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Research Article

A study on employment sustainability among Engineering students using a Statistical and Deep Learning framework

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ARTICLE INFO	ABSTRACT

In today's saturated job market, it has been one of the biggest challenges for the fresh engineering graduates from India to secure a satisfactory job offer. In this study, a Statistical and Deep learning (SDL) framework is proposed to predict students' academic achievement in terms of employability. The feature selection part of the framework is carried out with the help of a statistical module. A Deep Learning (DL) module is employed to predict their Cumulative Grade Point Average (CGPA) leading to sustainable employment. The DL module is based on Convolutional Neural Network (CNN) and attention based, stacked Bidirectional Long Short-Term Memory (BiLSTM). Lastly, to improve the interpretability of the framework, an explainability module is incorporated. The findings demonstrate how well the suggested framework forecasts students' employability over the long run and the areas in which work has to be done to make them employable as soon as they graduate. The features based on Binomial distribution yields the lowest Mean Squared Error (MSE) and Mean Absolute Error (MAE) with its superior accuracy over the Gaussian and Poisson distributions.

Keywords— Feature selection, CNN, Attention layer, StakcedBi-LSTM, explainability

I. INTRODUCTION

Every year, a significant number of engineering students are graduated from India's **Higher Education Institutions (HEI).** However, the national and worldwide job markets have not produced a proportionate number of jobs, and hence causing increased rate of unemployment. Regardless of their areas of expertise, individuals must differentiate themselves from the competition in order to receive a pleasant job offer. It is essential that engineering graduates' employability skills be strengthened in order to make them instantly employable. Prominent industrialists and academicians from India's premier institutions have suggested that the employment rate may rise with improvements by upgradation of the syllabus of professional core courses, adequate laboratory and classrooms infrastructure, and experienced and technically sound faculties. According to Sudha Murty, chairperson of the Infosys foundation, 85% of engineering graduates are not instantly employable, thus there is an urgent need to update the technical course curricula and increase the quality of education provided by engineering institutions **[1].** India's employability for engineering graduates has become a genuine concern for HEIs due to the large number of engineering graduates produced annually **[2].** The unemployment scenario of graduate engineers has been addressed by the researchers through the application of both **Machine Learning (ML) and Deep Learning (DL)** approaches. However, **SDL** approaches have not received much attention in the majority of this field's study. In order to fill this research vacuum, this study has proposed a DL-based framework guided by its statistical module to predict sustainable employment of BTech students, regardless of their engineering specializations. The rest of the paper is structured as follows. Some relevant research work in this field is included in **Section II.** The theoretical framework and methodologies are proposed in **Section III.** The experimental findings are presented in **Section IV.** The conclusion and potential future research are presented in **Section V.**

