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Stochastic Congruence Tuning Optimized Discriminative AI (SCOTO-DAI) Model Skill Based Employability Prediction In Higher Education

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ABSTRACT
Enhancing student usability is key priority for organization of superior education, as it enables early identification of students who may be at risk of unemployment after graduation. By predicting employability outcomes in advance, institutions take timely and effective measures to support these students. This proactive approach allows management to implement targeted training and boosting their chances of securing employment. Incorporating highly developed expertise namely ML, Deep Learning, to further improve the employability prediction. But the accurate employability prediction with minimal error is a major concern, especially when dealing with large or small scale datasets. To improve the accuracy of employability prediction, a novel **S**tochastic **Co**ngruence **T**uning **O**ptimized Discriminative **AI** (SCOTO-DAI) model is developed. The proposed SCOTO-DAI model utilizes Discriminative AI model called deep transfer learning for accurate student employability prediction in the given organization. The discriminative Artificial Intelligence (AI) is an efficient method for classification and prediction based on existing data. It includes different procedure namely data acquisition, pre-processing, feature selection, classification as well as fine tuning. During the data acquisition phase, student information samples are gathered as of relevant database to facilitate accurate prediction of employability. Deep transfer learning is employed by adapting a pre-trained deep learning classification model called Convolutional Neural Learning model for employability prediction. A CNL model comprises several layers. Within the hidden layers, data preprocessing is conducted to handle the missing values and eliminate outliers. Following this, dimensionality of database is reduced through choosing most significant aspects. Finally, classification occurs at the third hidden layer (fully connected layer), where features are analyzed to distinguish the student data samples into Employable and less Employable at output layer. Followed by, Knowledge acquired from the earlier predictions made by the pre-trained method is transmitted to new method, that helps improve the efficiency of feature learning and enhances prediction accuracy. A significant step in this process is fine-tuning; Shuffling Shepherd Optimization algorithm is employed to reduce training and validation errors, thereby boosting the precision of student employability prediction. Experimental evaluation of SCOTO-DAI is carried out with different factors with number of student data.

Keywords: Student Employability Prediction, Discriminative AI, Deep Transfer Learning, Fine-Tuning, Shuffling Shepherd Optimization.

1. INTRODUCTION

Student employability prediction is an important task for educational institutions. Employability reflects student educational performance however includes a range of skills, attributes, and competencies. With the integration of superior information analytics as well as ML methods, student's possible employability prediction process is carried out by analyzing the various academic, behavioral, and demographic factors. This predictive approach enables to identify students risk level. A MFO-Attention-LSTM was developed in [1] to predict in-class result through log information as of route learning. Though the model increases the overall accuracy, the error rate in predicting in-class performance was not examined. An Influence based Graph Auto encoder (IGAE) model was designed in [2] with the aim of graduate employment prediction. The model decreases error but it has high time complexity in employment prediction.

A Deep Learning (DL) was designed in [3] based inductive reasoning framework has been developed to forecast the employability rate of students after their graduation. However, advanced optimization techniques were not applied to achieve better results. A stacking ensemble ML method was developed in [4] to improve student's employability forecast. However, it failed to explore innovative methodologies to refine predictive models. An Optimization of Bagging classifiers were developed in [5] for forecasting usability of students. However, the model did not focus on improving the predictive performance for student employability. SVM was designed [6] for predicting usability of university graduates. But, the different feature selection methods were not investigated. A Large Language Models (LLMs) was introduced in [7] to increase the prediction accuracy. However, did not focus on improving classification performance for student employability prediction by implementing feature selection. A moderated mediation model was developed in [8] for employability prediction of undergraduates. However, it did not effectively enhance overall robustness or improve students' employability.

Data mining techniques were developed in [9] to predict student employability for higher education institutions. However, more accurate prediction of student employability was major challenging issues. A hierarchical relationship measure was employed in [10] for higher education employability prediction. However, robust deep learning technique was not employed to improve employability prediction performance. Ensemble learning techniques were developed in [11] for efficient prediction of student employability. However, the performance of error rate was not reduced. Random Forest model was proposed in [12] for graduate employability prediction. However, lack of incorporating more advanced machine learning techniques to further refine the predictive models. A curriculum framework was designed in [13] graduates' employment prediction. However, it did not improve the prediction accuracy by incorporating other deep learning models. Undergraduates' orientation and their employability confidence level were measured in [14]. However, it failed to boost their employable-related outcomes. Partial least squares structural equation method was designed [15] for predicting self-perceived employability of undergraduate students. However, the system was inefficient to improve the system performance.

1.1 Major Contributions

- To design a novel discriminative AI technique called SCOTO-DAI model for accurate and employability prediction by implementing pre-processing, feature selection and classification.
- A SCOTO-DAI model performs data pre-processing and relevant feature selection to minimize the time consumption of employability prediction.
- To improve accuracy of employability forecast as well as minimize classification error, Tamas correlation is employed to analyze data samples and provide the employable and less employable students. Moreover, the Shuffling Shepherd Optimization is applied for hyper parameter fine-tuning in transfer learning approach to further reduce the error rate and increases the sensitivity and specificity.
- Comparative study of SCOTO-DAI method has been evaluated based on conventional deep learning methods with various performance metrics.

1.2 Organization of Manuscript

Manuscript is organized as follows: Section 2 appraisal pertinent literature in the field. Section 3 presents proposed SCOTO-DAI model, offering a detailed explanation along with a workflow illustration. Section 4 explains experimental setup and database explanation. Section 5 highlights comparative result assessment based on various metrics. Finally, Section 6 summarizes the manuscript.

2. LITERATURE REVIEW

A six-step teaching method was introduced in [16] with the aim of improving the college student employability using Markov chain model. However, multilevel evaluation was not employed for complex systems. Categorical Boosting algorithm was designed in [17] to establish a student employment ability prediction. However, the error rate was not reduced effectively. DL method was developed [18] for improving accuracy of employability forecast. A machine learning framework was designed in [19] to predict the employment trajectories of college graduates. However, the framework demonstrated higher time consumption during the employment prediction process. Partial Least Square Structural Equation method framework was designed [20] for predicting the graduate employability. A statistical approach was developed in [21] for improving employment ability among undergraduate students. The metacognitive strategy was developed in [22] for graduate employability and learning sustainability prediction. However, it did not apply diverse sample sources by engaging a broader range of participants. Enhanced bat methods as well as SVM were designed [23] for employment forecast. However, it was not effective to include elevated-result calculating methods to improve the accuracy.

Artificial Neural Networks (ANN) was presented [24] for predicting the student usability. But, the ANN was inefficient in achieving higher accuracy in employability predictions. K-means clustering and the SimRank algorithm were proposed in [25] to develop an employment recommendation system for college graduates. However, implementing AI-driven recommendations posed significant challenges. Multiple linear regression analysis was designed in [26] for undergraduates' employability prediction. A quantitative approach was designed in [27] for employability prediction. However, it did not examine students' employability skills. Multi-target regression analysis was introduced in [28] for employment prediction. However, it did not offer a brief analysis to improve model's predictive capabilities. Engineering students' self-perceived employability prediction was introduced in [29]. CFA as well as SEM was designed [30] for engineering student's employability prediction.

3. RESEARCH METHODOLOGY

This section describes the methodology behind the newly proposed SCOTO-DAI model, which is employed for precise student employability prediction. The SCOTO-DAI model introduces an inventive approach applied to student datasets to enhance prediction accuracy while minimizing error rates. The SCOTO-DAI model begins with different processes namely data preprocessing, more significant features selection and classification. These steps collectively enhance entire result and effectiveness of employability prediction, represented in Figure 1.

