Natural Resources for Human Health
eISSN: 2583-1194

Original Research

Received 20 May 2026
Revised 28 June 2026
Accepted 20 July 2026

Natural Resources for Human Health 2026, Vol. 6 (8s): 506–522

KEYWORDS:
Employability prediction, educational institution, swallow search optimization, data preprocessing, student information acquisition

Moving Studentized Expectile Convolution Connectionist AI for Accurate Employability Prediction in Higher Educational Institutions

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ABSTRACT: Employability prediction has received large attention to recognize key predictors of employability among students in higher educational institutions. The student employability prediction is a major concern for higher educational institutions as it takes timely actions for increasing the institutional placement ratio. Different data mining techniques such as classification are used in existing research for predicting the employability of students. But, the existing techniques failed to address the overfitting issues and time consumption remained unaddressed. Therefore, a new convolution based AI model is introduced for performing accurate employability prediction. In this paper, a new Moving Studentized Expectile Convolution Connectionist AI (MStECCAI) Model is introduced to accurately predict the employability with minimum time consumption. The proposed MStECCAI Model comprises four processes namely student information collection, pre-processing, feature selection and classification. During student information acquisition phase, student samples (i.e., student class room videos with audio files, facial expression and head pose movement) are collected from input dataset. Subsequently, the proposed MStECCAI Model utilizes Connectionist AI model with DenseNet Convolutional Deep Belief Network for employability prediction. DenseNet Convolutional Deep Belief Network includes three Restricted Boltzmann Machines (RBMs) layers with hidden layer and pooling layer. First, the number of student samples is given to the visible layer of the DenseNet Convolutional Deep Belief Network. Subsequently, data preprocessing is performed in RBM layer 1 to handle missing data, to detect outliers and to normalize inputs for accurate employability prediction. Followed by, the feature selection process is carried out in RBM layer 2 by using regression analysis. Then, the proposed MStECCAI Model performs the classification process with relevant features in RBM layer 3 with higher employability prediction accuracy. At final stage, the fine tuning process is carried out in proposed MStECCAI Model to reduce the prediction error using nature-inspired swallow search optimization. Finally, accurate employability prediction results are obtained at the output layer. Experimental analysis of proposed MStECCAI Model is conducted with different metrics such as student employability prediction accuracy, precision, recall, F1-score, Matthews Correlation Coefficient, coefficient of determination and student employability prediction time. The quantitatively analyzed results reveal that the proposed model attains higher accuracy in student employability prediction with lesser

Natural Resources for Human Health
eISSN: 2583-1194

time consumption when compared to traditional deep learning methods.

INTRODUCTION

Student employability prediction is vital for identifying students' strengths and aligning their skills with labor market needs. Various AI and machine learning methods have been proposed, but each has limitations. CatBoost (1) improved data handling but not accuracy, while Quantized Embeddings Reduction (2) reduced time complexity but not precision. A data-driven approach (3) and multimodal framework (4) faced performance and computational issues. Feature selection with TLBO (5) did not improve recall. Methods such as IGAE (6), AHP–TOPSIS with KNN (7), and OPT-BAG (8) suffered from issues like low specificity, high time complexity, and prediction errors. Other models, including tree-based (9), hybrid deep learning (10), BEN-EM (11), and DBN (12), showed improvements but failed in efficiency or innovation. Additional approaches (13) – (15) also struggled with accuracy, error reduction, and scalability, highlighting the need for more efficient employability prediction models. The main contribution of proposed MStECCAI model is given as,

- To propose a Connectionist AI-based MStECCAI model for accurate employability prediction using data acquisition, preprocessing, feature selection, classification, and fine-tuning.
- To reduce prediction time through effective preprocessing and relevant feature selection using normalization and regression techniques.
- To improve prediction accuracy with minimal error using Cramér's Phi coefficient for classification, along with Swallow Search Optimization for efficient hyper parameter tuning and enhanced specificity.
- To evaluate the proposed model against existing methods using various performance metrics.

The paper is organized as follows: Section 2 reviews the literature in educational application. Section 3 presents the proposed MStECCAI model with the detailed explanation and architecture diagram. Section 4 describes the experimental evaluation with the dataset description. Section 5 explains the results based on different performance metrics. Lastly, Section 6 concludes the paper.

RELATED WORKS

Graduate employability remains a major challenge for higher education institutions, especially in developing economies. Several methods have been proposed to address this issue, but with notable limitations. The Influence-based Graph Auto Encoder (IGAE) in (16) modeled university representation based on graduate employment, yet failed to improve specificity. Kendall's Coefficient of Concordance framework in (17) enhanced interaction between employability and problem-based learning, but did not improve the coefficient of determination. A six-step teaching method in (18) supported practical training, though it lacked robustness. Curriculum frameworks in (19) improved employability and sustainability but did not enhance classification performance. Clustering and SimRank in (20) supported job recommendations, yet lacked feature selection. MFO-Attention-LSTM in (21) and BERT in (22) improved prediction capabilities but suffered from high error and complexity, respectively. DL-based reasoning in (23) and ML methods in (24), (25) failed to improve precision and true positive rates. Studies in (26)–(28) highlighted issues such as high computational complexity, increased prediction time, and lack of advanced techniques. Ensemble learning in (29) and feature selection with SVM in (30) also failed to improve MCC and reduce time complexity. Overall, existing methods suffer from low accuracy, precision, recall, F1-score, MCC, and high computational cost and time. To overcome these limitations, a novel Moving Studentized Expectile Convolution Connectionist AI (MStECCAI) model is proposed for efficient employability prediction.

METHODOLOGY

Employability prediction is crucial for preparing career-ready students and evaluating educational effectiveness. Employers seek a mix of academic, technical, practical, and soft skills. Modern approaches use multimodal data (video, audio, facial expressions, head movements) with AI and machine learning for accurate prediction. To improve performance, the MStECCAI model is proposed for efficient employability prediction.