II. REALTED WORK

A great deal of research has been carried out in the field of student's performance prediction using their demographics, examination grade and other relevant information. Researchers in this field have used a variety of Data Mining (DM) methodologies, such as ML and DL algorithms, to answer most of the research problems. Decision Tree (DT), Random Forest (RF), and Support Vector Machine (SVM) have been employed by C. D. Casuat and E. D. Festijo to forecast the employability of students based on their Grade Point Average (GPA) as well as their performance rating **[3].** N. Mezhoudi, R. Alghamdi, R. Aljunaid, G. Krishna, D. Dustegor have used Data-Driven (DD) and ML techniques to identify the shortcomings in students' technical skills, that needed curriculum modification expecting for long-term market demand **[4].** A. Bai and S. Hira presented a hybrid model of Deep Belief Network and Softmax Regression (DBN-SR) with Crow Search algorithm-based feature selection for student employability prediction **[5].** O. Saidani, L. J. Menzli, A. Ksibi, N. Alturki and A. S. Alluhaidan proposed an effective methodology to forecast students' employability based on internship opportunity availed by students. The authors have used Gradient Boosting classifiers to identify the most important predictive features impacting the employment opportunity of graduates **[6].** S. Huang, N. Fang proposed four prediction models to predict academic performance of individual students namely Multiple Linear Regression (MLR), Multi-Layer Perception network (MLP), Radial Basis Function network (RBFN), and SVM. The models were implemented on datasets that included student's CGPA, grades earned in pre-requisite courses, and scores on mid-term exams **[7].** A framework based on Explainable AI (XAI) and ML was created by P. Guleria, M. Sood to assess an educational dataset with an eye on the students' skill development and employability **[8].** To assist in categorizing students' inquiries, N. Kumar, H. Krishna, S. Shubham, and P.P. Rout created a text categorization framework **[9].** B. Sekeroglu, K. Dimililer, and K. Tuncal developed a framework by utilizing Backpropagation (BP), Long-ShortTerm Memory (LSTM), and Support Vector Regression (SVR) for predicting performance of students **[10].** To assess students' conceptual knowledge, M. Tadayon and G.J. Pottie developed a time series model based on the Hidden Markov (HM) model **[11].** A CNN and LSTM-based hybrid model was developed by T.T. Dien, T. -N. Nguyen, H. Nguyen, and S. Luu to predict students' performance in the upcoming semesters based on their course completion from the previous semesters **[12].** S. Jung, J. Moon, S. Park, and E. Hwang suggested an attention-based GRU model for autonomous load forecasting **[13].** Aljaloud et al. suggested a CNNLSTM-based model to evaluate students' learning outcomes **[14].** A collection of custom activation functions has been proposed by K. Biswas, S. Kumar, S. Banerjee, and A. Pandey **[15].**

III. METHODOLOGY

The proposed SDL framework is based on hybridization of three modules namely – Statistical module for feature selection, DL module for sequence prediction and explainability module for interpreting various factors responsible to sustainable employment of the students. The statistical modelling part is conducted by Generalized Linear Model (GLM) using three different distributions allowing for more precise and perceptive interpretations. An Attention based DL model is used for regression analysis. The DL module is designed using both Convolutional Neural Network (CNN) and Attention-based Stacked-Bidirectional Long Short-Term Memory (BiLSTM) to predict final CCGPA of the students. Finally, to make the framework more interpretable, an explainability module based on InterpretML is employed. The detailed explanation of each step of the SDL framework is given below:

A. Dataset preparation

The proposed **SDL framework** is implemented on a dataset collected from students graduated in six engineering departments - Mechanical Engineering (ME), Electrical Engineering (EE), Computer Science and Engineering (CSE), Information Technology (IT), Civil Engineering (CE), Electrical Engineering (EE), and Electronics and Communications Engineering (ECE) from one of the reputed universities from Assam **[16].** Data from four cohorts in the years 2019, 2020, 2021, 2022 are included in the dataset. It is comprised of **369 instances and 37 attributes** having three sets of information - Student's demographic data acquired from a survey, examination grades collected from the examination cell and placement related data gathered from the career development and placement cell of the university. The various attributes available in the dataset are listed in **TABLE I.** The categorical variables present in the dataset are converted to the numerical features before we proceed for further processing.

