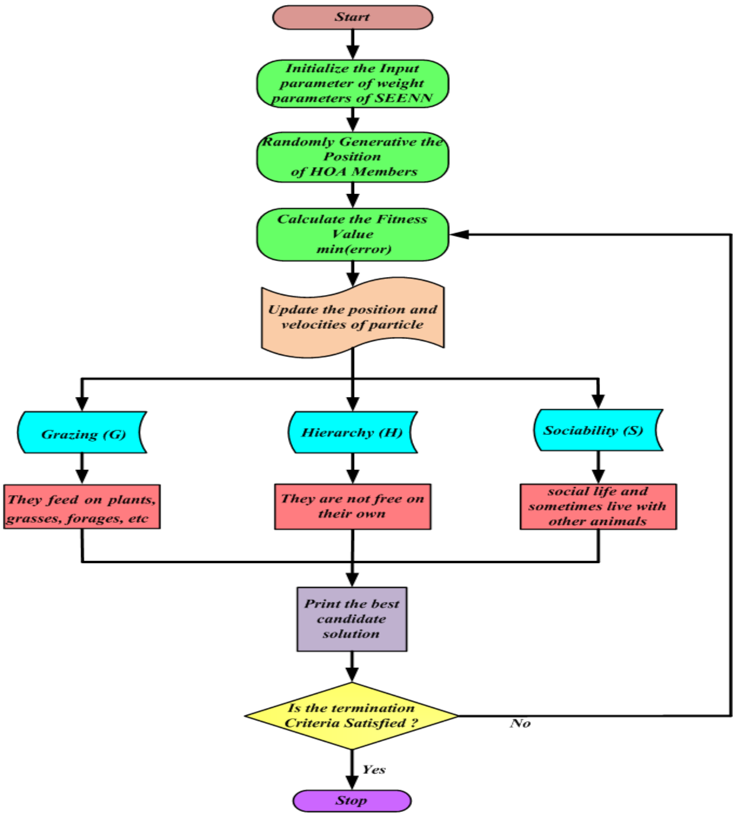

Fig 2: Flowchart of Horse herd optimization algorithm for Optimizing SEENN Weight Parameter

III. RESULT AND DISCUSSION

The outcomes of the CKMV-TEP-ASAS-SEENN method are discussed here. The CKMV-TEP-ASAS-SEENN method is then simulated in Python using performance metrics. The results of the proposed CKMV-TEP-ASAS-SEENN are compared to the existing RAC-TCT-HVE-RNN [11], TTE-VES-CNN [12] and ABPNN-TQE-HVE-BPNN [13].

A. Performance measures

Selecting the ideal classifier is a pivotal phase. Performance evaluation involves examining metrics such as accuracy, computation time, error rate, F1-score, precision, recall, ROC curve, sensitivity, and specificity. The decision has been made to employ the confusion matrix as a benchmark for scaling these performance indicators.

1) Accuracy

This is calculated by eqn (21),

$$accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{21}$$

TP signifies true positive, TN refers true negative, FP refers false positive, FN implies false negative.

2) Error Rate

This is determined by eqn (22),

$$Error\ Rate = 100 - Accuracy \tag{22}$$

3) F1-Score

F-score is determined through eqn (23),

$$F - score = \frac{TP}{TN + \frac{1}{2}[FN + FP]} \quad (23)$$

4) Precision (P)

It measures an amount of proper positive prediction using eqn (24),

$$\Pr ecision = \frac{TP}{(TP + FP)} \quad (24)$$

5) Receiver Operating Characteristic Curve (ROC)

ROC provides an overall performance indicator for the whole probable Classification. ROC is expressed in equation (25)

$$ROC = 0.5 \times \left(\frac{T_p}{T_P + F_N} + \frac{T_N}{T_N + F_P} \right) \quad (25)$$