Natural Resources for Human Health
eISSN: 2583-1194

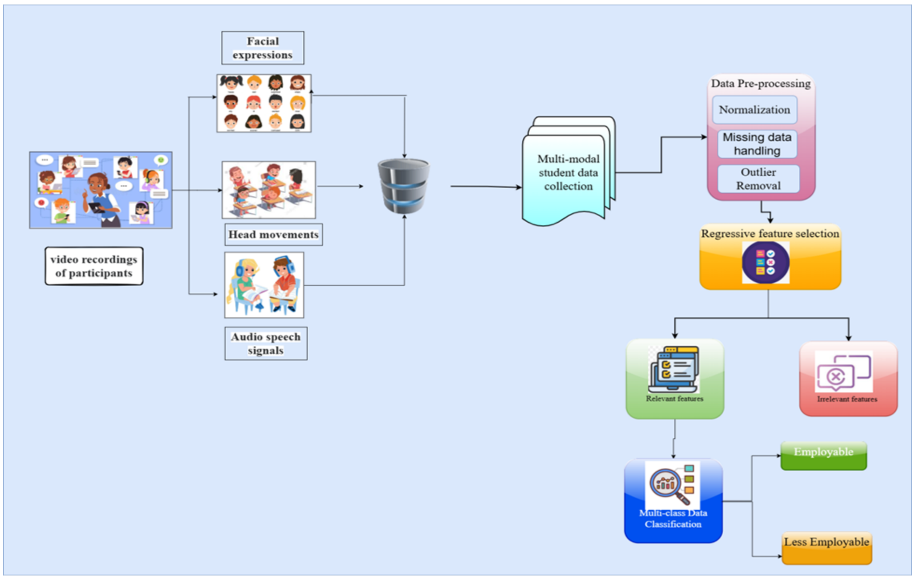


Figure 1 Architecture Diagram of MStECCAI Model

Student Information Acquisition

The first process of MStECCAI Model is student information acquisition for performing the employment prediction. Student information acquisition is the process of collecting student multimodal information from input dataset. In proposed MStECCAI Model, Multimodal Student Attention Dataset is employed for performing employment prediction. The URL of the dataset is given as https://www.kaggle.com/datasets/colabsss/multimodal-student-attention-dataset?select=audio_attention_dataset.csv. The dataset contains multimodal student engagement data from online sessions, including synchronized video and audio. It captures visual (facial expressions, attention) and auditory (speech, interaction) behaviors. The data is divided into video and audio components, with each record representing a student's attention state. Labels are classified into Attentive, Partially Attentive, and Inattentive. The present study was designed as a well-organized pipeline that links various stages of machine learning aimed at lung cancer prediction. Initially, the demographic and symptom-related dataset is preprocessed to handle missing values and prepare the features appropriately. Following this, the issue of class imbalance is addressed using the Synthetic Minority Oversampling Technique (SMOTE). To enhance model accuracy and efficiency, a Genetic Algorithm is incorporated for both feature selection and hyper parameter tuning of the Random Forest classifier. Finally, the performance of the optimized model is compared against multiple baseline classifiers to demonstrate its robustness and effectiveness. The entire experiment was carried out on a system equipped with an Intel i7 processor and 16 GB of RAM. A graphical illustration of this comprehensive machine learning workflow is presented in Figure 1.

Table 1: Dataset Feature Description

Video Dataset Description		
S.No	**Feature Name**	**Description**
1.	Face_Visibility	Learner face visibility during session
2.	Eye_Gaze_Score	Learner gaze is directed toward screen
3.	Head_Pose_Stability	Steadiness of learner head orientation over time
4.	Blink_Rate	Frequency of eye blinks observed during learning
5.	Facial_Expression_Intensity	Strength of facial expressions
6.	Body_Posture_Score	Learner posture in terms of attentiveness
7.	Movement_Level	Extent of body or head movement during session
8.	Focus_Duration	Visually focused duration of learner
9.	Screen_Orientation	Learner orientation toward the screen
10.	Attention_Score	Overall visual attention indicator
11.	Target	Learner attention state
12.	General Class	Learner Attention level

Audio Dataset Description		
1.	Speech_Presence	Learner voice presence during session
2.	Voice_Energy	Learner voice intensity during interaction
3.	Speech_Clarity	Learner speech clarity
4.	Background_Noise_Level	Audio disturbance level
5.	Speaking_Rate	Learner speaking speed
6.	Pause_Frequency	Pauses occurrence during speech
7.	Response_Delay	Time taken by the learner to respond
8.	Interaction_Frequency	Learner verbal participation count
9.	Audio_Engagement_Score	Indicator of audio-based engagement
10.	Listening_Consistency	Steadiness of attentive listening behavior
11.	Target	Learner attention state
12.	General_Class	Learner attention level

Moving Studentized Huber Convolution Connectionist AI

After data acquisition, the MStECCAI model uses a Connectionist AI framework with a DenseNet Convolutional Deep Belief Network to predict employability. DCNN extracts multimodal features, while DBN with RBM layers learns feature relationships. The three RBM layers handle preprocessing, feature selection, and classification. Each layer is trained individually and fine-tuned to optimize hyperparameters, improving accuracy and reducing prediction time.

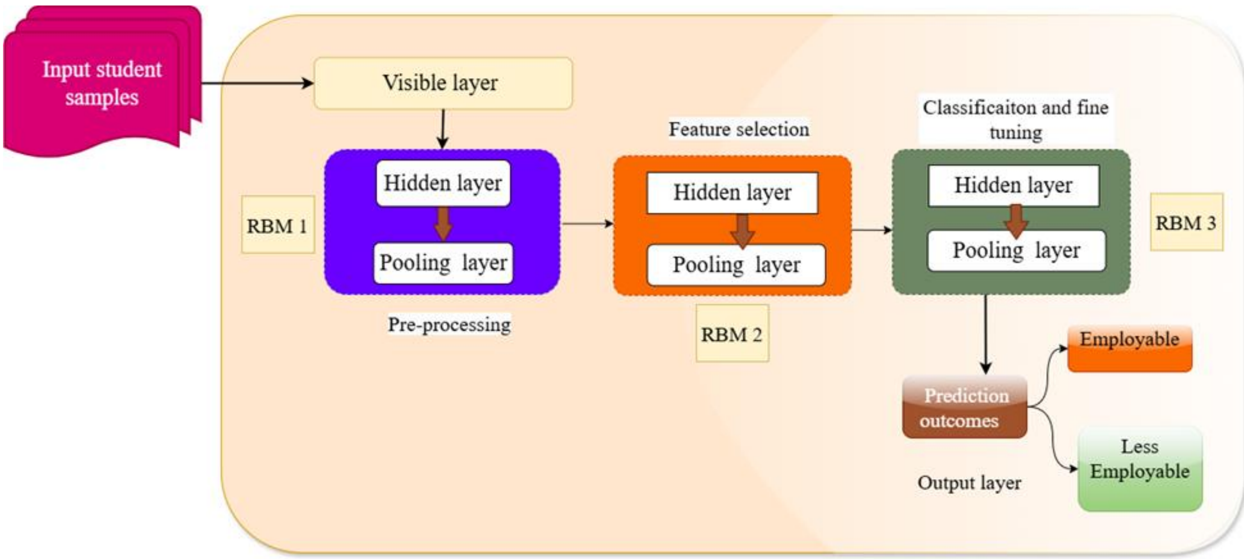


Figure 2: Structure of DenseNet Convolutional Deep Belief Network

Figure 2 shows the DenseNet Convolutional Deep Belief Network architecture in the MStECCAI model. Student data are input to the visible layer, followed by RBM 1 for preprocessing, RBM 2 for feature selection, and RBM 3 for classification. Each layer passes processed data to the next, with outputs of one RBM serving as inputs to the next, enabling continuous learning and improving prediction accuracy with reduced time. DenseNet Convolutional Deep Belief Network considers the training set {〖SS〗_i,Y_c} where '〖SS〗_i' indicates the training student samples '〖SS〗_i={〖SS〗_1, 〖SS〗_2,…, 〖SS〗_n }' collected from multimodal student dataset and class label 'Y_c' denotes the prediction output for employment. Neuron activation probability indicates the likelihood of a neuron becoming active for given inputs. It is computed from the weighted sum of inputs and bias, which is passed through a sigmoid function to produce the probability of activation. Therefore, the neuron activation probability in the hidden layer '〖AP〗_h' is given below,

$$AP_h = \sigma_{sig}(\sum_{i=1}^{n} SS_i * w_{vh}) + b \quad (1)$$

From (1), 'SS_i' symbolizes the input student samples. The weight between visible and hidden layer is denoted as 'we_{vh}'. 'b' symbolizes the bias. 'σ_{sig}' indicate the sigmoid activation function.