TABLE I. LIST OF COLUMNS USED IN THE DATASET

SL.	Name of the fields	Description of each field	Values

Number			
1	Sl. No.	Serial Number	0-368
2	SUS_EMPP LOYEMEN T	Sustainable employment	YES, NO
3	BATCH	Four Batch of engineering	2019,2020,20 21,2022
4	Branch	Branch of engineering	ME, CE, EE, CSE, ECE, IT
5	Program	Undergraduate engineering	BTech
6-13	SGPA _1 to SGPA_8	Semester Grade Point Average after each semester	0.0-10.0
14	CGPA	Cumulative Grade Point Average after completion of BTech 8th semester	0.0-10.0
15	CLASS_X_ GRADE	Class X th result	0.0-10.0
16	C_X_B	Class Xth board	State Board, Central Board
17	C_XII_GRA GE	Class XIIth Grade	0.0-10.0
18	Class XII Board	C_XX_B	State Board, Central Board
19	Student's overall attendance from1st semester r to 8th semester of BTech	OVERALL _ATTEND ANCE	0%-100%
20	NUMBER_ OF_INTER NSHIPS	Number of internships pursued by the BTech students	1-10
21	M_F	Gender	Male, Female
22	CURRENT_ HLTH	The health of the student during BTech days	Poor, Good, Excellent
23	FAM_TYPE	Family Type	Nuclear, Joint
24	EDU_LN	The students pursued BTech with Education loan?	Yes, No
25	SCHL_RCV	The students received any scholarship during BTech?	Yes, No
26	URB_RUR	The student hails from Urban or Rural area?	Urban, Rural
27	INT_CONN	Internet connectivity is available during study hours?	Yes, No
28	NO_OF_ST UDY_HRS	Study hours	0-24
29	NO_VALU E_ADDED_ COURSE	Attended any value-added program?	Yes, No
30	SPOR_PSN	Is the student a sports person?	Yes, No
31	COC_PART	Participated in any co-curricular activity	Yes, No
32	COC_PART _ROLE	Role in cocurricular activity	Team Leader, Volunteer
33	ON_CAMPUS_PACEMENT	Received the job offer through Campus placement	Yes, No
34	OFF_CAMPUS_PACEMENT	Received the job offer through Off campus placement	Yes, No
35	PLAN_HIGHER_STUDY	Plan for Higher study	Yes, No
36	PLACED	Is the student placed?	Yes, No
37	PLAN_ENT ERPRENEURSHIP	Plan for Entrepreneurship	Yes, No

B. Statistical analysis of the predictors

The GLMs are advanced statistical tools based on 'simple' linear regression models **[17].** These models can be used for both classification or regression purpose to predict the response variable. The classification or regression is based on type of distributions and link function **[18].** Mathematically, GLM relates the weighted sum of predictors with the mean value of the probable distribution as shown in the following expression.

$$g(E_Y(y|x)) = \beta_0 + \beta_1 x_1 + \dots \beta_p x_p$$

The GLMs consist of three components: The link function **g** that ensures statistical validity and practical significance of the model's predictions. The second component is the weighted sum known as the linked predictor denoted as XTβ. The third component is the probability distribution chosen from the exponential family **EY [19].** The result summary from the trained GLM helps to perform statistical analysis of the model.

C. Feature selection

As per the summarized results obtained from the trained GLM, three sets of features are selected based on three distributions – Binomial, Gaussian and Poisson. Some of the features have positive linear regression coefficient, while others have negative linear regression coefficients. Only the features having positive regression coefficient are used as selected features for the proposed **SDL framework.**

D. Sequence prediction

The students' achievement can be evaluated based on academic performance as well as their potential for success in the workplace. Their academic performance is assessed using DL based regression model, where CGPA is considered as the target variable and SGPAs and other demographic variables act as the independent variables. The DL model is comprised of - one CNN layer, three Bi-LSTM layers stacked on top of one another followed by a dense layer. After receiving the selected features by GLM, the CNN performs the second stage of features selection. The Bidirectional Long Short-Term Memory (Bi-LSTM), a recurrent neural network, processes the input sequences provided by the CNN layer. The stacked-Bi-LSTM has the ability to handle data in both directions. The forward LSTM tracks future information, whereas the reverse LSTM processes and manipulates prior data. As a result, the model is better able to comprehend how the student's prior academic achievement, demographics, and CGPA relate to their future academic success. Each layer of BiLSTM is integrated with batch normalization and dropout. A custom attention layer is added as one of the hidden layers of BiLSTM that helps the model to focus on inputs with higher weight. The loss function, optimizer, and performance metrics are the three hyperparameters that are used to compile the model. The "Mean Squared Error (MSE)" and "Mean Absolute Error (MAE)" are used as loss functions so that the model learns from the discrepancies between the actual and expected output. The "Adam" optimizer, a well-known stochastic gradient method, is used to automatically modify the weights in response to errors found in the neural network's output layer. Following the compilation process, the model is trained using the training data, making use of the ideal number of hidden layers and nodes inside each hidden layer to achieve optimal performance. "Early stopping" is a technique used to stop model training after a predetermined number of epochs if validation error does not decrease during the course of each epoch.