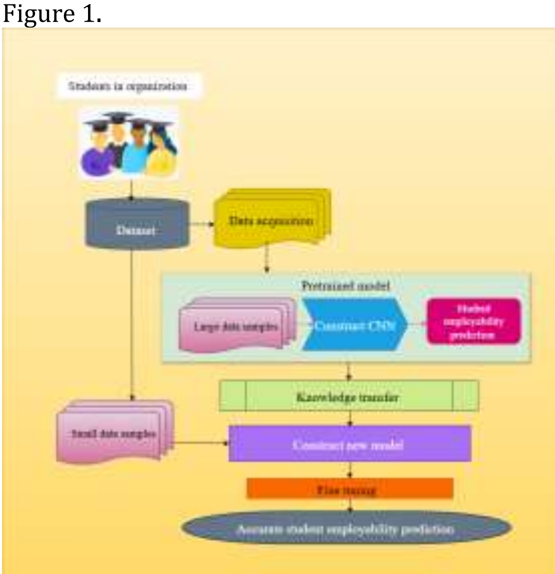


Figure 1 Overall Structural Diagram of SCOTO-DAI Model

Figure 1 depicts overall structural diagram of the proposed SCOTO-DAI model developed to offer precise predictions of student employability in the educational institutions. The model consists of two primary phase's. Initially, the pre-trained model is constructed using huge amount of training information samples acquired as of relevant database. In the next phase, a new model is constructed, which utilizes the knowledge gained from the pre-trained model through transfer learning. The SCOTO-DAI model integrates these two phases into an incorporated structure, which operates through four major phases. Each of these components contributes significantly to the accuracy and effectiveness of the prediction process.

3.1 Data Acquisition Phase

The first stage of the SCOTO-DAI model involves collecting more student data samples collected from a Students' Employability Dataset considered as of https://www.kaggle.com/code/sayakghosh001/students-employability-dataset/input. Data is collected as of various academe organizations across the Philippines with 2,982 and includes 10 distinct features or attribute such as Name of Student, General Appearance, and so on.

3.2 Transfer Learning Model

TL is discriminative AI method that utilizes previously learned knowledge from one task to enhance the learning process. On the contrary to conventional deep learning methods, transfer learning offers faster training times and better performance, particularly when working with large datasets, making it a more efficient approach. In this section, the SCOTO-DAI model adopts transfer learning to improve the accuracy and speed of Students' Employability prediction.

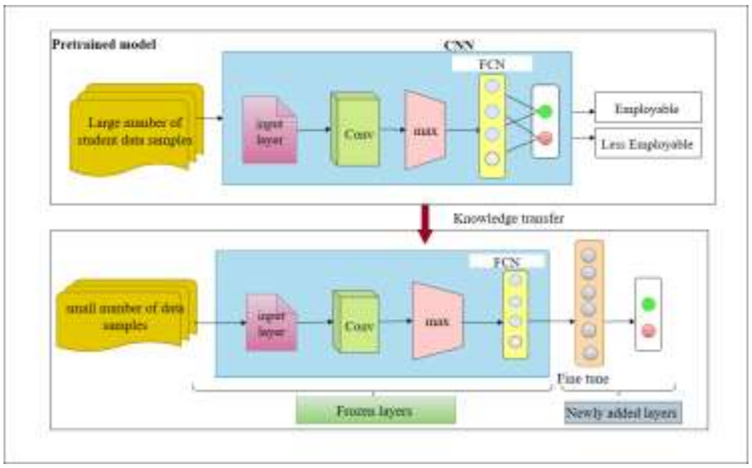


Figure 2 Schematic Structure of Deep Transfer Learning Model

Figure 2 depicts schematic structure of a DTL method, which consists of two types of model such as pre-trained model and new model. In pre-trained method, CNN is employed as DL architecture consisting of input layer, one or more hidden (middle) layers namely Conv layer, maxpooling layer, FCN and an output layer. In a transfer learning framework, a small number of student data samples are taken as input to create a new model based on existing pre-trained model, such as a CNN. As illustrated in Figure 2, frozen layers refer to portion of the pre-trained model remain fixed during training and add the two new layers for task-specific fine-tuning and output layer, as illustrated in figure 2.

3.2.1 Pre-Trained Model

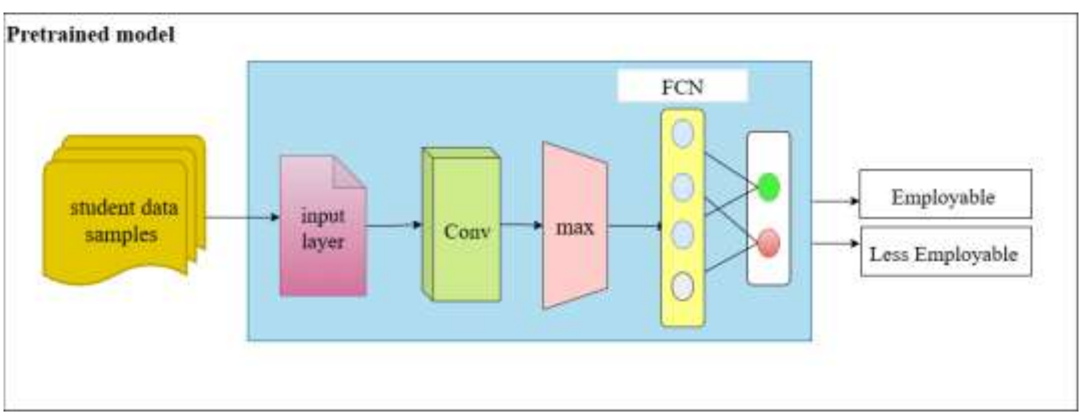


Figure 3 Structure of CNN

Figure 3 illustrates the structure of a CNN to perform the classification of student employability. Inputs as well as output layers are always single levels, as hidden layers include numerous sub-layers namely convolutional layer, maxpooling layer and FCN. Neural network layers are composed of small individual units called artificial neurons or nodes. Each neuron receives inputs, processes them, and transmits the output to neurons in subsequent layers. The connections between these neurons, known as synapses, are assigned weights that determine the strength of the connections between layers.

Let us consider a number of Features '$F = \{F_1, F_2, \dots, F_m\}$' and Samples '$S = \{S_1, S_2, \dots, S_N\}$ given to the input layer of CNN. In the input layer, each neuron receives this input features with data samples. The neurons in the layer computed the weighted sum as follows,

$$X = \sum_{i=1}^{n}(S_i * W_{in\_h}) + b \qquad (1)$$

Where, X denotes a weighted sum output, W_{in_h} represents weights among input as well as hidden layer, number of samples 'S_i', 'b indicates bias which saved value is '1'. Input is transmitted to convolutional layer for data preprocessing.

- **Convolutional Layer**

The input data samples are transferred into the hidden layer 1 (Convolutional layer), where data preprocessing is performed. In the data preprocessing, missing data handling and outlier data removal process is executed. The linear regression method is employed in this layer to handle the missing data in the given input dataset. The regression is ML method employed for analyzing available data samples and generating the new value as missing data. Linear regression basis of missing data managing is expressed as follows,

$$S_{miss} = \delta_0 + S_1\delta_1 + S_2\delta_2 + \cdots + S_n\beta_n \qquad (2)$$

Where, S_{miss} denotes a missing data samples, $\delta_0, \delta_1, \delta_2 \dots \delta_n$ indicates a regression coefficient, $S_1, S_2, S_3, \dots S_n$ denotes a number of available data samples. Followed by, outlier data is identified from the dataset by statistical test. Normalized residual statistical test employed to analyze the student information samples within database and detect outlier data. For each data samples, normalized residual test applied to distinguish outliers' information samples.

$$NRT = arg\ max\ \frac{|S_i - \mu|}{\sigma} \qquad (3)$$

Where, NRT indicates Normalized residual statistical test outcomes, S_i denotes information samples at particular cell, μ denotes mean, σ represents deviation among information samples. The maximum 'NRT' results indicates that the data samples are outlier and it removed from the dataset.