Pre-processing

Data preprocessing in the MStECCAI model cleans student data in RBM 1 to improve accuracy and efficiency. It includes normalization (using standard range scaling), class balancing, missing value handling (via moving average imputation), and outlier detection (using the Studentized Residual Test), ultimately enhancing data quality and reducing prediction time.

Let us consider the input as student dataset 'DS' with student samples 'SS_i' and features '$\{fe_1, fe_2, \dots, fe_m\}$' organized in the matrix format. Consequently, the input matrix is calculated as,

$$Mat \quad = [fe_1 fe_2 \dots fe_m SS_{11} SS_{12} \dots SS_{1n} SS_{21} SS_{22} \dots SS_{2n} \vdots \vdots \cdots \vdots SS_{m1} SS_{m2} \dots SS_{mn}] \tag{2}$$

From (2), 'Mat ' symbolizes the input data matrix. Every column 'n' represent the number of features. Every row 'm' indicates the number of student samples respectively. Initially, data normalization is performed to bring all features to a common scale, as varying scales can reduce classification performance. This ensures more accurate and consistent prediction. Standard range scaling has mean and standard deviation. It is formulated as,

$$SS_{norm} = \frac{SS_i - Mean}{StandardDeviation} \tag{3}$$

From (3), the normalization is carried out for every student samples. 'SS_{norm}' represent the normalized student samples. After data normalization, the student samples in the matrix 'Mat ' is given as,

$$NMat \quad = [Nfe_1 Nfe_2 \dots Nfe_m NSS_{11} NSS_{12} \dots NSS_{1n} NSS_{21} NSS_{22} \dots NSS_{2n} \vdots \vdots \cdots \vdots NSS_{m1} NSS_{m2} \dots NSS_{mn}]$$
(4)

From (4), '$NMat$ ' symbolizes the normalized input matrix. '$Nfe_1, Nfe_2 \dots, Nfe_m$' denotes the normalized feature values. Then, the missing values are identified in the given input dataset. After detecting missing values, moving average imputation is applied, where each missing data point is replaced with the average of its neighboring values to ensure continuity and data completeness. It is formulated as,

$$MA_{imputed} = \frac{SS_{t-1} + SS_{t-2} + SS_{t-3} + \cdots \dots \dots SS_{t-n}}{n} \tag{5}$$

From (5), '$MA_{imputed}$' symbolizes the imputed output. '$SS_1, SS_2, \dots, SS_n$' symbolizes the number of student samples. Missing data are handled using imputation, while outliers are detected using the Studentized Residual Test. This method identifies data points that significantly deviate from others by standardizing residuals (residual divided by estimated standard deviation). Detected outliers are then removed to improve data quality for prediction. It is formulated as,

$$T_{SR} = \frac{e(SS_i)}{SD(SS_i)} \tag{6}$$

From (6), 'T_{SR}' represent the residual for student samples. '$SD(SS_i)$' symbolizes the estimated standard deviation of residual. '$e(SS_i)$' denotes the residual of student samples. Samples with the highest residual deviation from the mean are identified as outliers and removed from the dataset. The pooling layer further reduces dimensionality by eliminating such anomalies. The cleaned and reduced data is then passed to the next RBM layer for further processing.

Feature Selection

After preprocessing, RBM layer 2 performs feature selection to identify the most relevant attributes for employability prediction. Expectile Regression is used to evaluate feature contributions, remove irrelevant ones, and reduce dimensionality, resulting in improved efficiency and reduced time consumption. The expectile regression analysis is expressed as follows,

$$_k = {Nfe_m}^T \hat{PO} + error \tag{7}$$

$$Nfe_m = [Nfe_1 Nfe_2 \vdots Nfe_m] \tag{8}$$

$$\hat{PO} = argarg \sum \quad we_\tau(\ _k)(\ _k - {Nfe_m}^T PO)^2 \tag{9}$$

$$we_{\tau}(\ _k) = \{\tau; \quad _k \geq Nfe_k{}^T \hat{P}O 1 - \tau; \quad _k < Nfe_k{}^T \hat{P}O \qquad (10)$$

From (7), (8), (9) and (10), '$\ _k$' symbolizes the observed response of feature and objective (i.e., employability prediction). 'Nfe_m' represent the column vector of normalized features. '$Nfe_m{}^T$' denotes the transpose of 'Nfe_m'. It measures the difference between observed responses '$\ _k$' and the predicted output 'PO'. '$we_{\tau}(\ _k)$' denote the asymmetric weights. 'τ' symbolizes the expectile parameter in the range 0 to 1. In the MStECCAI model, the expectile parameter (τ) is used to evaluate feature relevance. Lower τ values indicate irrelevant features, while higher τ values represent important features for employability prediction. The output value '1' denotes a relevant feature, whereas '0' indicates irrelevance and leads to feature removal. This approach effectively selects a subset of meaningful features, reduces redundancy, and minimizes computational complexity, thereby improving prediction efficiency.

Classification

After feature selection, RBM layer 3 performs classification to predict employability by categorizing student data as employable or less employable. This uses the Nominal Cramer's Phi Association Coefficient to measure the relationship between selected features in training and testing data, projecting them into a lower-dimensional space for accurate and efficient prediction. It is formulated as,

$$efe_a = \{efe_1, efe_2, efe_3, ..efe_p\} \in DS \qquad (11)$$

From (11), 'efe_j' denotes the extracted features in input dataset. The association between extracted features and testing employable student sample features is formulated as,

$$\varphi_{NCAC} = \left[\frac{\sum_{a=1}^{p} \sum_{b=1}^{q} |efe_a - efe_b|^2}{(p-1)+(q-1)}\right] \qquad (12)$$

From (12), 'φ_{NCAC}' symbolizes the Nominal Cramer's Phi Association Coefficient outcomes. 'efe_a' represent the extracted features of training student samples from input database. 'efe_b' denotes the extracted features of testing attentive student samples. The coefficient 'φ_{NCAC}' is employed to evaluate the correlation between extracted feature student samples and testing attentive student samples. It is formulated as,

$$\varphi_{NCAC} = \{1; Attentive 0.5 Partially Attentive$$

$$0; Inattentive \qquad (13)$$

From (13), the student sample is classified into different classes. Cramer's Phi ranges from 0 to 1, indicating no, partial, and strong correlation between features and employability, enabling effective classification. Student attentiveness reflecting engagement, discipline, and learning efficiency plays a key role in employability. Higher attentiveness leads to better employment outcomes, while lower attentiveness reduces opportunities. Hence, employability prediction is based on attentiveness along with academic and skill-based attributes.

