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Job and Career Recommendation System using Dynamically Stabilized Recurrent Neural Network Optimized with Secretary Bird Optimization Algorithm

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Abstract- The pressure to find employment for college graduates is growing as a result of the ongoing expansion of college and university enrolment scales. This emphasizes the inadequacies in college students' employability, which can be strengthened and improved by political also ideological education's function. In this manuscript, Job and Career Recommendation system using Dynamically Stabilized Recurrent Neural Network Optimized with Secretary Bird Optimization Algorithm (JCRS-DSRNN-SBOA) is projected. The input information is collected via Real time information set. The pre-processing segment then receives the information. In pre- processing segment, it removes unwanted information also replaces the missing values using Strong Tracking Variational Bayesian Adaptive Kalman Filter (STVBAKF). A preprocessed data is given to Synchro-Transient-Extracting Transform (STET) in order to extract the attributes of enterprise description and pupil conduct. Then extracted attributes are fed into Dynamically Stabilized Recurrent Neural Network (DSRNN) for job and career recommendation. Generally speaking, DSRNN does not disclose the application of optimization techniques to ascertain the ideal parameters for ensuring an accurate career and job recommendation system. Hence, Secretary Bird Optimization Algorithm (SBOA) is suggested here to optimize DSRNN, which precisely construct the job and career recommendation system. The proposed JCRS-DSRNN-SBOA method is implemented and the performance measures like Accuracy, Precision and Root Mean Square Error (RMSE) are evaluated. Proposed JCRS-DSRNN-SBOA method attains 21.19%, 23.82% and 21.98% higher accuracy, 23.54%, 22.65% and 23.18% higher precision are analyzed with existing techniques like Employment Management for College Students based on Deep Learning and Big Data (EMCS-DL-BD), C3-IoC: A career guidance system for assessing student skills using machine learning and network visualization (CGS-ASS-ML), and Enhanced Deep Semantic Structure Modelling method for job recommendation (EDSSM-JR) respectively.

Keywords- Dynamically Stabilized Recurrent Neural Network, job and career recommendation, Secretary Bird Optimization Algorithm, Strong Tracking Variational Bayesian Adaptive Kalman Filter and Synchro-Transient-Extracting Transform

I. INTRODUCTION

The number of recent college and university graduates nationwide has only gone up in recent year [1]. Furthermore, the number of graduates who have never held a job has increased, and competition for jobs is getting fiercer [2]. College students' work circumstances are generally getting worse [3]. It is certain that the employment pressure on recent graduates will continue to be significant for a considerable amount of time to come [4]. College students who get ideological and political education may develop healthy world views, perspectives on life, and moral principles [5]. It enables college students to develop a correct understanding of employment and to comprehend their employment condition accurately [6]. It assists students in developing a complete and objective understanding of them, boosting their self-assurance in the workplace, and consistently enhancing their employability [7, 8]. The system matches users with roles that match their qualifications and interests by analyzing massive databases of job listings, industry trends and labor market demands [9]. The recommendation process begins with users entering their personal information and preferences, which the system uses to generate personalized job offers [10]. Deep learning capabilities enable the system to tailor recommendations based on user behavior and preferences [11]. Recommendation algorithms must be used in order to obtain accurate employment in order to increase the employment rate and lessen the pressure on recent graduates to find work [12]. A work landscape and circumstances for college students have grown more complex as higher education has become more popular, which makes it more difficult for them to be employed in a logical and scientific manner in the future [13]. Colleges and universities should, in this regard, improve student employment management, give student employment management a full role, improve student employment guidance so that students are aware of the course of their subsequent growth, and encourage effective student employment [14]. This means that in order to raise the standard of college applicants and, consequently, the standard of college personnel education and the understanding of relevance of college students' management of employment in real-world settings, attention must be paid to both the development and innovation of jobs held by college student's supervision in context of higher education[15].