- **Max Pooling Layer**

The preprocessed dataset is then transferred to the max-pooling layer for selecting the more pertinent features. Max pooling is a second hidden layer of CNN which is down sampling method to minimize spatial size of input dataset by removing the outlier data. Proposed method uses congruence coefficient to choose the important aspects as of database. A congruence coefficient used to measure similarity among the aspects and target results.

$$Cf = \frac{\sum F_j * T_k}{\sqrt{\sum {F_j}^2 \sum {T_k}^2}} \qquad (4)$$

Where, Cf denotes a congruence coefficient, $\sum F_j * T_k$ indicates total number of product of paired score of 'F_j' and target 'T_k',$\sum {F_j}^2$denotes squared score of F_j as well as $\sum {T_k}^2$ indicates squared score of T_k. Cf gives values from '- 1' to '+1'. A Cf value close to '+1' denotes elevated degree of resemblance. The value close to 0 represents minimum degree of resemblance. Finally, value near to -1 represents elevated degree of dissimilarity. Therefore, high degree of similarity results aids to accurately choose significant aspects as of database and other immaterial aspects are removed as of database.

- **FCN**

Selected aspects are passed to a fully connected (dense) layer, which serves as the final stage in the neural network model. This layer performs the classification task by analyzing the learned feature representations and categorizing the student data samples into two classes namely 'employable' and 'less employable'. The output is typically determined using an activation function such as sigmoid for binary classification. The Tamas correlation is a matching coefficient for analyzing the training and testing data samples

$$TC = 1 - \frac{|D_{tr,ts}|^2}{n} \qquad (5)$$

$$D_{tr,ts} = |S_{tr} - S_{ts}| \quad (6)$$

Where, TC denotes a Tamas correlation output, D indicates a distance among two information samples S_{tr} , S_{ts} and n denotes a number of data samples. The correlation output value ranges from 0 to 1. In this way, student employability is classified and the results are observed at output layer with sigmoid activation function.

$$Y_{pre} = A_{sig}\,(W_{ho}\, h_t) \quad (7)$$

Where, Y_{pre} denotes a classification output from pre-trained model, h_t represents hidden layer output, W_{ho} symbolizes weights among hidden as well as output layer A_{sig} in output layer for binary categorization output.

$$A_{sig} = \begin{cases} 1\ ; & Employable \\ 0\ ; & Less\ employable \end{cases} \quad (8)$$

Where, activation provides the output '1' indicates employable class and a value of 0 implies that less employable class. The algorithm step of pre-trained model is described as follows,

// Algorithm 1: Pre-Trained Classification Model
Input: **Dataset, features** $F_1, F_2, \dots, F_m$ **and data samples** $S_1, S_2, S_3, \dots S_n$ **Output:** Student Employability Prediction
Begin **Construct the pre-trained model** **1.** **Collect n**umber of data samples $S_1, S_2, S_3, \dots S_n$ **at the input layer** **2.** **For each training** samples S_i **--- Hidden layer 1** **3.** Measure the neuron activation probability using (1) **4.** Handling missing data according to (2) **5.** Outlier data removal according to (3) **6.** **End for** **7.** **For each pre-processed dataset --- Hidden layer 2** **8.** Measure the congruence coefficient between features using (4) **9.** **If** $(Cf = +1)$ **then** **10.** Indicates a high degree of similarity **11.** Select the high similarity features **12.** else **13.** Remove other dissimilarity features **14.** **End if** **15.** **For each** training and testing data samples do --- **--- Hidden layer 3** **16.** Measure the Tamas correlation using (5) **17.** Apply sigmoid activation function using (7) --- **output layer** **18.** **If (** $A_{sig} = 1)$ **then** **19.** Classify the data samples into 'employable' **20.** **else** **21.** Classify the data samples into 'less employable' **22.** **End if** **23.** **End for** **End**

Algorithm 1 describes the approach used for predicting student employability by constructing a classification model through transfer learning. A large dataset of student records is gathered for training purposes. A CNN serves as the pre-trained classifier, composed of multiple layers to process and learn from the input data. Initially, the training samples are introduced at the input layer. For each input, weights and biases are calculated and passed forward to the neurons in the subsequent hidden layers. The first hidden layer performs data pre-processing, including handling missing values and eliminating outliers. In the second hidden layer, feature selection is conducted using the congruence coefficient to retain only the most relevant features and discard the irrelevant ones. The third hidden layer performs classification by measuring the Tamas correlation to compare patterns between training and test samples. Finally, output layer applies A_{sig} to generate the final prediction, classifying individuals as either 'employable' or 'less employable'.

3.2.2 Create New Classification Model

In a transfer learning approach, a limited set of data samples is utilized to construct a new model using an already trained network, such as a CNN. As shown in Figure 2, frozen layers are components of pre-trained method wherever weights remain unchanged throughout training process. These layers preserve the knowledge observed from the original model. For constructing to a new task, additional layers, including a new output layer and fine-tuned. The input data samples are passed through the frozen layers typically the initial input and hidden layers which are excluded from the training updates. Freezing these layers helps to speed up training and lower the overall computational time.

To build the new model, the architecture retains the input layer and the first three hidden layers by freezing them, while two additional layers are added for task-specific fine-tuning and output. A small set of input data sample is used and transferred through the hidden layers, where initial data pre-processing is performed. This includes handling missing values using linear regression and detecting outliers with the normalized residual test. In the second hidden layer (max pooling layer), significant features are selected using the congruence coefficient. Finally, classification is conducted in the third hidden layer (FCN) by applying the Tamas correlation function.

The output of the disease classification in hidden layer is fine-tuned by applying a shuffling shepherd optimization algorithm thereby minimizing both training and validation errors and improving the accuracy of the disease prediction. For each classification result, the error rate is measured based on squared difference between the actual results and prediction results.

$$error\ rate\ (Err) = \left[Y_{actual} - Y_{prediction}\right]^2 \qquad (9)$$

Where, 'Y_{actual}' denotes an actual results, $Y_{prediction}$ represents an employability prediction outcomes. In the fine-tuning process, error back-propagation method is used to adjust hyper parameter (i.e. weights) between the layers to enhance accuracy of employability forecast through gradient method. The Nester Accelerated Gradient descent technique is used for updating weight.

$$W_{t+1} = W_t - \eta\ \rho_t \qquad (10)$$

$$\rho_t = \beta\ \rho_{t-1} + (1-\beta)\frac{\partial Err}{\partial W_t} \qquad (11)$$

Where, W_{t+1} denotes updated weight, W_t designates present weight, η indicates learning rate($\eta < 1$), '$\frac{\partial Err}{\partial W_t}$' indicates a partial derivative of the error 'Err' regarding current weight 'W_t', β indicates default value0.9. The updating process is iterated until finding the minimum error. By applying shuffling shepherd optimization proposed optimization algorithm, the initial population of weights (i.e. sheep) is randomly generated within the search space.

$$W = \{W_1, W_2, \dots, W_k\} \qquad (12)$$

After generating the initial population, the fitness is computed based on error rate.

$$Q = arg\ min\ Err \qquad (13)$$

Where, Q denotes a fitness function, Err denotes error rate. Based on error rate, herd of sheep are arranged into ascending order to partition the total populations into number of groups. For each herd, the shepherd or agent is assigned for directing the sheep to search better grazing area. The sheep position in the particular herd is updated as follows,

$$X_i^{\,t+1} = X_i^{\,t} + \alpha.0.5\left|X_{best}^{\ \ t} - X_i^{\,t}\right| + \varphi.r(0,1) \qquad (14)$$

Where, $X_i^{\,t+1}$ indicates a updated position of the sheep in the specific herd, $X_i^{\,t}$ denotes a current position of the sheep's, α, φ denotes a parameters that control exploration and exploitation, respectively,

$|X_{best}{}^{t} - X_i{}^{t}|$ denotes a divergence, $r(0,1)$ specifies a random number between 0 and 1, $X_{best}{}^{t}$ indicates a current best solution in particular herd which has high fitness.