Fine-tuning

Fine-tuning is the method of tuning student sample results for attaining the employability prediction performance results with minimum error. For each student sample classification prediction, the prediction error rateis formulated as,

$$E_{pre} = [APR - OPR]^2 \qquad (14)$$

From (14), 'E_{pre}' symbolizes the prediction error. 'APR' denotes actual prediction results. 'OPR' represent the observed prediction results. In the MStECCAI model, the fine-tuning stage optimizes the DenseNet Convolutional Deep Belief Network by adjusting hyperparameters using an adaptive momentum algorithm. This process iteratively updates layer weights to reduce prediction error and improve employability prediction performance. It is formulated as,

$$we_{new} \quad = \beta_t - \eta \frac{\delta_1 K_{t-1} + (1-\delta_1)\left[\frac{\partial E pre}{\partial \beta_t}\right]}{\sqrt{\delta_2 L_{t-1} + (1-\delta_2)\left[\frac{\partial E pre}{\partial \beta_t}\right]^2 + \varepsilon}} \quad (15)$$

From (15), 'we_{new}' symbolizes the updated weights. 'β_t' represent the current weight. 'η' symbolizes the learning rate. '$\frac{\partial E_{pre}}{\partial \beta_t}$' denote the partial derivative of prediction error with respect to current weight 'β_t'. 'δ' denotes momentum parameter. 'K_t' represent the first moment. 'L_t' symbolizes the second moment (i.e. variance). Depending on the updating results, various weight values are observed. Among different weights, an optimal weight is identified using Nature-inspired Swallow Swarm Optimization for minimizing employability prediction with minimum error and higher accuracy.

Nature-inspired Swallow Swarm Optimization is a population based meta-heuristic inspired by organized movement of swallows. The swallow population is initialized in the search space as '$we = we_1, we_2, \ldots . we_b$'. '$we$' denotes weights between layers. After population initialization, the fitness of weight is computed. It is computed as,

$$ff(we) = argargE_{pre} \qquad (16)$$

From (16), '$f(we)$' denotes the fitness function. '$argargmin$' symbolizes the argument of minimum function. 'E_{pre}' indicate the prediction error. Based on fitness value, diverse roles of wallows are computed namely explorer, wandering particle, local leader and global leader. The velocity of Explorer particles is updated based on total velocity. The total velocity is computed as,

$$vel_{Tot} = vel_{gl(i+1)} + vel_{(i+1)} \qquad (17)$$

$$vel_{gl(i+1)} = vel_{gl}(t) + r_1|x_{best} - x_i| + r_2|vel_{gl}(t)) - x_i| \qquad (18)$$

$$vel_{(i+1)} = vel \quad (t) + r_3|x_{best} - x_i| + r_4|vel \quad - x_i| \qquad (19)$$

From (17), (18) and (19), '$vel_{gl(i+1)}$' denotes the updated velocity of global leader. '$vel_{gl}(t)$' represent the current velocity of global leader. '$vel_{(i+1)}$' symbolizes the updated velocity of local leader. '$vel \quad (t)$' indicates the current velocity of local leader. 'rv_1, rv_2, vr_3, rv_4' are the random numbers. '$|X_{best} - X_i|$' represent the divergence between best solution and the current position. The algorithm gets iterated until maximum number of iteration is reached. After convergence of iteration, the optimal weight is attained for fine tuning of deep learning model and minimizes the employability prediction error. At last, accurate employability prediction results with lesser error are attained at the output layer. It is observed as,

$$Y = \sigma_{soft}(h_t) \qquad (20)$$

From (20), 'Y' represent the employability prediction output. 'h_t' symbolize the hidden layer output. 'σ_{soft}' denotes the softplus activation function at the output layer. This in turn, Densenet Convolutional Deep Belief Network accurately performs the employability prediction in educational institutions.

EXPERIMENTAL RESULTS

The proposed MStECCAI model is experimentally evaluated using two existing methods, CatBoost (1) and Quantized Embeddings Reduction (2), implemented in Python. The analysis uses a Multimodal Student Attention Dataset containing video and audio records from online classroom sessions. The dataset includes 2000 instances with 12 features capturing visual and auditory student behavior. Students are classified into three categories: attentive, partially attentive, and inattentive. Attentive students have higher employability potential, while partially attentive and inattentive students show lower chances of employment.

The proposed MStECCAI model is employed to compute the effectiveness in student employability prediction. The performance of proposed MStECCAI model includes student sample acquisition, preprocessing, feature selection and classification with multimodal student attention dataset collected from the Kaggle repository. Initially, the 2000 student video samples are gathered from input dataset as illustrated in the figure 3 (A) for evaluating the performance of MStECCAI model.