Some recommendation algorithms are developed to attain precise employment so as to raise employment percentage as well as lessen the pressure on graduates to find work. Since deep learning (DL) has advanced, some research has used DL to make recommendations, but it occur lack of problems such as low Accuracy and high RMSE. In order to address the problems, some solutions must be proposed. However, the task is not completed with high accuracy and precision using the current technique. The shortcomings of the current methods inspired this work.

In this study, a DSRNN recommendation model is used to efficiently connect and analyze correlations between student information and enterprise data, allowing for joint training of both datasets to improve employment and satisfaction rates in colleges and universities. This research provides a solid and reliable theoretical foundation for future discussions on graduate service processes, as well as approaches to ideological and political education. It is anticipated that the study will help alleviate the employment pressures faced by recent college graduates.

The major Contribution of this work includes;

- In this research work, JCRS-DSRNN-SBOA is projected.
- Firstly, the real time data is collected. Then, it is pre-processed using STVBAKF.
- Afterwards, feature extraction is done by STET. Later, Job and Career recommendation using DSRNN.
- DSRNN optimized with SBOA.
- The suggested method is analysed with existing method like EMCS-DL-BD, CGS-ASS- ML and EDSSM-JR respectively.

Remaining manuscripts arranged as below: section 2 describes literature review; section 3 depicts suggested method, section 4 exhibits outcomes with discussions, section 5 conclusion.

II. LITERATURE SURVEY

Several research works were recommended in literature associated DL based Job and Career Recommendation system; few current works reviewed here,

In 2023, Shi[16] have presented EMCS-DL-BD. To shed light on the connection among ideological also political education alsoservice management of college scholars, the second section highlights the reasons there is a deficiency in this area when it comes to developing employability among students. In order to enhance the correlation between student also business information is successfully linked using the DL recommendation model, which also examines the employment rate also employment satisfaction of colleges and universities. It provides high accuracy also it attains low precision.

In 2023, José-García, et.al, [17] have presented a C3-IoC: A career guidance system for assessing student skills utilizing machine learning (ML) also network visualization. In this work, we offer a solution powered by AI designed to assist students in exploring IT career choices based on their educational background, skill set, and prior experience. With the aid of a distinct knowledge base, profiling of user skills, job role matching, also visualization modules, C3-IoC assists pupils in assessing their own abilities also comprehending their relevance to the latest IT positions. It attains high precision and it provides high RMSE.

In 2022, Mishraand Rathi[18] have presented an Enhanced DSSM,methodfor a job referral. The efficacy of the DSSM system is enhanced by representing skill entities and job descriptions in the format of a character trigram, which is achieved through the semantic representation of sparse data. When compared to various embedding model variants, experimental outcomes indicate that DSSM Embedding methodalso its other versions offer promising outcomes in overcoming cold start problems. It provides low RMSE and it attains low accuracy.

In 2022, Parida, et.al, [19] have provided a prediction of suggested employment usingML procedures and geo-area based recommender structure. In addition, a brief introduction to the recommender system and its various categories are covered in this paper. Data is cleansed right from the beginning by removing unnecessary data and duplicates. It makes use of many ML techniques, and the findings indicate that, when compared to other techniques, the Random

Forest Classifier (RFC) provides the greatest notable expectation accuracy. It offers high precision and it attains low accuracy.

In 2022, Liuand Ge[20] have presented a Job and employee embeddings: A joint DL method. It creates a distinct neural network method for employee embeddingsalso jobs in this paper. Three parts make up the suggested method for modelling career data at three different granularities. A shallow neural network is constructed to collect contextual data from job sequences, an RNN encoder-decoder designs is designed to learn representations of employees' career pathways, and a transformer model is optimized to become knowledgeable about semantics of large amounts of text found in job materials. The created approach's superiority is demonstrated by the experimental outcomes using real-world information sets. It attains high accuracy and it provides low RMSE.