In order to perform the shuffling, the sheep's from the multiple herds are randomly selected according to (15).

$$h = rand\ (W_k)\ \in H \qquad (15)$$

Where, W denotes a set of sheep selected from herd H, h denotes a sheep randomly chosen using a random integer function '$rand$'. Then combine all sheep's selected from the herd.

$$W_{merge} = \sum_{l=1}^{k} W_l \qquad (16)$$

Where, W_{merge} indicates the merged sheep from herd H. Following the merging step, the global best position among the sheep is determined based on their fitness scores. If the fitness value of a newly updated position increases than the previous best, it becomes the new optimal solution. This iterative process continues until predefined highest number of iterations completed. In end, the most optimal solution weight is chosen for minimizing the error rate. Finally, the newly accurate classification results are obtained at output layer.

$$Y_{new} = A_{sig}\ (W_{ho}\ h_t) \qquad (17)$$

Where, Y_{new} denotes a final classification output of newly constructed model, h_t represents hidden layer output, W_{ho} symbolizes weights among hidden as well as output layer, A_{sig} in output layer for binary categorization output.

$$A_{sig} = \begin{cases} 1\ ; & Employable \\ 0\ ; & Less\ employable \end{cases} \qquad (18)$$

Where, activation output 'A_{sig}' of '1' represents the employable category, while an output of '0' indicates the less employable category. Therefore, the accurate classification outcomes of the cardiovascular disease prediction results are attained at output layer through sigmoid activation function.

// Algorithm 2: New Classifier Model Based Employability Prediction
Input: Dataset, features $F_1, F_2, \ldots, F_m$ and data $S_1, S_2, S_3, \ldots S_n$ **Output:** Increase the of student employability prediction accuracy
Begin **1. Collect n**umber of features $F_1, F_2, \ldots, F_m$, and small number of data samples $S_1, S_2, S_3, \ldots S_n$**--- input layer** **2. For each** sample S_i **3.** Compute the neuron activation probability using (1) **4.** Perform Data Pre-processing **using** (2)(3) **-----[Hidden layer 1]** **5. End for** **6. For each pre-processed output** **7. Select more relevant feature** set using (4) **-----[Hidden layer 2]** **8. End for** **9. For each** training and testing data samples **10.** Measure the correlation using (5) -----[**Hidden layer 3**] **11.** Obtain the classification results **12. End for** **13. For each classification result** -----[**Hidden layer 4**] **14.** Measure the error rate 'Err' using (9) **15.** Update the weights using (10) **16. End for** **17.** Initialize the population of the weights $W_1, W_2, W_3 \ldots . W_k$ **18. While (t < t_{max}) do** **19. for each** weight 'W_k' **20.** Compute the fitness 'Q' using (13) **21. End for**

22. **Sort the** weights based on fitness
23. Partitions weights into herds
24. **For each** weight W_k in herd 'H'
25. Update the position using (14)
26. **End for**
27. Perform shuffling process using (15)
28. **For each** weight W_k in merged herd 'H
29. Find fitness using (13)
30. **End for**
31. Replace global best solution
32. t**= t+1**
33. Go to step 18
34. E**nd while**
35. **Return (**optimal weight)
36. Apply sigmoid activation function using (17) **--- output layer**
37. **If (** $A_{sig} = 1$) **then**
38. Classify the data samples into 'employable'
39. **else**
40. Classify the data samples into 'less employable'
41. **End if**

End

Algorithm 2 outlines a new model constructed in transfer learning approach developed to improve accuracy of student employability forecast as reducing prediction errors. Process begins by initializing weights and biases for a small set of student training samples at the input layer. These inputs are then passed to the hidden layers, where data pre-processing is performed to manage missing values and identify outliers. In the subsequent hidden layer, dimensionality reduction is achieved by selecting the more pertinent features. The third hidden layer performs classification using the correlation to improve predictive performance. After classification, a fine-tuning phase is initialized using the shuffling shepherd optimization algorithm. Followed by, an optimal weight is selected that provides the lowest error rates. The final prediction is generated using A_{sig} at output layer, resulting in improved accuracy and specificity of student employability prediction.

4. EXPERIMENTAL SETUP

This part presents the experimental evaluation of SCOTO-DAI model with existing approaches, MFO-Attention-LSTM [1] and IGAE [2], were implemented and executed using the Python programming platform. To conduct experiment, the Students' Employability database is employed and considered as of https://www.kaggle.com/code/sayakghosh001/students-employability-dataset/input. It consists of mock job interview outcomes for 2,982 students, with ratings ranging as of 1 to 5 across 10 different features or attributes.

4.1 Implementation Results

The SCOTO-DAI model is comprehensively examined to assess its effectiveness in analyzing student employability prediction within higher education institutes. The evaluation includes several core stages, utilizing Students' Employability Dataset taken from Kaggle repository. First, the numbers of student data sample data are collected from the dataset and class distribution is shown in Figure 4.

The dataset comprises 2982 labeled data samples, which are evenly uniformly distributed among two distinct categories such as employable and less employable. This class distribution ensures that the model receives a representation of data samples.

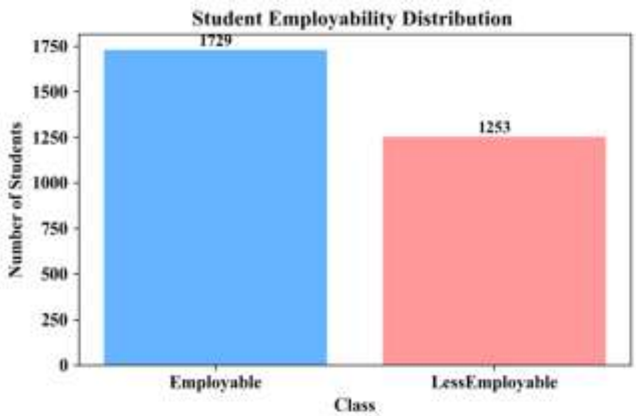
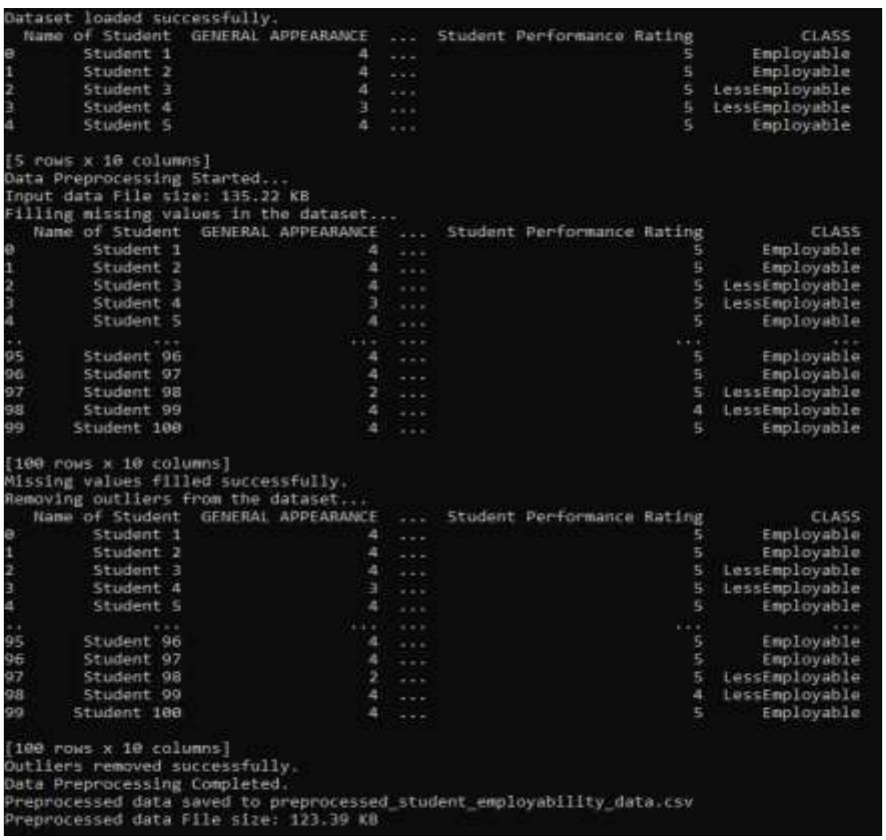