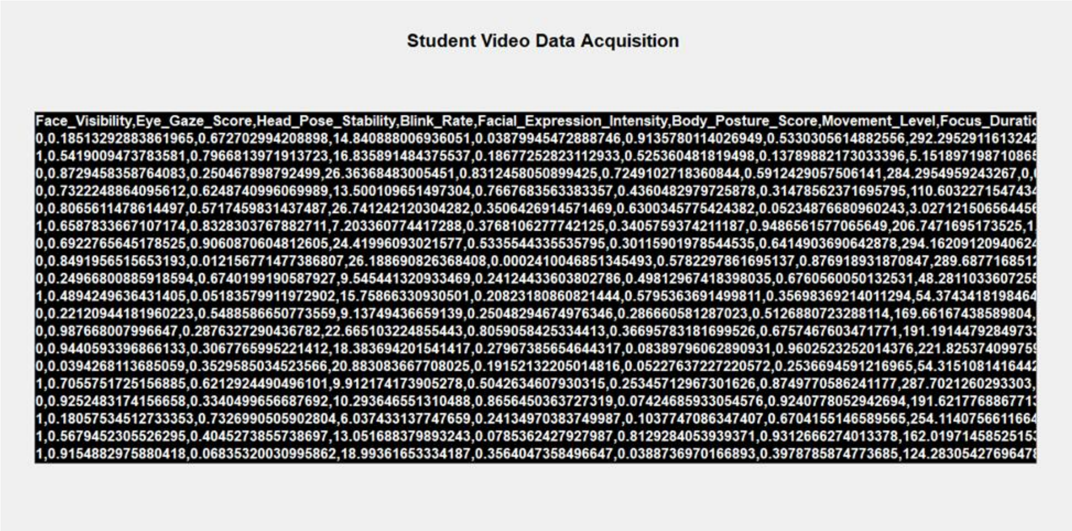


Figure 3(A): Video Sample Collection Results

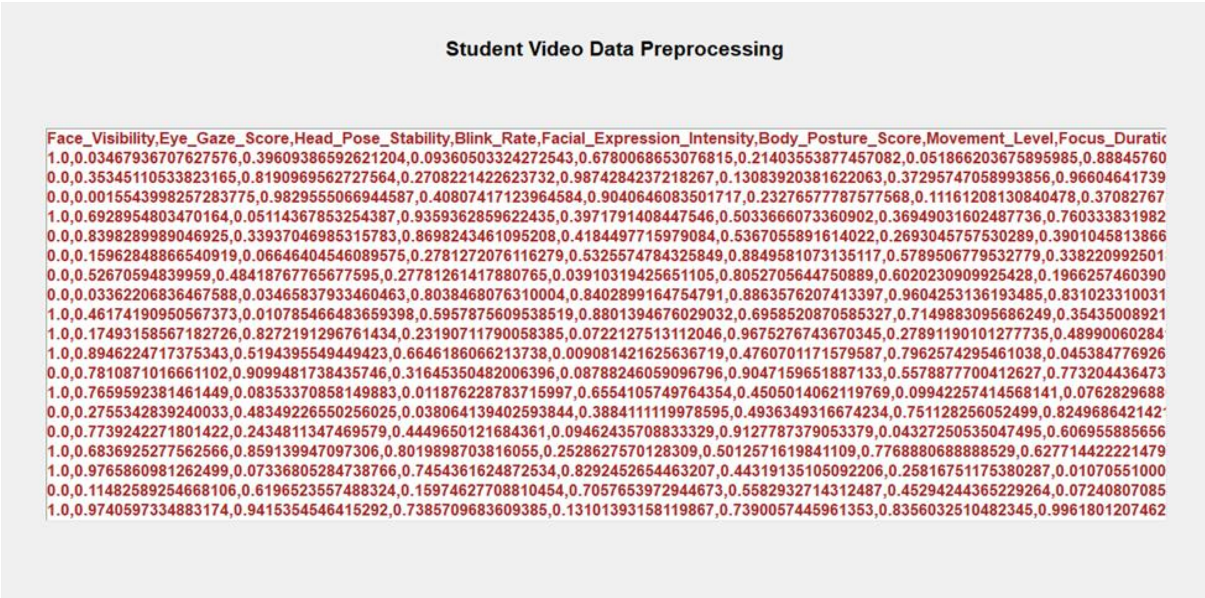
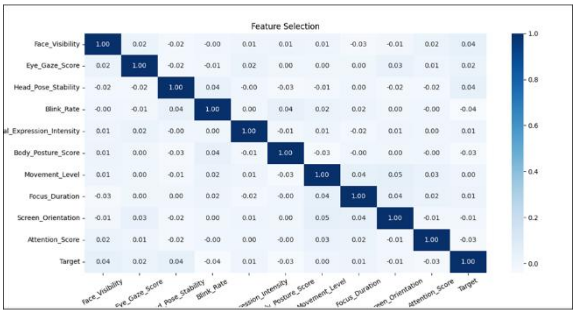


Figure 3(B): Video Sample preprocessing results

After performing the video sample collection, preprocessing is carried out with normalization, missing data handling and outlier detection steps. The size of 2000 sample is 341KB that gets minimized to 294KB after performing the preprocessing. The data preprocessing results are illustrated in figure 3 (B).



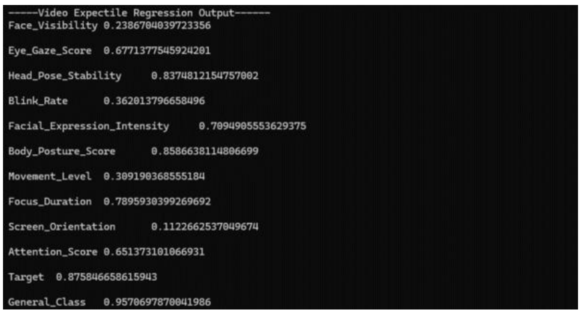


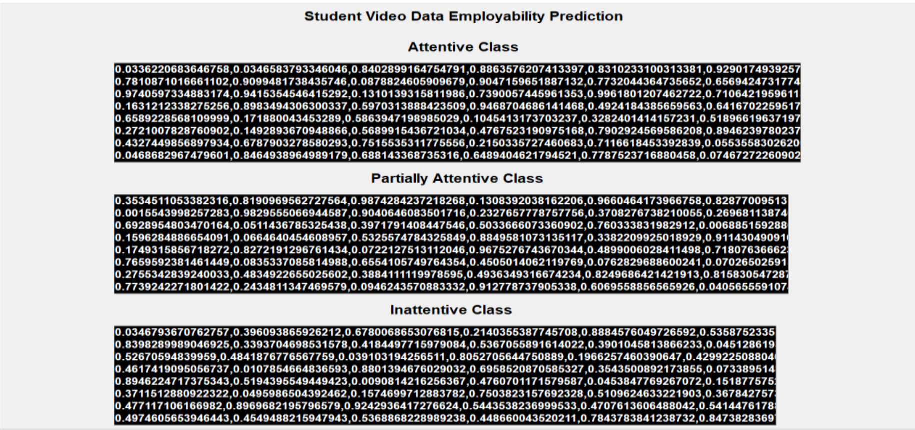
Figure 4(A) and 4 (B) Feature Selection Results of Video Samples

After pre-processing task, the proposed MStECCAI model identifies the relevant features for efficient student employability prediction. The relevant feature selection is performed through expectile regression analysis. The above figure 4 shows the feature selection results. The regression analysis chooses 8 relevant features from the 12 features to reduce the student employability prediction time. The selected feature is shown in below figure 5.

```
-----Relevant Features-------
Eye_Gaze_Score

Head_Pose_Stability

Facial_Expression_Intensity

Body_Posture_Score

Focus_Duration

Attention_Score

Target

General_Class
```

Figure 5 Selected Features List of Video Samples

Depending on the selected features, the student sample classification is carried out using nominal cramér's phi association coefficient. The proposed model is trained with the selected features to differentiate between attentive, partially attentive and inattentive class with minimum error. The student sample classification results are illustrated in below figure 6.