6) Sensitivity

Sensitivity is calculated using the following equation (26)

$$Sensitivity = \frac{T_P}{T_P + F_N} \quad (26)$$

7) Specificity

The rate of true negatives that the model properly recognizes using eqn (27),

$$Specificity = \frac{TN}{TN + FP} \quad (27)$$

Accuracy, Computation time, Error rate, F1-score, precision, recall, Sensitivity specificity

B. Performance Analysis

The simulation outcomes for the suggested CKMV-TEP-ASAS-SEENN method are depicted in Figures 3 to 10. This method is associated sequentially with the RAC-TCT-HVE-RNN, TTE-VES-CNN, and ABPNN-TQE-HVE-BPNN techniques.

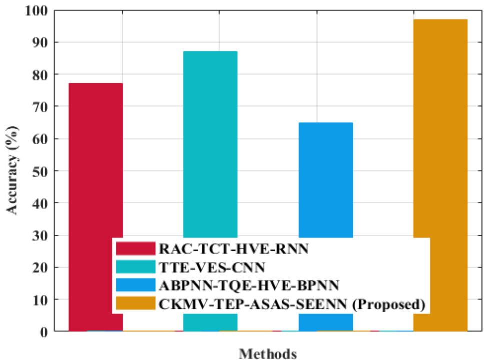

Fig.3. Accuracy analysis

Figure 3 presents the accuracy analysis. The accuracy of the CKMV-TEP-ASAS-SEENN method is 24.5%. In comparison, the accuracies of the existing methods RAC-TCT-HVE-RNN, TTE-VES-CNN, and ABPNN-TQE-HVE-BPNN are 23.5%, 22.5% and 24%, respectively. Thus, the CKMV-TEP-ASAS-SEENN method demonstrates superior accuracy relative to the existing methods.

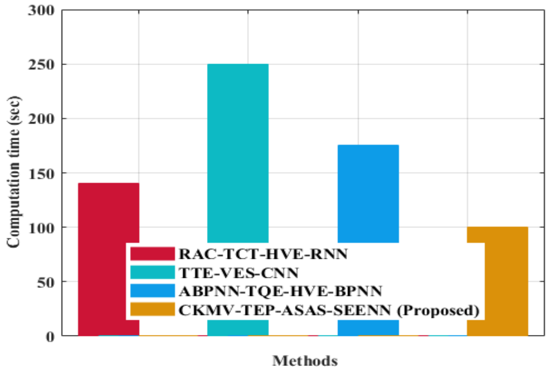

Fig 4: Computation time analysis

Figure 4 shows computation time analysis. The CKMV-TEP-ASAS-SEENN method proposed here demonstrates a computation time of 14.5sec. In comparison, existing methods like RAC-TCT-HVE-RNN, TTE-VES-CNN, and ABPNN-TQE-HVE-BPNN require 17.3sec, 20.4sec, and 18.6sec respectively. Notably, the proposed CKMV-TEP-ASAS-SEENN method exhibits a lower computation time evaluated to the existing models.

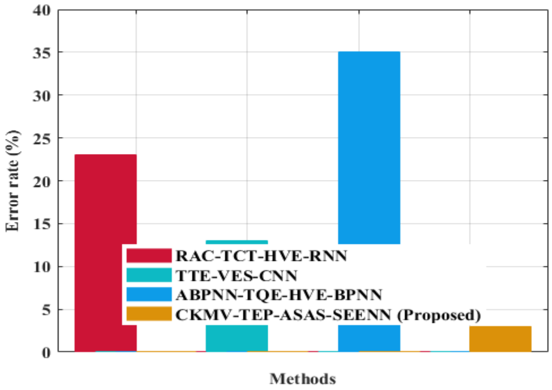

Fig 5: Error Rate analysis

Fig 5 depicts error rate analysis. The CKMV-TEP-ASAS-SEENN method proposed here demonstrates an error rate of 4.5%. In contrast, existing methods like RAC-TCT-HVE-RNN, TTE-VES-CNN, and ABPNN-TQE-HVE-BPNN exhibit error rates of 18.9%, 14.5%, and 19.5% respectively. It's noteworthy that the proposed CKMV-TEP-ASAS-SEENN method shows a lesser error rate analyzed with other models.