Figure 4 Class Distribution of Dataset

After data collection, preprocessing steps were performed, including handling missing values and eliminating outliers. The dataset size was initially 135.22 KB, which was reduced to 123.39 KB after preprocessing.



```
Dataset loaded successfully.
  Name of Student  GENERAL APPEARANCE  ...  Student Performance Rating           CLASS
0       Student 1                   4  ...                           5      Employable
1       Student 2                   4  ...                           5      Employable
2       Student 3                   4  ...                           5  LessEmployable
3       Student 4                   3  ...                           5  LessEmployable
4       Student 5                   4  ...                           5      Employable

[5 rows x 10 columns]
Data Preprocessing Started...
Input data File size: 135.22 KB
Filling missing values in the dataset...
   Name of Student  GENERAL APPEARANCE  ...  Student Performance Rating           CLASS
0        Student 1                   4  ...                           5      Employable
1        Student 2                   4  ...                           5      Employable
2        Student 3                   4  ...                           5  LessEmployable
3        Student 4                   3  ...                           5  LessEmployable
4        Student 5                   4  ...                           5      Employable
..             ...                 ...  ...                         ...             ...
95      Student 96                   4  ...                           5      Employable
96      Student 97                   4  ...                           5      Employable
97      Student 98                   2  ...                           5  LessEmployable
98      Student 99                   4  ...                           4  LessEmployable
99     Student 100                   4  ...                           5      Employable

[100 rows x 10 columns]
Missing values filled successfully.
Removing outliers from the dataset...
   Name of Student  GENERAL APPEARANCE  ...  Student Performance Rating           CLASS
0        Student 1                   4  ...                           5      Employable
1        Student 2                   4  ...                           5      Employable
2        Student 3                   4  ...                           5  LessEmployable
3        Student 4                   3  ...                           5  LessEmployable
4        Student 5                   4  ...                           5      Employable
..             ...                 ...  ...                         ...             ...
95      Student 96                   4  ...                           5      Employable
96      Student 97                   4  ...                           5      Employable
97      Student 98                   2  ...                           5  LessEmployable
98      Student 99                   4  ...                           4  LessEmployable
99     Student 100                   4  ...                           5      Employable

[100 rows x 10 columns]
Outliers removed successfully.
Data Preprocessing Completed.
Preprocessed data saved to preprocessed_student_employability_data.csv
Preprocessed data File size: 123.39 KB
```

Figure 5 Dataset Preprocessing

SCOTO-DAI model focuses on identifying relevant input features that enhance the accuracy of student employability prediction. To achieve this, it utilizes congruence coefficient to select 8 key features which has similarity score close to '1'.

```
Congruence coefficient for GENERAL APPEARANCE: 0.764
Congruence coefficient for MANNER OF SPEAKING: 0.772
Congruence coefficient for PHYSICAL CONDITION: 0.768
Congruence coefficient for MENTAL ALERTNESS: 0.772
Congruence coefficient for SELF-CONFIDENCE: 0.764
Congruence coefficient for ABILITY TO PRESENT IDEAS: 0.762
Congruence coefficient for COMMUNICATION SKILLS: 0.763
Congruence coefficient for Student Performance Rating: 0.753
Significant features: ['GENERAL APPEARANCE', 'MANNER OF SPEAKING', 'PHYSICAL CONDITION', 'MENTAL ALERTNESS', 'SELF-CONFI
DENCE', 'ABILITY TO PRESENT IDEAS', 'COMMUNICATION SKILLS', 'Student Performance Rating']
Significant features saved to significant_features.csv
```

Figure 6 Selected Features

Figure 6 illustrates the feature selection analysis helps identify the 8 relevant attributes such as General appearance, Manner of Speaking, and so on used to perform student employability prediction.

```
Prediction Results:

            Actual       Predicted
0       Employable      Employable
1   LessEmployable      Employable
2   LessEmployable      Employable
3   LessEmployable  LessEmployable
4   LessEmployable  LessEmployable
..             ...             ...
890     Employable      Employable
891     Employable      Employable
892 LessEmployable  LessEmployable
893 LessEmployable  LessEmployable
894     Employable      Employable

[895 rows x 2 columns]
```

Figure 7 Student Employability Prediction Results

Finally, the student employability forecast is performed by transfer learning model. The method is trained using 8 selected relevant features from student data samples to differentiate between employable and less employable students, thereby minimizing the difference between actual and predicted outcomes.

5. PERFORMANCE COMPARISON ANALYSIS

Result of SCOTO-DAI model with conventional MFO-Attention-LSTM [1] and IGAE [2] are evaluated by numerous estimation parameters across varying student data sample sizes.

5.1 Evaluation Metrics

Accuracy: Accuracy represents the proportion of total predictions that are correct to assess the overall effectiveness of skill-based student employability prediction methods. The mathematical expression for calculating accuracy is presented below.

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} * 100 \quad (19)$$

Where, accuracy 'Acc' is mathematically represented to be the percentage ratio of 'TP' and 'TN', FP' and 'FN' .

Precision: It is a performance metric that evaluates the accuracy of student employability prediction made by a model. Precision is defined as given below.

$$Pre = \frac{TP}{TP+FP} \quad (20)$$

Where, precision 'Pre' is measured using the true positive 'TP' and the false positive 'FP' respectively.

Recall: It also called as sensitivity, computes capability of method to properly recognize actual positive cases. It is measured as proportion of TP to sum of TP and FN. It is measured as follows,

$$Rec = \frac{TP}{TP+FN} \quad (21)$$

Where, 'Recindicates recall, TP' represents true positive rate, FN'symbolize false negative rate

F1 Scores: It also known as F-measure refers to harmonic mean of Pre as well as $Rec$and it expressed as,

$$F1\ score = 2 * \left[\frac{Pre*Rec}{Pre+Rec}\right] \quad (22)$$

Where, PS denotes a precision, RL denotes a recall.

Specificity: It reflects the model ability to correctly differentiate between employable and less employable. The corresponding mathematical formulation is provided below.

$$SP = \frac{TN}{TN+FP} \quad (23)$$

Where, 'SP 'denotes a specificity, TN indicates true negative and'FP' represents false positive.

Error Rate: It is measured as ratio of incorrect employability predication made by algorithm from the total number of data samples.

$$ER = \sum_{i=1}^{N} \left(\frac{S_{IC}}{S_i}\right) * 100 \quad (24)$$

Where, error rate 'ER' is measured based on the samples considered for experimental analysis 'S_i' and the samples incorrectly 'S_{IC}' predicted.

Prediction Time: It is defined as time duration of the method required to identify the student employability prediction. It is calculated using the following formula,

$$PT = \sum_{i=1}^{n} S_i * Time\ [EP] \quad (25)$$

Where, PT indicates the Prediction Time, $Time\ [EP]$ represents a time for employability prediction 'EP'. It is calculated in milliseconds (ms).