Student Video Data Employability Prediction

Attentive Class

```
0.0336220683646758,0.0346583793346046,0.8402899164754791,0.8863576207413397,0.8310233100313381,0.9290174939257
0.781087101661102,0.9099481738435746,0.0878824605909679,0.9047159651887132,0.7732044364735652,0.6569424731774
0.9740597334883174,0.9415354546415292,0.1310139315811986,0.7390057445961353,0.9961801207462722,0.7106421959611
0.1631212338275256,0.8983494306300337,0.5970313888423509,0.9468704686141468,0.4924184385659563,0.6416702259517
0.6589228568109999,0.171880043453289,0.5863947198985029,0.1045413173703237,0.3282401414157231,0.5189661963719
0.2721007828760902,0.1492893670948866,0.5689915436721034,0.4767523190975168,0.7902924569586208,0.8946239780237
0.4327449856897934,0.6787903278580293,0.7515535311775556,0.2150335727460683,0.7116618453392839,0.0553558302620
0.0468682967479601,0.8464938964989179,0.688143368735316,0.6489404621794521,0.7787523716880458,0.07467272260902
```

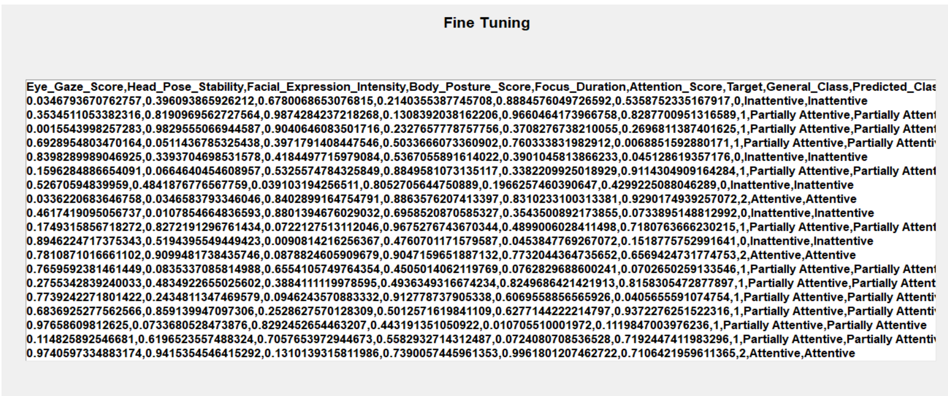
Partially Attentive Class

```
0.3534511053382316,0.8190969562727564,0.9874284237218268,0.1308392038162206,0.9660464173966758,0.82877009513
0.0015543998257283,0.9829555066944587,0.9040646083501716,0.2327657778757756,0.3708276738210055,0.26968113874
0.6928954803470164,0.0511436785325438,0.3971791408447546,0.5033666073360902,0.760333831982912,0.006885159288
0.1596284886654091,0.0664640454608957,0.5325574784325849,0.8849581073135117,0.3382209925018929,0.91143049091
0.1749315856718272,0.8272191296761434,0.0722127513112046,0.9675276743670344,0.4899006028411498,0.71807636662
0.7659592381461449,0.0835337085814988,0.6554105749764354,0.4505014062119769,0.0762829688600241,0.07026502591
0.2755342839240033,0.4834922655025602,0.3884111119978595,0.4936349316674234,0.8249686421421913,0.81583054728
0.7739242271801422,0.2434811347469579,0.0946243570883332,0.912778737905338,0.6069558856565926,0.040565559107
```

Inattentive Class

```
0.0346793670762757,0.396093865926212,0.6780068653076815,0.2140355387745708,0.8884576049726592,0.5358752335
0.8398289989046925,0.3393704698531578,0.4184497715979084,0.5367055891614022,0.3901045813866233,0.045128619
0.52670594839959,0.4841876776567759,0.039103194256511,0.8052705644750889,0.1966257460390647,0.429922508804
0.4617419095056737,0.0107854664836593,0.8801394676029032,0.6958520870585327,0.3543500892173855,0.073389514
0.8946224717375343,0.5194395549449423,0.0090814216256367,0.4760701171579587,0.0453847769267072,0.151877575
0.3711512880922322,0.0495986504392462,0.1574699712883782,0.7503823157692328,0.5109624633221903,0.367842757
0.477117106166982,0.8969682195796579,0.9242936417276624,0.5443538236999533,0.4707613606488042,0.541447617
0.4974605653946443,0.4549488215947943,0.5368868228989238,0.448660043520211,0.7843783841238732,0.8473828369
```

Figure 6 Classification Results of Video Samples



Fine Tuning

```
Eye_Gaze_Score,Head_Pose_Stability,Facial_Expression_Intensity,Body_Posture_Score,Focus_Duration,Attention_Score,Target,General_Class,Predicted_Clas
0.0346793670762757,0.396093865926212,0.6780068653076815,0.2140355387745708,0.8884576049726592,0.5358752335167917,0,Inattentive,Inattentive
0.3534511053382316,0.8190969562727564,0.9874284237218268,0.1308392038162206,0.9660464173966758,0.8287700951316589,1,Partially Attentive,Partially Attent
0.0015543998257283,0.9829555066944587,0.9040646083501716,0.2327657778757756,0.3708276738210055,0.2696811387401625,1,Partially Attentive,Partially Attent
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0.8398289989046925,0.3393704698531578,0.4184497715979084,0.5367055891614022,0.3901045813866233,0.045128619357176,0,Inattentive,Inattentive
0.1596284886654091,0.0664640454608957,0.5325574784325849,0.8849581073135117,0.3382209925018929,0.9114304909164284,1,Partially Attentive,Partially Attent
0.52670594839959,0.4841876776567759,0.039103194256511,0.8052705644750889,0.1966257460390647,0.4299225088046289,0,Inattentive,Inattentive
0.0336220683646758,0.0346583793346046,0.8402899164754791,0.8863576207413397,0.8310233100313381,0.9290174939257072,2,Attentive,Attentive
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0.7739242271801422,0.2434811347469579,0.0946243570883332,0.912778737905338,0.6069558856565926,0.0405655591074754,1,Partially Attentive,Partially Attenti
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```

Figure 7 Fine-tuning Results of Video Samples

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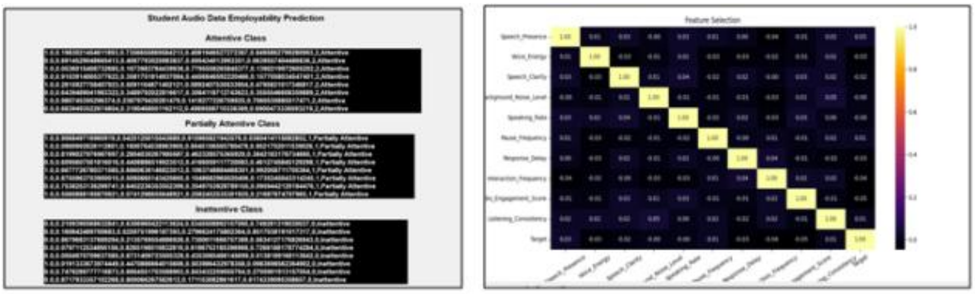
Figure 7 shows the fine-tuning results of student employability prediction. Fine-tuning process employed nature-inspired swallow search optimization to reduce prediction error by improving the true positives and true negatives for accurate student employment prediction. In the student audio sample collection, proposed MStECCAI model is used to determine the efficiency in student employability prediction. The proposed MStECCAI model comprised the student sample acquisition, preprocessing, feature selection and classification with multimodal student attention dataset gathered from the Kaggle repository. Initially, the 2000 student audio samples are collected from the input dataset as shown in the figure 8 a) for proposed MStECCAI model evaluation.

Figure 8 A) Audio Sample Collection Results B) Audio Sample Preprocessing Results



(a) (b)

Figure 9(A) and (B) Feature Selection Results of Audio Samples

The above figure 9 illustrates the feature selection results of proposed MStECCAI model. The regression analysis selects 7 relevant features from 12 features with minimum time consumption for student employability prediction. The selected features list is illustrated in below figure 10.