In 2023, Li, et.al, [21] have offereda customized endorsement structurefounded on MOOC system integrating DLalso big information. In this work, explore a personalized reference system founded on the Massive Open Online Course (MOOC) system by integrating DLalso big information technologies. Itstarts by outlining the open dataset's acquisition and preprocessing. Lastly, develop a domain feature variance learning technique to enhance the reference performance of model and extract deep feature dataamong course texts. It attains low RMSE and it attains low precision

III. PROPOSED METHOD

In this section, JCRS-DSRNN-SBOA is proposed. This process contains five steps: Information Acquisition, Pre-processing, Feature extraction, organizationalso optimization. In the proposed job and career recommendation undergo pre-processing to prepare them for further analysis. After preprocessing, the information is extracted to obtain the enterprise description attributes and the attributes related to student behavior. These features are then organized into a feature vector. The final step involves employing a DSRNN for Job and Career Recommendation, with the feature vector serving as input. The SBOA method is introduced for optimizing the DSRNN. The block diagram of proposed JCRS-DSRNN-SBOA technique is represented in Fig 1. Accordingly, detailed description of all step given as below,

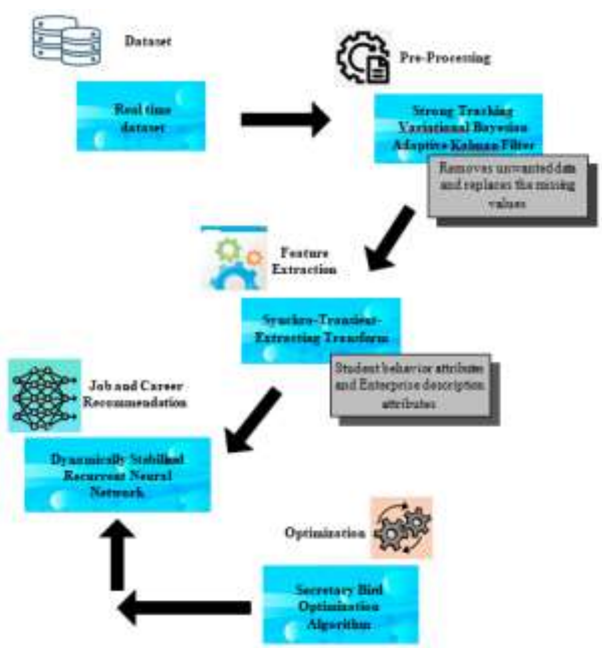

Figure 1: Block Diagram for Proposed JCRS-DSRNN-SBOA Method

1. Dataset

The input information is collected via Real time information set. The initial information set includes information on the pursuits that the graduates made time for over 4 years of education as well as information on their places of employment. It includes the following details: the student's basic information, marks, totalmarks, rankings among all classes, grade test results, time, information about intramural activities, information about competitions, information about student positions on campus, information about student awards, information about the company where the student works, where the file receipt is located, and details about the type of employment.

2. Pre-processing using Strong Tracking Variational Bayesian Adaptive Kalman Filter

STVBAKF[22] for removing unwanted data and replaces the missing values. Based on the changing dynamics of the system, STVBAKF modifies its parameters. Better tracking performance is made possible by this adaptability, particularly in situations when the system's behaviour varies over time or in non-linear systems. Because of its adaptability, it can be used to solve a variety of real-world issues in industries including processing, robotics, and banking.STVBAKF based on various fading variables as given in equation (1)

$$\hat{w}_{l|l-1} = \rho\left(\hat{w}_{l-1|l-1} - D - 1\right) + D + 1 \quad (1)$$

Where, ˙ represent the covariance matrix, D denotes the dynamic system, $\hat{W}_{l|l-1}$ inear matrix. In order to identify and eliminate outliers from the data, the filter must be able to swiftly and precisely track abrupt changes or transients in the data. This is made possible by the robust tracking function. Then the Linear matrix of the data is given in equation (2)

$$\hat{W}_{l|l-1} = \rho\hat{W}_{l-1|l-1} \quad (2)$$

Where, $\hat{W}_{l|l-1}$ represent linear matrix. By utilizing the underlying temporal and probabilistic structure of the data, STVBAKF can efficiently forecast and replace missing values, resulting in more accurate and contextually relevant imputations. The data frequency is calculated as given in equation (3)

$$\tilde{z} = Tr[M_l] \Big/ \sum_{i=1}^{D} \mu_i N_l^{ii} \quad (3)$$

Where, T_r represents missing value matrix's trace; μ_i implies weight of unwanted fading factor; M_l represents to suppress the data and N_l^{ii} represents the linear parameter.