Table 1 Comparison of Accuracy

Student data Samples	**Accuracy (%)**		
	Proposed SCOTO-DAI	**MFO-Attention-LSTM [1]**	IGAE[2]
250	97.2	94	95.2
500	96.56	90	94.56
750	95.02	89.55	93.05
1000	93.63	86.35	91.1
1250	91.52	84.15	89.56
1500	92.56	84	88.35
1750	94.56	87.15	89.04
2000	96.26	89.05	92.41
2250	97.45	90.15	92.63
2500	97.20	92	93.6

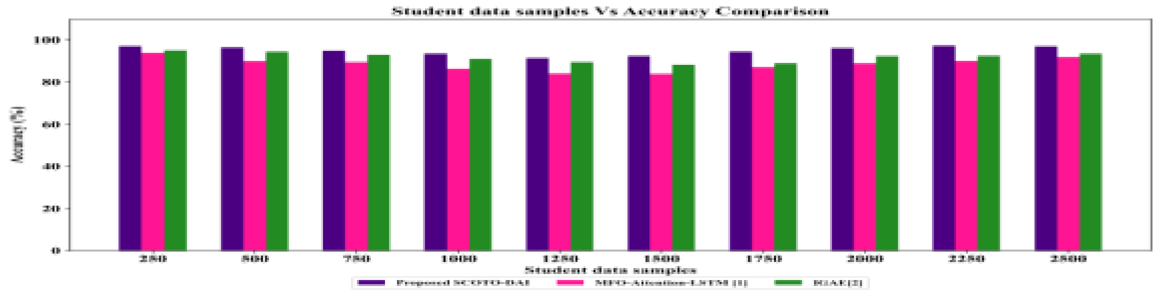


Figure 8 Performance Analysis of Accuracy

Figure 8 illustrates the accuracy versus number of student data samples. Graph illustrates SCOTO-DAI model constantly better the models described in MFO-Attention-LSTM [1] and IGAE [2]. Overall, the proposed SCOTO-DAI model improved student employability prediction accuracy by approximately 7% compared to [1] and 4% compared to [2]. This improved performance is due to the application of a transfer learning approach. This model examines both training and testing data samples by applying the Tamas correlation within the hidden layers of a CNN. By transferring the knowledge from a pre-trained model, it effectively processes feature vectors, leading to improved accuracy in student employability prediction.

Table 2 Comparison of Precision

Student Data Samples	**Precision**		
	Proposed SCOTO-DAI	**MFO-Attention-LSTM [1]**	IGAE[2]
250	0.978	0.957	0.965
500	0.963	0.932	0.952
750	0.955	0.915	0.932
1000	0.945	0.906	0.921
1250	0.942	0.897	0.912
1500	0.925	0.886	0.905
1750	0.946	0.885	0.911
2000	0.967	0.896	0.942
2250	0.962	0.925	0.944
2500	0.958	0.916	0.936

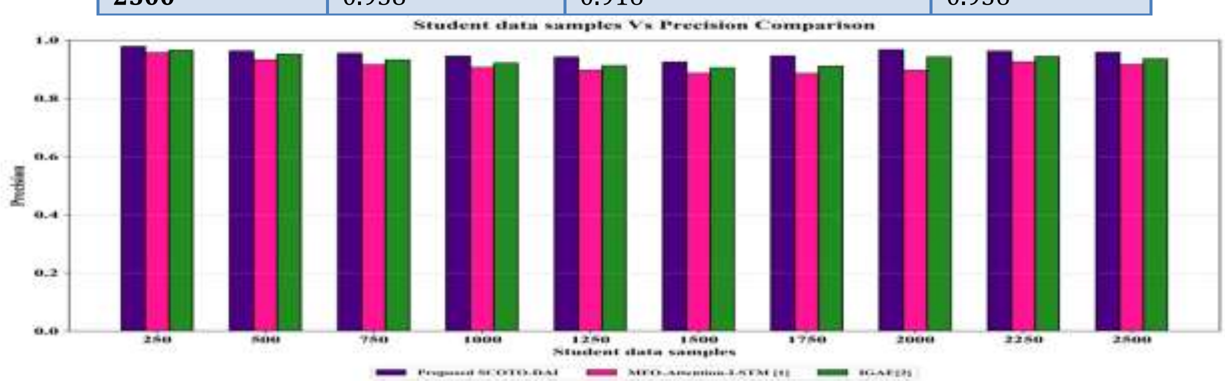


Figure 9 Performance Analysis of Precision

Figure 9 presents a performance comparison of precision against number of student information samples. Among the three methods, the SCOTO-DAI model demonstrates superior precision compared to other existing deep learning approaches. For each result, different runs were employed and compared. A comparative analysis of the SCOTO-DAI model and the existing methods demonstrates an improvement of 5% in precision compared to [1] and 2% compared to [2]. The enhanced performance results from deep transfer learning framework to effectively analyze student data samples. In addition, shuffling shepherd optimization method is used to refine method layers, aiming to minimize errors during both training and validation phases. This approach considerably enhances prediction accuracy by increasing the true positive rate and decreasing false positive instances in student employability prediction, thereby increasing the precision.

Table 3 Comparison of Recall

Student Data Samples	Recall		
	Proposed SCOTO-DAI	**MFO-Attention-LSTM [1]**	IGAE[2]
250	0.991	0.973	0.982
500	0.982	0.938	0.968
750	0.972	0.926	0.962
1000	0.968	0.922	0.945
1250	0.955	0.905	0.922
1500	0.957	0.908	0.926
1750	0.974	0.915	0.942
2000	0.978	0.924	0.947
2250	0.985	0.932	0.951
2500	0.982	0.934	0.953

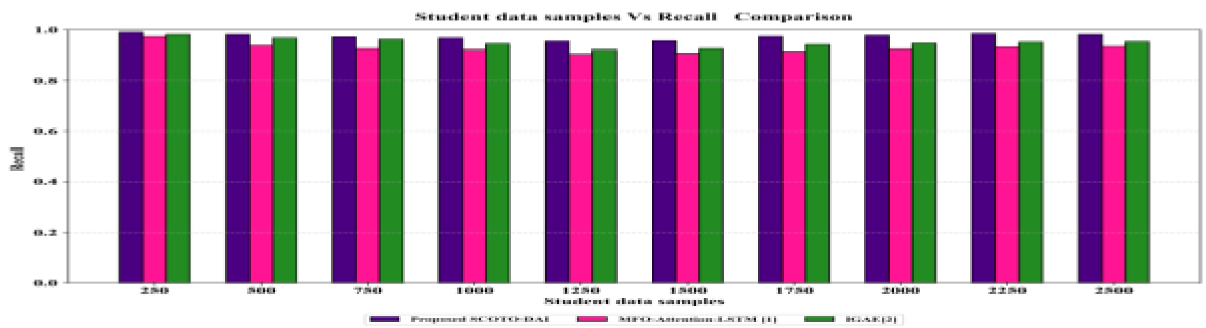


Figure 10 Performance Analysis of Recall

Figure 10 displays the recall performance versus number of data samples gathered as of database. Notably, SCOTO-DAI model shows a noticeable improvement in recall compared to methods MFO-Attention-LSTM [1] and IGAE [2]. Multiple runs were conducted for each result to ensure comparison. The findings indicate that the SCOTO-DAI model consistently achieves superior recall performance compared to the two existing approaches. When compared with methods [1] and [2], the SCOTO-DAI model increases the performance of recall approximately 5% and 3%, respectively. The observed improvement of SCOTO-DAI model is the result of the fine-tuning process in DTL method. By employing a DTL approach, method reduces the squared error between predicted and actual outcomes through optimal weight selection using shuffling shepherd optimization algorithm. This iterative process continues until reached minimal error, leading to a decrease in false-negative rates and an increase in true positive outcomes for student employability prediction.