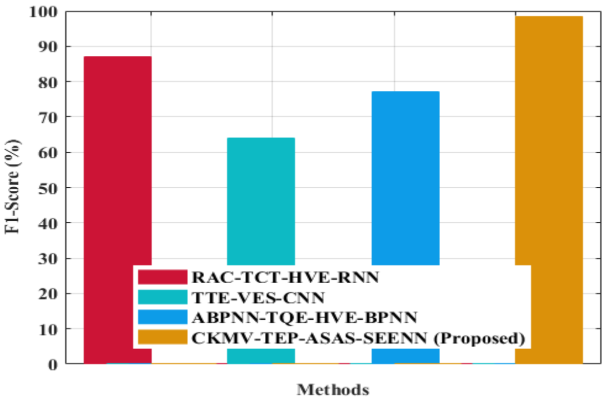

Fig 6: F1-Score evaluation

Figure 6 displays F1-Score evaluation. The CKMV-TEP-ASAS-SEENN method proposed here achieves an F1-Score of 24.5%. In contrast, existing methods like RAC-TCT-HVE-RNN, TTE-VES-CNN, and ABPNN-TQE-HVE-BPNN yield F1-Scores of 21.4%, 17.6%, and 18.5% respectively. Remarkably, the proposed CKMV-TEP-ASAS-SEENN method demonstrates a greater F1-Score compared with other models.

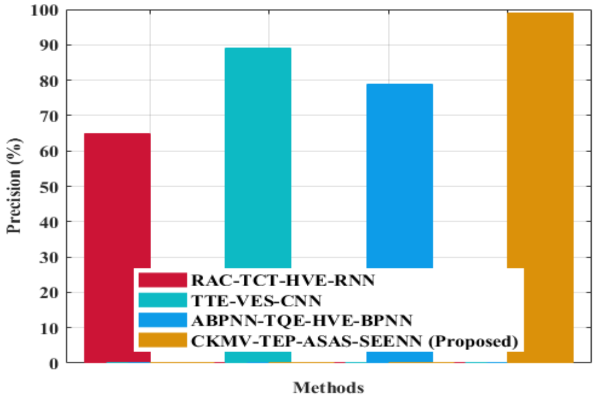

Fig 7: Precision examination

Fig 7 presents precision analysis. The CKMV-TEP-ASAS-SEENN method proposed here achieves a precision of 24.7%. In contrast, existing methods like RAC-TCT-HVE-RNN, TTE-VES-CNN, and ABPNN-TQE-HVE-BPNN attain precisions of 24.06%, 23.33% and 22.98% respectively. Notably, the proposed CKMV-TEP-ASAS-SEENN method demonstrates higher precision compared to the existing methods.

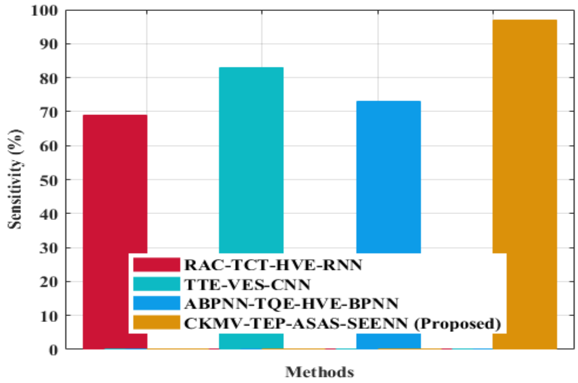

Fig 8: Sensitivity assessment

Figure 8 displays sensitivity analysis. The CKMV-TEP-ASAS-SEENN method proposed here achieves a sensitivity of 24.1%. In contrast, existing methods like RAC-TCT-HVE-RNN, TTE-VES-CNN, and ABPNN-TQE-HVE-BPNN attain sensitivities of 24.12%, 22.33% and 23.98% respectively. Notably, the proposed CKMV-TEP-ASAS-SEENN method demonstrates higher sensitivity compared with existing models.