E. Interpretation of the model's prediction

Eventually, the influence of various predictors in sustainable employment (SUS_EMPLOYMENT) can be evaluated using an interpretable framework. The DL-based models are considered as black boxes for their lack of interpretability to identify the inputs that contribute to the prediction process both in positive and negative direction. Microsoft offers an interpretability framework - InterpretML that has the ability to train interpretable Glass box models and explain black box models like DL and Neural Network (NN). This study uses Explainable Boosting Machine (EBM), a glass box paradigm that implements both global and local explainability functions of InterpretML. The EBMs are able to precisely forecast and explain the overall prediction process **[20, 21].** The advanced level of model's interpretability is performed with DP-EBMs, a differentially private learning algorithm for Generalized Additive Models (GAMs) due to its exceptionally higher accuracy. The InterpretML is implemented using DP-EBMs for both classification and regression purposes on numerical datasets **[22].**

The effectiveness of the projected **SDL framework** is deliberated in the following section as Results and Discussion.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The outcome of the suggested work is divided into the following categories for simpler analysis:
A. Performance evaluation of the GLM based statistical model
The statistical model of GLM is trained with features selected on the basis of different types of distributions. The **Fig. 1** shows the summarized results of the trained model such as - log likelihood, deviance, linear

regression coefficients, standard errors, p values, z scores, and 95% confidence level etc. with respect to types of exponential family. As shown in **Fig 1**, the input features are associated with either positive or negative **linear coefficients.** Only the features having positive regression coefficient are used as selected features for the proposed **SDL framework.**

Generalized Linear Model Regression Results

Dep. Variable:	SUS_EMPPLOYEMENT	No. Observations:	369
Model:	GLM	Df Residuals:	333
Model Family:	Poisson	Df Model:	35
Link Function:	Log	Scale:	1.0000
Method:	IRLS	Log-Likelihood:	-312.42
Date:	Sat, 06 Apr 2024	Deviance:	68.833
Time:	14:56:36	Pearson chi2:	59.0
No. Iterations:	5	Pseudo R-squ. (CS):	0.2135
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	7.3167	153.536	0.048	0.962	-293.608	308.242
BATCH	-0.0036	0.076	-0.048	0.962	-0.152	0.145
Branch	0.0295	0.055	0.536	0.592	-0.079	0.138
Program	-0.1432	0.416	-0.344	0.731	-0.959	0.672
SGPA_1	-0.0383	0.125	-0.308	0.758	-0.283	0.206
SGPA_2	0.1084	0.174	0.622	0.534	-0.233	0.450
SGPA_3	-0.0127	0.073	-0.174	0.862	-0.155	0.130
SGPA_4	0.0484	0.142	0.341	0.733	-0.230	0.327
SGPA_5	0.0169	0.114	0.148	0.882	-0.207	0.241
SGPA_6	-0.0686	0.122	-0.561	0.575	-0.308	0.171
SGPA_7	-0.0342	0.230	-0.149	0.882	-0.484	0.416
SGPA_8	0.0570	0.231	0.247	0.805	-0.395	0.509
CGPA	0.0230	0.211	0.109	0.913	-0.390	0.436
CLASS_X_GRADE	-0.0304	0.082	-0.371	0.710	-0.191	0.130
C_X_B	-0.1648	0.180	-0.917	0.359	-0.517	0.187
C_XII_B	0.1313	0.183	0.717	0.473	-0.228	0.490
CLASS_XII_BOARD	0.0012	0.011	0.114	0.909	-0.019	0.022
OVERALL_ATTENDANCE	-0.0194	0.101	-0.193	0.847	-0.217	0.178
NUMBER_OF_INTERNSHIPS	-0.0707	0.074	-0.952	0.341	-0.216	0.075
M_F	-0.0036	0.204	-0.018	0.986	-0.404	0.397
CURRENT_HLTH	-0.0205	0.149	-0.138	0.891	-0.312	0.271
FAM_TYPE	-0.1040	0.210	-0.495	0.620	-0.515	0.307
EDU_LN	0.0274	0.194	0.141	0.888	-0.353	0.408
SCHL_RCV	-0.1792	0.201	-0.892	0.372	-0.573	0.215
URB_RUR	0.1484	0.154	0.964	0.335	-0.153	0.450
INT_CONN	-0.1185	0.234	-0.507	0.612	-0.577	0.340
NO_OF_STUDY_HRS	-0.0034	0.074	-0.046	0.963	-0.148	0.141
NO_VALUE_ADDED_COURSE	0.0056	0.035	0.160	0.873	-0.063	0.074
SPOR_PSN	0.1200	0.176	0.681	0.496	-0.225	0.465
COC_PART	-0.1116	0.107	-1.047	0.295	-0.321	0.097
COC_PART_ROLE	0.0058	0.153	0.038	0.970	-0.293	0.305
ON_CAMPUS_PACEMENT	-0.0568	0.174	-0.326	0.744	-0.398	0.285
OFF_CAMPUS_PACEMENT	-0.0279	0.173	-0.161	0.872	-0.367	0.311
PLAN_HIGHER_STUDY	-0.1006	0.162	-0.619	0.536	-0.419	0.218
PLACED	1.4366	0.273	5.266	0.000	0.902	1.971
PLAN_ENTERPRENEURSHIP	0.5188	0.165	3.142	0.002	0.195	0.842