Table 4 Comparison of F1 Score

Student data samples	F1 score		
	Proposed SCOTO-DAI	**MFO-Attention-LSTM [1]**	IGAE[2]
250	0.984	0.964	0.973
500	0.972	0.934	0.959
750	0.963	0.920	0.946

1000	0.956	0.913	0.932
1250	0.948	0.900	0.916
1500	0.940	0.896	0.915
1750	0.959	0.899	0.926
2000	0.972	0.909	0.944
2250	0.973	0.928	0.947
2500	0.969	0.924	0.944

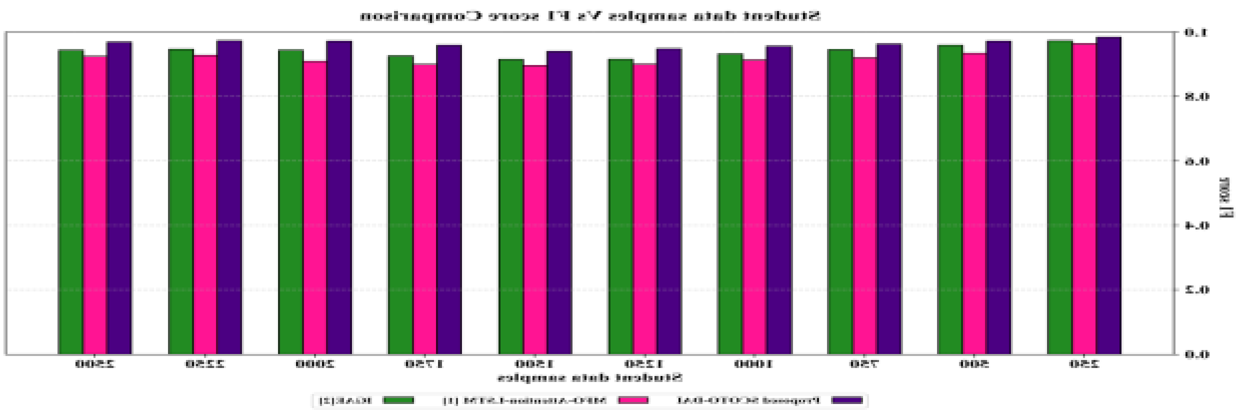


Figure 11 Performance Analyses of F1 Score

Figure 11 presents a performance comparison of F1-scores versus the number of student data samples using three models namely the proposed SCOTO-DAI model, MFO-Attention-LSTM [1] and IGAE [2]. F1-score returns balance among *Pre* as well as *Rec*. This enhanced performance is due to the effective implementation of the deep transfer learning framework, which improves student employability classification accuracy. Overall, the comparative analysis reveals that the SCOTO-DAI model increases the F1-score by approximately 5% compared to [1] and 3% compared to [2].

Table 5 Comparison of Specificity

Student Data Samples	**Specificity**		
	Proposed SCOTO-DAI	**MFO-Attention-LSTM [1]**	IGAE[2]
250	0.722	0.523	0.6
500	0.715	0.521	0.588
750	0.705	0.546	0.596
1000	0.698	0.586	0.623
1250	0.712	0.611	0.636
1500	0.723	0.543	0.574
1750	0.762	0.574	0.605
2000	0.785	0.582	0.612
2250	0.802	0.542	0.617
2500	0.785	0.574	0.611

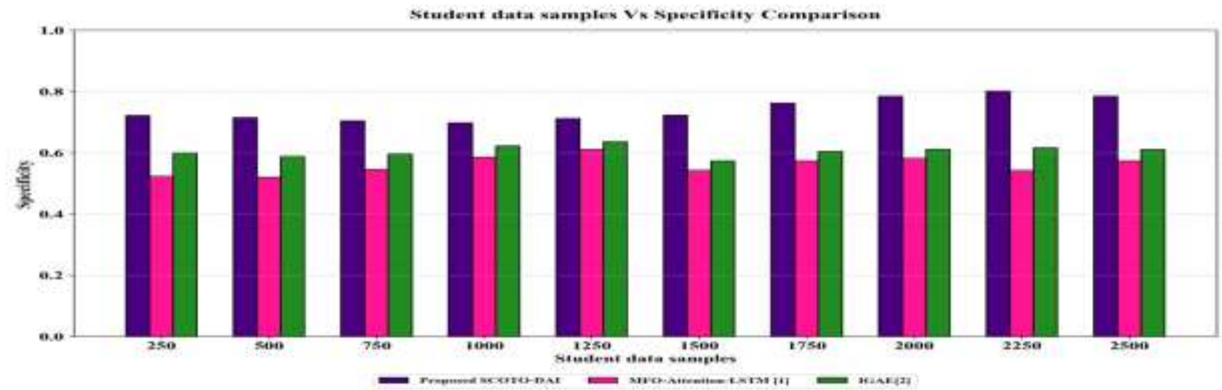


Figure 12 Performance Analyses of Specificity

Figure 12 illustrates the specificity performance with student data samples. Experimental outcomes indicate SCOTO-DAI model outperforms the two existing deep learning methods in terms of specificity. The comparison demonstrates that the SCOTO-DAI model improved specificity by 33% compared to method [1] and by 22% compared to method [2].

Table 6 Comparison of Error Rate

Student Data Samples	**Error rate (%)**		
	Proposed SCOTO-DAI	**MFO-Attention-LSTM [1]**	IGAE[2]
250	2.8	6	4.8
500	3.44	10	5.44
750	4.98	10.45	6.95
1000	6.37	13.65	8.9
1250	8.48	15.85	10.44
1500	7.44	16	11.65
1750	5.44	12.85	10.96
2000	3.74	10.95	7.59
2250	2.55	9.85	7.37
2500	2.88	8	6.4

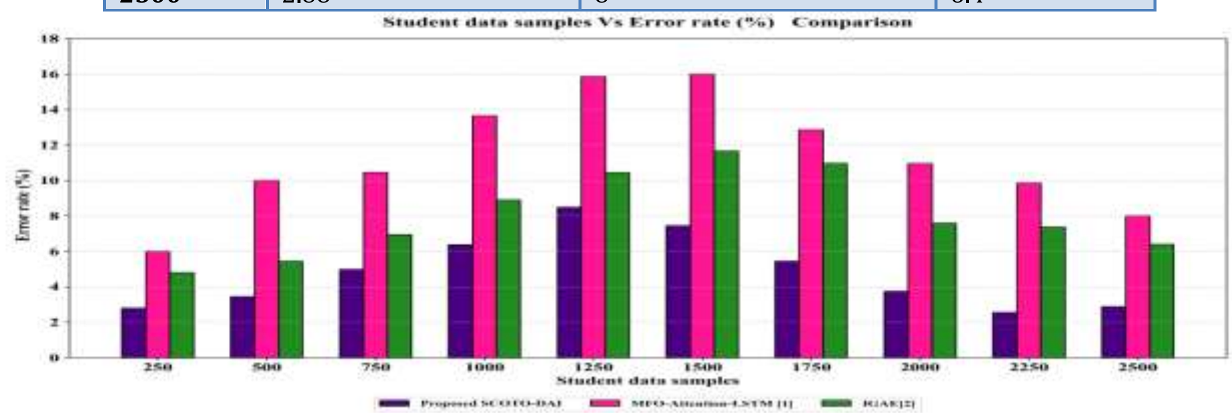


Figure 13 Performance Analyses of Error Rate

Figure 13 provides an analysis of the error rate in student employability prediction versus number of information samples. Performance results of error rate in student employability prediction is reduced. Average of comparison outcomes denotes SCOTO-DAI model demonstrated a 59% reduction in error rate compared to

[1] and a 41% reduction compared to [2]. This significant reduction is achieved due to the integration of shuffling shepherd optimization algorithm within DTL method. Optimization method is effectively employed for fine tuning the hyper parameters to minimize classification errors. This combination allows the SCOTO-DAI model to substantially reduce the error rate during employability prediction.