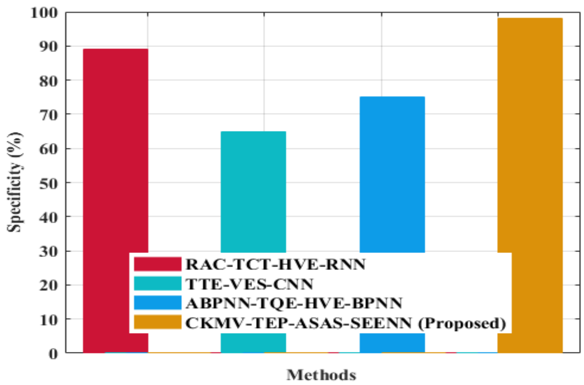

Fig 9: Specificity examination

Figure 9 illustrates specificity analysis. The CKMV-TEP-ASAS-SEENN method proposed here achieves a specificity of 24.4%. In contrast, existing methods like RAC-TCT-HVE-RNN, TTE-VES-CNN, and ABPNN-TQE-HVE-BPNN attain specificities of 23.5%, 18.5%, and 19.4% respectively. Notably, the proposed CKMV-TEP-ASAS-SEENN method demonstrates higher specificity compared to the existing methods.

C. Discussion

The suggested document offers a thorough method for creating knowledge maps that are specific to technical and vocational education programs, emphasizing improving academic assessments and student learning experiences. The proposed CKMV-TEP-ASAS-SEENN method aims to improve accuracy and efficiency in academic assessment by integrating multiple techniques, including Spiking Early-Exit Neural Networks (SEENN) for vocational personality type prediction, Signed Cumulative Distribution Transform (SCDT) for feature extraction, and Invariant Collaborative Filtering (ICF) for data cleaning. The importance of vocational and technical education in preparing students for practical and specialized employment could be a major topic of discussion. Since vocational education frequently places a strong emphasis on practical experience and specialized knowledge pertinent to particular sectors, it is critical to appropriately evaluate students' aptitude and preparedness for these fields. Personalized learning experiences and career coaching can be facilitated by instructors by utilizing tools such as knowledge mapping and machine learning algorithms, which provide deeper insights into students' strengths, limitations, and occupational inclinations. In this results section, the existing methods such as RAC-TCT-HVE-RNN, TTE-VES-CNN, and ABPNN-TQE-HVE-BPNN notable improvements, with higher accuracy rates of 23.5%, 22.5%, and 24%, respectively. Precision rates of 24.06%, 23.33%, and 22.98% are observed, along with sensitivity percentages of 24.12%, 22.33%, and 23.98%, respectively.

IV. CONCLUSION

In this manuscript, Construction of Knowledge Mapping for Vocational and Technical Education Programs and Its Application in Students' Academic Assessment using HOA-SEENN (CKMV-TEP-ASAS-SEENN) was successfully implemented. The proposed CKMV-TEP-ASAS-HOA-SEENN approach is implemented in Python. Initially, data are collected from Holland Code (RIASEC) Test Responses data set. Spiking Early-Exit Neural Networks (SEENN) is proposed to predict vocational personality type. This work attains greater output of Knowledge Mapping Vocational and Technical Education Programs. The performance of the proposed CKMV-TEP-ASAS-HOA-SEENN method attains 23.5%, 22.5% and 24% higher accuracy, 24.06%, 23.33% and 22.98% higher Precision, 24.12%, 22.33% and 23.98% higher sensitivity, when analyzed to the existing methods like RAC-TCT-HVE-RNN, TTE-VES-CNN and ABPNN-TQE-HVE-BPNN methods respectively.

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