Finally By using STVBAKF removed unwanted data and replaced the missing values from the collected data. Then, the preprocessed data is given to feature extraction phase.

3. Feature Extraction using Synchro-Transient-Extracting Transform

In this section, STET[23] is used for extracting the characteristics of the enterprise description and behavior of students. The improved time-frequency resolution provided by STETs makes it possible to precisely identify and characterize transitory components in signals. Because of this, it is very useful in applications where transitory analysis is crucial, including biological feature analysis. ThenSTET is given in equation (4)

$$\hat{\mu}^{[2]}(s,\mu) = c + ds \quad (4)$$

Here, $\hat{\mu}$ indicates centre frequency of the features; (s,μ) is denotes the partial derivative of the data and c + ds is denotes the accurately locate the employment rate. The properties of students and businesses in the employment recommendation scenario include numerous distinct features, like college and place of origin. One-heat vectors are typically used to encode these properties. Thus, student behavior attributes are given in equation (5)

$$\hat{s}^{[2]}(s,\mu) = \frac{\delta_\mu \hat{s}(s,\mu)}{\delta_\mu \hat{\mu}(s,\mu)}\left(\mu - \hat{\mu}(s,\mu)\right) + \hat{s}(s,\mu) \quad (5)$$

Here, $s^{\wedge[2]}$ (s,μ) is denotes the improved the signal extraction; In the fundamental qualities of the pupil module, embedding for the student's basic attributes is created by stacking the vectors that continuous features include separate characteristics. The attributes of enterprise description are provided in equation (6)

$$|d| = \varphi^{-2/3} \quad (6)$$

Here, $|d|$ is denotes the chirp rate of the data extraction and $\varphi^{-2/3}$ is denotes the imaginary function. Organizations may make better judgements and take more calculated strategic action by putting STET into practice. Then, by using STET student behavior attributes and enterprise description attributes are extracted. The extracted features are fed to recommendation system.

4. Recommendation using Dynamically Stabilized Recurrent Neural Network

In this section, DSRNN[24] is debated for job and career recommendation. By eliminating problems like vanishing and exploding gradients that are typical in conventional RNNs, DSRNNs are made to handle long-term dependencies in sequential data better. The DSRNN is given in equation (7)

$$g_t = \sum_{i=1}^{k} \{\alpha_i g_{t-i}\} + \varphi_g(g_{t-1}, w_t) \quad (7)$$

Where, g_t is a hidden state of the network, k denotes as a parameter, α_i is a diagonal matrix, $(\varphi_g(.))$ is an activation function and w_t is the input. DSRNNs can simulate the fluid character of career progression also individual tastes over time by utilizing the advantages of RNNs in processing sequential data. Then, it is given in equation (8)

$$p_{t+1} = \nabla_p e(p_t, w_t)\Big|_{\substack{pt=p^f \\ w_t=w^f}} p_t + \nabla_w e(p_t, w_t)\Big|_{\substack{p_t=p^f \\ w_t=w^f}} w_t + h.o.t. \tag{8}$$

Where, p_t denotes as state, p^f is the equilibrium pair, e (.) is the neighbourhood of the equilibrium pair and h.o.t are the actual nonlinear system's higher-level terms, ∇_p denotes the accurate recommendation system. To maximize recommendation accuracy and relevance, combine ranking loss functions with categorical cross-entropy. Divide the data into test, validation, and training sets. Make use of methods like k-fold cross-validation to guarantee resilience.Thus, the DSRNN is recommending job by calculating the equation (9)

$$\frac{\partial \varepsilon_t}{\partial g_{t-0}} = \frac{\partial \varepsilon_t}{\partial g_t}\left(\Delta g_1^0 + \Delta g_2^0\right) \tag{9}$$