```
-----Relevant Features------
Speech_Presence

Voice_Energy

Response_Delay

Interaction_Frequency

Audio_Engagement_Score

Target

General_Class
```

Figure 10 Audio Samples of Selected Features List

With the selected features of proposed MStECCAI model, the student sample categorization is carried out with help of nominal Cramer's phi association coefficient. The proposed MStECCAI model performed student classification with the selected features to categorize the samples into attentive, partially attentive and inattentive class. The student sample classification results are shown in the figure 11.

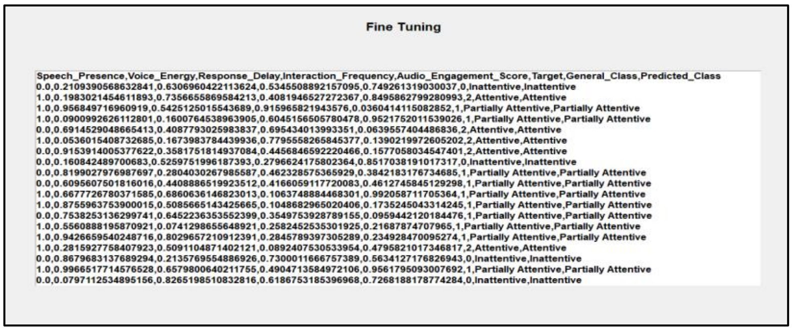


Figure 11 Classification Results of Audio Samples

In proposed MStECCAI model, the association coefficient is employed for performing accurate student employability prediction. After obtaining the classification results, the nature-inspired swallow search optimization based fine-tuning process is performed. The fine-tuning results of audio samples are illustrated in the figure 12.

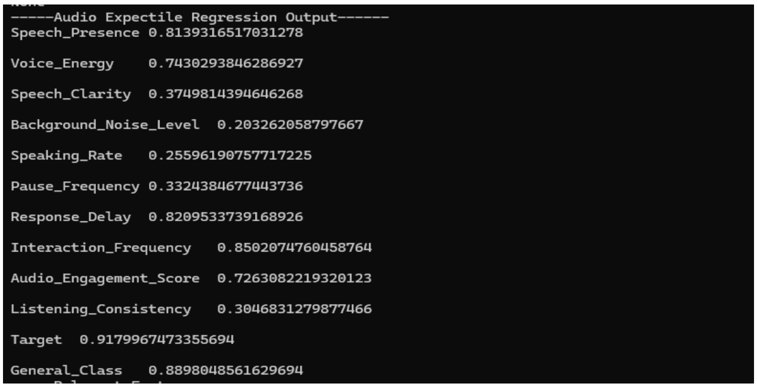


Figure 12 Fine-tuning Results of Audio Samples

Figure 12 illustrates the fine-tuned student employability prediction results of audio samples. The audio sample fine-tuning process is carried out using nature-inspired swallow search optimization through increasing the true positives and true negatives for student employment prediction.

DISCUSSION

The performance evaluation of three different methods, namely proposed MStECCAI model, existing CatBoost algorithm [1] and existing Quantized Embeddings Reduction [2] are evaluated for different performance parameters such as student employability prediction accuracy, precision, recall, F1 score, specificity and student employability prediction time across different number of student data. Table 2 shows the student employability prediction accuracy result using three methods for both audio and video samples. Recall is used to correctly identify actual positive cases of student samples. Table 4 shows the recall result using three methods for both audio and video samples. F1-score is defined as the harmonic mean of precision and the recall. Table 5 illustrates the f1-score performance of audio and video samples. Specificity is defined as the model ability to distinguish between the employable and less employable student samples. Table 6 illustrates specificity result using three methods for both audio and video samples. MCC is calculated based on the true positives, true negatives, false positives and false negatives in student employability prediction. Table 7 illustrates matthews correlation measure result using three methods for both audio and video samples. Student employability prediction time is defined as the amount of time consumed by the algorithm to predict the student employability. Table 8 illustrates the student employability prediction time for both video samples and audio samples. Coefficient of determination is a performance metric used for efficient student employability prediction outcomes. Table 9 illustrates the coefficient of determination result using three methods.

Table 2 Tabulation of Student Employability Prediction Accuracy of Video and Audio Samples

Number of samples	Student Employability Prediction Accuracy (%)					
	Video Samples			Audio Samples		
	Proposed MStECCAI model	Existing CatBoost algorithm	Existing Quantized Embeddings Reduction	Proposed MStECCAI model	Existing CatBoost algorithm	Existing Quantized Embeddings Reduction
200	98.12	94.19	92.14	97.85	92.25	91.85
400	98.88	92.74	91.68	97.94	9135	90.65
600	97.67	92.42	91.14	97.14	90.41	90.41
800	96.33	91.98	90.98	97.71	90.98	89.52
1000	97.74	92.74	90.18	97.65	91.17	89.66
1200	98.25	93.35	92.97	97.78	92.35	90.98
1400	98.96	92.41	91.65	97.23	91.95	90.74
1600	97.11	92.98	91.27	97.42	90.14	90.52
1800	98.98	93.74	92.73	97.97	91.36	91.14
2000	98.87	93.85	92.74	97.32	92.78	92.95

Table 3 shows the precision result using three methods for both audio and video samples.

Table 3 Tabulation of Precision of Video and Audio Samples

Number of samples	Precision					
	Video Samples			Audio Samples		
	Proposed MStECCAI model	Existing CatBoost algorithm	Existing Quantized Embeddings SReduction	Proposed MStECCAI model	Existing CatBoost algorithm	Existing Quantized Embeddings SReduction
200	0.985	0.967	0.956	0.981	0.955	0.951
400	0.987	0.965	0.951	0.982	0.941	0.948
600	0.983	0.962	0.946	0.984	0.954	0.949
800	0.984	0.967	0.941	0.983	0.959	0.941
1000	0.983	0.968	0.946	0.978	0.948	0.943
1200	0.987	0.966	0.932	0.979	0.957	0.947
1400	0.982	0.965	0.946	0.976	0.944	0.935
1600	0.984	0.956	0.945	0.965	0.958	0.944
1800	0.986	0.950	0.948	0.974	0.945	0.938
2000	0.987	0.952	0.949	0.972	0.942	0.934

Table 4 Tabulation of Recall of Video and Audio Samples

Number of samples	Recall					
	Video Samples			Audio Samples		
	Proposed MStECCAI model	Existing CatBoost algorithm	Existing Quantized Embeddings SReduction	Proposed MStECCAI model	Existing CatBoost algorithm	Existing Quantized Embeddings Reduction
200	0.992	0.952	0.942	0.980	0.940	0.932
400	0.987	0.948	0.938	0.978	0.932	0.921
600	0.985	0.936	0.944	0.970	0.930	0.938