Table 7 Comparison of Prediction Time

Student Data Samples	**Prediction Time**		
	Proposed SCOTO-DAI	**MFO-Attention-LSTM [1]**	IGAE[2]
250	**20**	**26.5**	**23.5**
500	**22.8**	28.5	25.8
750	**24.6**	31.2	28.2
1000	**28.2**	33.4	30.7
1250	**30.2**	35.7	32.5
1500	**32.6**	37.5	34.6
1750	**34.7**	40.2	38.2
2000	**37.2**	43.6	41.4
2250	**40.5**	44.5	42.9
2500	**42.7**	47.6	44.8

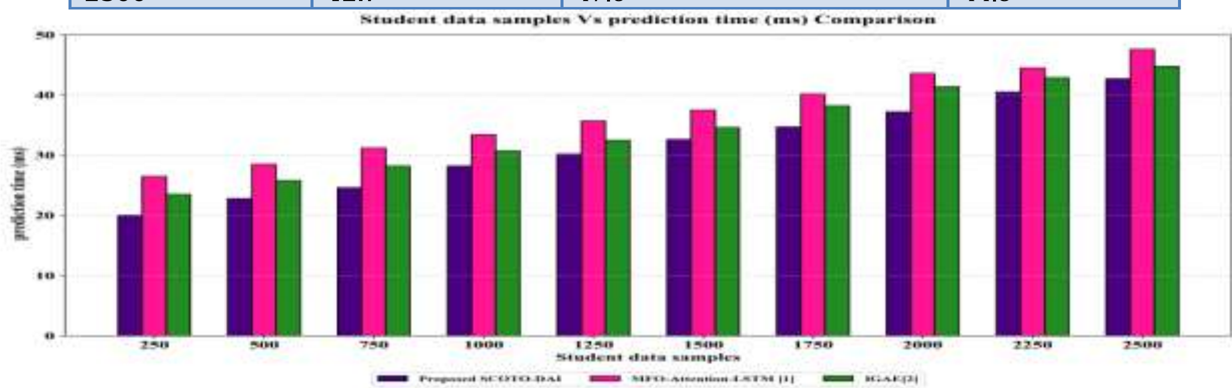


Figure 14 Performance Analyses of Error Rate

Figure 14 presents the prediction time using three different models. Each method was tested over 10 runs using a dataset of 25000 student data samples. However, SCOTO-DAI model consistently demonstrated faster prediction times compared to the other approaches. This improvement is primarily achieved due to efficient data preprocessing and the significant feature selection integrated into the hidden layer of transfer learning model. The overall comparison results showed a reduction in prediction time of approximately by 16% compared to method [1] and 9% compared to method [2].

5.3 Confusion Matrix Analysis

The confusion matrix is a commonly used evaluation method in student employability prediction, offering a detailed assessment of classification performance. It compares the predicted results against the true labels using a dataset of 2500 student data samples. In this section, the confusion matrix is utilized to estimate as well as compare result of three models namely SCOTO-DAI model, MFO-Attention-LSTM [1] and IGAE [2].

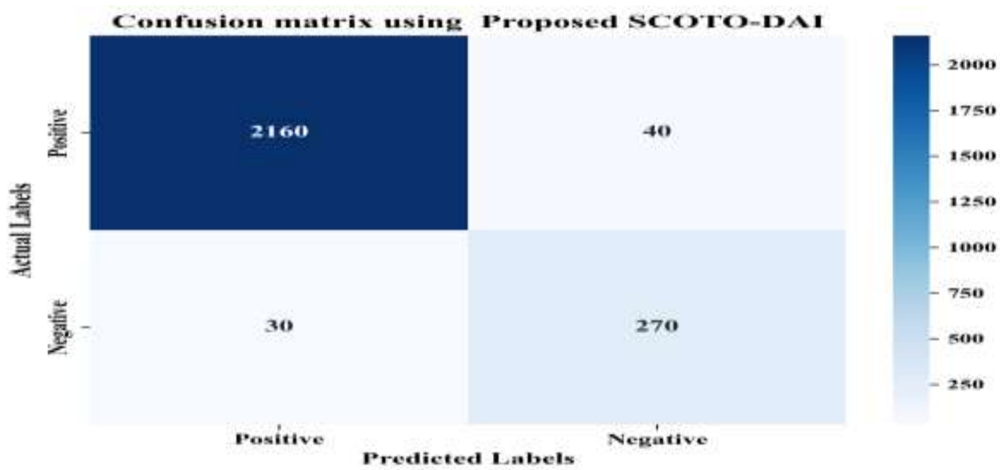


Figure 15 Confusion Matrix

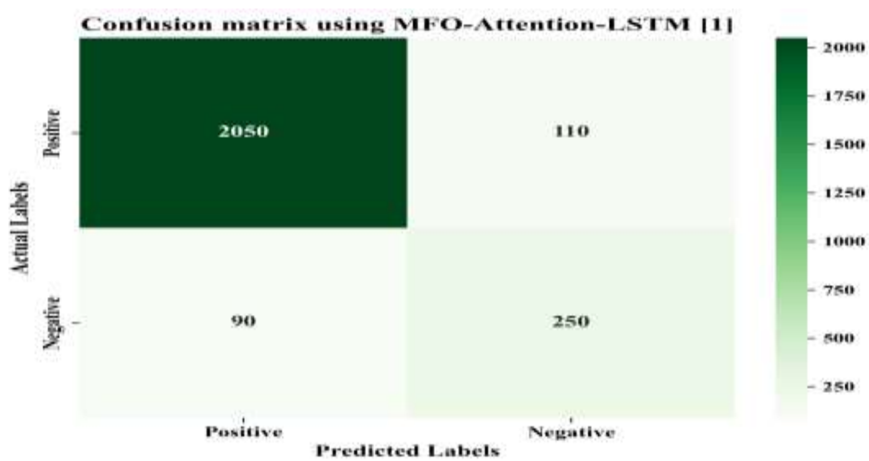


Figure 16 Confusion Matrix

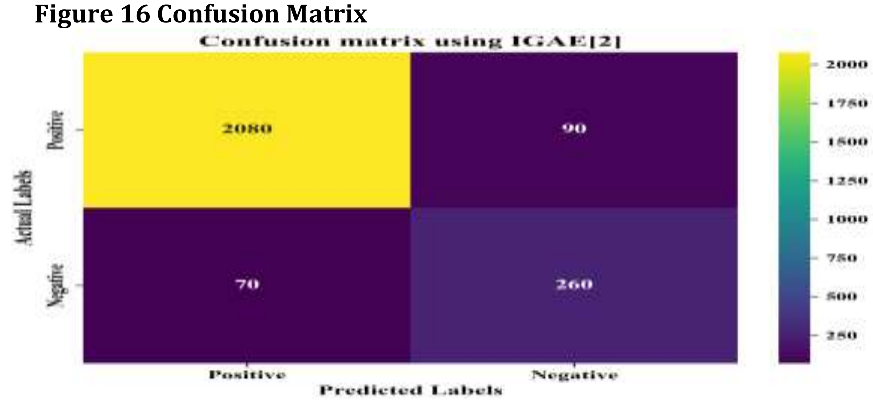


Figure 17 Confusion Matrix Using IGAE [2]

Figures 15, 16, and 17 depict the confusion matrices generated by three classification approaches namely the proposed SCOTO-DAI model, MFO-Attention-LSTM [1] and IGAE [2]. These matrices offer a visual analysis of detecting student employability prediction levels categorized as employable and less employable based on 2500 samples. Each confusion matrix displays TP, FP, FN, and TN.

6. CONCLUSION

Student employability prediction acts vital part in determining educational success at specific organizations. However, with the growing complexity of modern educational systems, maintaining high levels of employability prediction is a major challenge. This paper introduces a new discriminative AI model termed the SCOTO-DAI model, specifically developed to accurately predicting the student employability within educational settings. The transfer learning technique initiates with a data preprocessing and significant feature selection phase aimed at reducing the overall prediction time. It incorporates a knowledge transfer capacity of the model to facilitate efficient samples analysis based on correlation measures to enhance classification accuracy. To further boost the model's performance, fine-tuning is applied to reduce error rates associated with student employability prediction. A thorough assessment was conducted using numerous result indicators across various student data samples. Experimental outcomes confirm that the SCOTO-DAI model improved the performance than the traditional deep learning methods, offering improved accuracy, lower time, as well as reduced prediction errors.

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