Where, Δg_1^0 is the tree's edge indicating the corresponding partial derivatives and $\frac{\partial \varepsilon_t}{\partial g_t}$ is the mistake can be tracked back via a number of branches until it will reach. Utilizing the sequential and dynamic nature of user interactions and career pathways, a DSRNN for job and career advice is possible. The DSRNN is recommending the career by calculating the equation (10)

$$\binom{i+j}{i}\left(\frac{\partial g_t}{\partial g_{t-1}}\right)^i \cdot \left(\frac{\partial g_t}{\partial g_{t-2}}\right) \tag{10}$$

Where, the origin of $\left(\frac{\partial \varepsilon_t}{\partial g_{t-6}}\right)$ for a parameter-based DSRNN $(k=2)$;This method raises user t•6 • pleasure and engagement on job sites while also increasing proposed accuracy. Finally, DSRNN model recommended job and career. Due to its convenience, pertinence, AI-depend Optimization approach is taken into account in DSRNN classifier. Here SBOAis employed to optimize the DSRNN. Here, SBOA is employed for tuning weight, bias variable of DSRNN.

5. Optimization using Secretary Bird Optimization Algorithm

A proposed SBOA [25] is utilized to enhance weights parameters g_t and α_i of proposed DSRNN. The parameter g_t is implemented for increasing the accuracy and α_i reducing the RMSE. The Secretary Bird is a remarkable African raptor that stands out for both its unusual habits and looks. Here, step by step procedure for obtaining appropriate DSRNNvalues using SBOA is described. To creates a uniformly distributed population for optimizing the ideal DSRNNparameters. The entire step method is then presented in below,

Step 1: Initialization

Initial population of SBOA is initially generated by randomness. Then the initialization is derived in equation (11).

$$Z = \begin{bmatrix} z_{1,1} & z_{1,2} & \cdots & z_{1,j} & \cdots & z_{1,\dim} \\ z_{2,1} & z_{2,2} & \cdots & z_{2,j} & \cdots & z_{2,\dim} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ z_{i,1} & z_{i,2} & \cdots & z_{i,j} & \cdots & z_{i,\dim} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ z_{n,1} & z_{n,2} & \cdots & z_{n,j} & \cdots & z_{n,\dim} \end{bmatrix}_{n\times d} \tag{11}$$

Where, Z indicates the group of secretary bird; z_i indicates the i^{th} secretary bird; $z_{i,j}$ indicate the i^{th} secretary bird and j th value of variable; n indicates the n^{th} group members of the secretary bird also dim indicates the issue with changing dimensions.

Step 2: Random generation

The input weight parameter gt and •i developed randomness via SBOA method.

Step 3: Fitness function

It makes random solution via initialized values. It is calculated by optimizing parameter. Then the formula is derived in equation (12)

$$\text{Fitness Function} \cdot \text{optimizing } [g_t \text{ and } \alpha_i] \quad (12)$$

Where, gt is implemented for increasing the accuracy and •i is used to reducing the RMSE.

Step 4: Hunting strategy of secretary bird for Optimizing gt Secretary birds usually start their hunting season by looking for possible prey, particularly snakes. Because of their exceptionally keen vision, secretary birds can detect snakes concealed in the savannah's dense grass with ease. With their lengthy legs, they carefully scan the ground, keeping an eye on their surroundings and looking for any indications of snakes. They can stay quite secure away from snakes thanks to their lengthy necks and legs. This comes up during the early stages of optimization, when investigation is quite important using equation (13).

$$A_i = \begin{cases} A_i^{New\,S1}, \text{ if } G_i^{New,S1} \\ \dfrac{A_i}{g_t}, \quad else \end{cases} \quad (13)$$

Where, A_i; $A_i^{New\,S1}$ symbolizes the initial stage of the new condition of the i[th] secretary bird also $G_i^{New,S1}$ indicates objective function's fitness value.