800	0.974	0.940	0.935	0.975	0.935	0.932
1000	0.984	0.947	0.930	0.980	0.945	0.928
1200	0.988	0.942	0.936	0.979	0.938	0.932
1400	0.987	0.939	0.925	0.985	0.935	0.920
1600	0.990	0.948	0.936	0.988	0.930	0.927
1800	0.991	0.952	0.940	0.990	0.940	0.931
2000	0.995	0.960	0.952	0.992	0.952	0.943

Table 5 Tabulation of F1-Score of Video and Audio Samples

Number of samples	F1-score					
	Video Samples			Audio Samples		
	Proposed MStECCAI model	Existing CatBoost algorithm	Existing Quantized Embeddings Reduction	Proposed MStECCAI model	Existing CatBoost algorithm	Existing Quantized Embeddings Reduction
200	0.988	0.954	0.945	0.979	0.944	0.937
400	0.987	0.951	0.948	0.978	0.941	0.935
600	0.984	0.955	0.945	0.974	0.942	0.937
800	0.985	0.958	0.941	0.972	0.946	0.932
1000	0.982	0.949	0.938	0.976	0.942	0.937
1200	0.986	0.951	0.949	0.971	0.941	0.938
1400	0.984	0.957	0.941	0.976	0.945	0.936
1600	0.987	0.948	0.932	0.975	0.938	0.937
1800	0.983	0.952	0.944	0.978	0.937	0.940
2000	0.986	0.950	0.946	0.979	0.939	0.942

Table 6 Tabulation of Specificity of Video and Audio Samples

Number of samples	Specificity					
	Video Samples			Audio Samples		
	Proposed MStECCAI model	Existing CatBoost algorithm	Existing Quantized Embeddings Reduction	Proposed MStECCAI model	Existing CatBoost algorithm	Existing Quantized Embeddings Reduction
200	0.826	0.687	0.665	0.778	0.665	0.658
400	0.812	0.678	0.647	0.798	0.657	0.641
600	0.838	0.689	0.656	0.778	0.681	0.652
800	0.847	0.672	0.653	0.789	0.667	0.649
1000	0.845	0.668	0.649	0.837	0.654	0.640
1200	0.849	0.661	0.657	0.825	0.657	0.651
1400	0.843	0.665	0.667	0.838	0.660	0.664
1600	0.837	0.674	0.657	0.825	0.670	0.649
1800	0.847	0.668	0.647	0.838	0.661	0.635
2000	0.849	0.662	0.638	0.842	0.658	0.629

Table 7 Tabulation of Matthews Correlation Coefficient of Video and Audio Samples

Number of samples	Matthews Correlation Coefficient					
	Video Samples			Audio Samples		
	Proposed MStECCAI model	Existing CatBoost algorithm	Existing Quantized Embeddings Reduction	Proposed MStECCAI model	Existing CatBoost algorithm	Existing Quantized Embeddings Reduction
200	0.938	0.877	0.857	0.925	0.867	0.847
400	0.935	0.872	0.851	0.921	0.865	0.843
600	0.932	0.878	0.852	0.926	0.862	0.845
800	0.936	0.879	0.858	0.925	0.863	0.842
1000	0.931	0.874	0.855	0.924	0.861	0.844
1200	0.935	0.871	0.858	0.929	0.862	0.849
1400	0.934	0.871	0.855	0.921	0.868	0.848
1600	0.932	0.876	0.857	0.924	0.866	0.845
1800	0.938	0.878	0.859	0.921	0.863	0.842
2000	0.932	0.875	0.858	0.926	0.869	0.845

Table 8 Tabulation of Student Employability Prediction Time of Video and Audio Samples

Number of samples	Student employability prediction time (ms)					
	Video Samples			Audio Samples		
	Proposed MStECCAI model	Existing CatBoost algorithm	Existing Quantized Embeddings Reduction	Proposed MStECCAI model	Existing CatBoost algorithm	Existing Quantized Embeddings Reduction
200	18.7	28.8	30.8	19.8	29.8	31.5
400	20.8	30.5	32.2	21.9	32.5	33.8
600	22.9	32.6	34.7	23.7	35.4	35.4
800	26.2	34.1	36.9	27.5	37.5	39.6
1000	28.3	36.4	40.6	29.4	39.7	41.7
1200	30.5	39.2	42.4	31.2	40.4	43.9
1400	33.1	41.7	44.7	34.3	42.3	45.2
1600	36.5	43.6	46.1	37.1	44.3	47.1
1800	39.9	44.2	49.8	40.4	47.2	50.9
2000	41.2	47.7	51.5	41.9	48.9	52.6

Table 9 Tabulation of Coefficient of Determination of Video and Audio Samples

Number of samples	Coefficient of Determination					
	Video Samples			Audio Samples		
	Proposed MStECCAI model	Existing CatBoost algorithm	Existing Quantized Embeddings Reduction	Proposed MStECCAI model	Existing CatBoost algorithm	Existing Quantized Embeddings Reduction
200	0.941	0.916	0.905	0.937	0.906	0.894
400	0.945	0.912	0.902	0.938	0.903	0.895
600	0.938	0.908	0.901	0.933	0.902	0.899
800	0.945	0.911	0.905	0.932	0.901	0.892
1000	0.947	0.912	0.906	0.931	0.909	0.891
1200	0.939	0.915	0.901	0.938	0.908	0.894
1400	0.948	0.918	0.905	0.937	0.907	0.895
1600	0.937	0.917	0.906	0.938	0.908	0.896
1800	0.949	0.911	0.904	0.934	0.905	0.897
2000	0.928	0.913	0.903	0.935	0.902	0.895

Natural Resources for Human Health
eISSN: 2583-1194

CONCLUSION

Employment prediction in education leverages data analytics and AI to forecast students' future employability. This study proposed a novel MStECCAI model for accurate student employability prediction, enabling institutions to identify employable students at an early stage. The model integrates a DenseNet Convolutional Deep Belief Network to enhance prediction performance. It includes preprocessing to clean data and select relevant features, reducing time consumption and improving efficiency. Classification is performed using correlation-based measures to analyze training and testing samples, ensuring accurate categorization of employable and less employable students. A fine-tuning process further optimizes model parameters to minimize prediction error. The model is evaluated using metrics such as accuracy, precision, recall, F1-score, specificity, Matthews Correlation Coefficient, coefficient of determination, and prediction time. Experimental results demonstrate that the MStECCAI model outperforms conventional deep learning methods by achieving higher accuracy with reduced computational time.

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