Step 5: Escape Strategy of Secretary Bird for Optimizing α_i

Large predators like eagles, hawks, foxes, and jackals are the natural enemies of secretary birds because they can attack them or take their food. Secretary birds usually use a variety of evasion techniques to defend themselves or their food when faced with these hazards. These tactics can be divided roughly into two primary groups. The first tactic is either quick running or fighting.

Because of their incredibly long legs, secretary birds are able to run at very high speeds using equation (14).

$$A_{i,j}^{New,S2} = \begin{cases} Z_1 : a_{best} + (2 \times RandY - 1) \times \left(1 - \dfrac{T}{t}\right)^2 \times a_{i,j}, \text{ if } R \text{ and} < R_i \\ Z_2 : a_{i,j} + Rand_2 \times \left(a_{Random} - L \times \dfrac{a_{i,j}}{\alpha_i}\right), else \end{cases} \quad (14)$$

Where, $A_{i,j}^{New,S2}$ symbolizes the initial stage of new condition of i[th] secretary bird; $Z_1$and Z_2 indicates an environment also fly or run away; a_{best}; ; $Rand_2$ indicates the array of dimension 1•dim is randomly generated via normal distribution; a_{Ramdom} symbolizes the current iteration's random candidate solution; L denotes picking of an integer at random 1 or 2 the total number of iteration. and T and t indicate

Step 6: Termination

The generator's weight value for parameters g_t and $\alpha_i$from DSRNN is optimized by utilizing SBOA; and it will recurrence step 3 until it obtains its hesitant criteria Z=Z+1. Then JCRS- DSRNN-SBOA accurately recommended job and career by higher accuracy, lessening RMSE.

IV. RESULT & DISCUSSION

Investigational result of suggestedtechnique is discoursed. AsuggestedJCRS-DSRNN-SBOA method is executed in Python.

The performance of JCRS-DSRNN-SBOA method is evaluated under some metrics. Obtained outcomes of proposed method are analyzed with existing techniques likes EMCS-DL-BD [16], CGS-ASS-ML [17] and EDSSM-JR [18] respectively.

1. Performance Measures

Performance of proposed method is examined utilizing Accuracy, Precision and Root Mean performance metrics.

Accuracy

Accuracy describes detection rate that are correctly analyze the recommendation system. The formula is derived in eqn (15).

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \quad (15)$$

Here, TP signifies True Positive; TN denotes True Negative; FP indicates False Positive also FN meansFN.

Precision

Predicting total among all the positives in the dataset, positive illness classifications are the primary function of precision as shown in equation (16).

$$\Pr ecision = \frac{TP}{TP+FP} \quad (16)$$

Root Mean Square Error

An MSE variation is RMSE. It is square root of MSE and indicates average size of prediction errors. RMSE is commonly selected because it is easier to read when it is in the same units as the target variable. The RMSE is given in equation (17)

$$RMSE = \sqrt{MSE} \quad (17)$$

Where, RMSE denotes the RMSE, MSE denotes Mean squared error.

2. Performance Analysis

Fig 2-4 defines performance analysis of JCRS-DSRNN-SBOA technique. Then, JCRS-DSRNN-SBOA technique is compared with existing EMCS-DL-BD, CGS-ASS-ML and EDSSM-JR method.

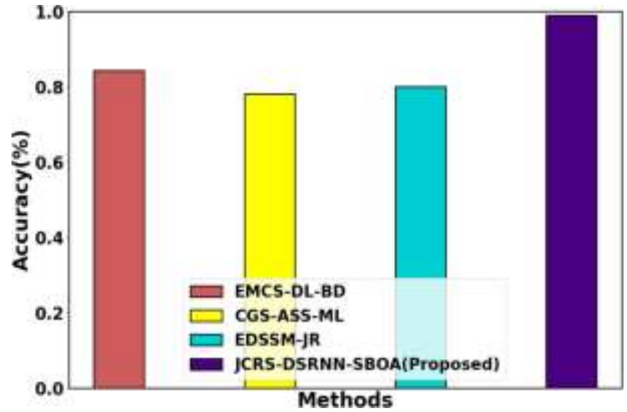

Figure 2: Accuracy Analysis

Fig 2 depicts accuracy analysis. An accuracy graph shows how well a model performs in various contexts or configurations and is frequently used in the context of DSRNN. The many iterations or settings that were employed throughout the model's evaluation are represented by this axis. The accuracy metric being measured is shown on the y-axis. This can be the accuracy percentage. The accuracy that the model achieves for each relevant iteration or setting on the x- axis is represented by the methods on the graph.The JCRS-DSRNN-SBOAattains 21.19%, 23.82% and 21.98% higher accuracy; when evaluated to existing EMCS-DL-BD, CGS-ASS-ML and EDSSM-JR method.

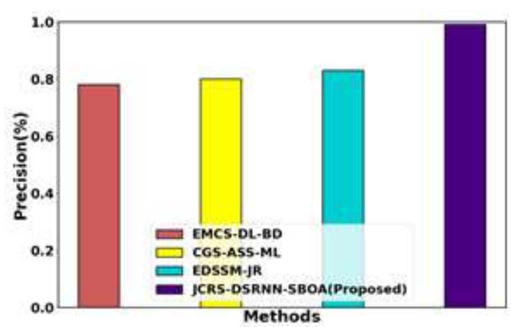

Figure 3: Precision Analysis

Fig 3shows precision analysis. A binary recommended model's performance is visually represented using a precision graph, especially in situations when there is an imbalance among the classes. The recall is usually arranged on x-axis of precision graph. The relation of true positives to the entire of TP's and FP's is used to calculaterecall. The JCRS-DSRNN- SBO Aattains 23.54%, 22.65% and

23.18% higher precision; when evaluated to existing EMCS- DL-BD, CGS-ASS-ML and EDSSM-JR methods.

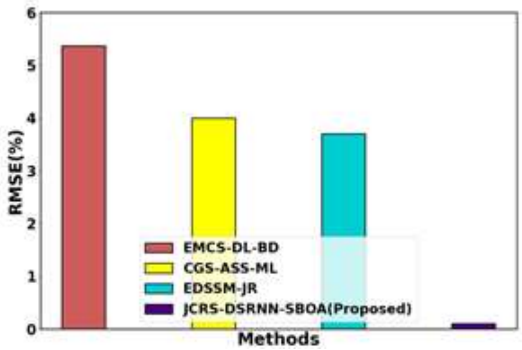

Figure 4: Root Mean Square Error Analysis

Fig4 shows RMSE analysis. Regression method accuracy in predicting the dependent variable from the independent variables is measured by RMSE. As it means smaller prediction errors, lower RMSE is indicative of greater method presentation. RMSE normally drops as training goes on, demonstrating how the model is improving its predictions and learning new abilities. The RMSE may eventually plateau, indicating that additional training has little effect on improving methods performance. AJCRS-DSRNN-SBOAattains 21.43%, 20.89% and 21.32% lower RMSE; when evaluated to existing EMCS-DL-BD, CGS-ASS-ML and EDSSM-JR methods.

V. CONCLUSION

In this section, JCRS-DSRNN-SBOA is successfully implemented. Considering the growing pressure on college students to find employment, research into improving their employability is imperative. This is a long road that will involve planning, investigation, and study over time. Political and ideological education is definitely a useful tool for battle these days. The DSRNN- based algorithm model for job and Career recommendations that is presented here offers some benefits. The performance of JCRS-DSRNN-SBOA method contains 21.43%, 20.89% and 21.32% lower RMSEis analyzed to the existing EMCS-DL-BD, CGS-ASS-ML and EDSSM-JRmethods.

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