Fig. 1 Generalized Linear Model Regression Results (Mo del family: Binomial)

The TABLE II shows the list of features selected by GLM with respect to three types distributions – Binomial, Gaussian and Poisson having positive coefficients.

TABLE II. LIST OF FEATURES NOMINATED BY GLM

GLM (Distributions)	Selected features
Binomial	CGPA, BATCH, Branch, SGPA_1, SGPA_4, SGPA_5, SGPA_8, C_XII_B, M_F, FAM_TYPE, INT_CONN, COC_PART_ROLE, ON_CAMPUS_PACEMENT, PLAN_HIGHER_STUDY, PLACED, PLAN_ENTERPRENEURSHIP
Gaussian	CGPA, BATCH, Branch, SGPA_2, SGPA_4, SGPA_5, SGPA_8, C_XII_B, CLASS_XII_BOARD, EDU_LN, URB_RUR, NO_OF_STUDY_HRS, NO_VALUE_ADDED_COURSE, SPOR_PSN, COC_PART_ROLE, PLAN_ENTERPRENEURSHIP, PLACED
Poisson	CGPA, Branch, SGPA_2, SGPA_4, SGPA_5, SGPA_8, C_XII_B, CLASS_XII_BOARD, EDU_LN, URB_RUR, NO_VALUE_ADDED_COURSE, SPOR_PSN, COC_PART_ROLE, PLACED, PLAN_ENTERPRENEURSHIP

The selected features as listed in the TABLE II, are used to train the statistical model of GLM. The TABLE III shows the performance of the statistical model of GLM using three subsets of features as listed in TABLE II.

TABLE III PERFORMANCE EVALUATION OF GLM

GLM (Distribution)	**Selected features**	**Accuracy**
Binomial	CGPA, BATCH, Branch, SGPA_1, SGPA_4, SGPA_5, SGPA_8, C_XII_B, M_F, FAM_TYPE, INT_CONN, COC_PART_ROLE, ON_CAMPUS_PACEMENT, PLAN_HIGHER_STUDY, PLACED, PLAN_ENTERPRENEURSHIP	1

Gaussian	CGPA, BATCH, Branch, SGPA_2, SGPA_4, SGPA_5, SGPA_8, C_XII_B, CLASS_XII_BOARD, EDU_LN, URB_RUR, NO_OF_STUDY_HRS, NO_VALUE_ADDED_COURSE, SPOR_PSN, COC_PART_ROLE, PLAN_ENTERPRENEURSHIP, PLACED	0.97
Poisson	CGPA, Branch, SGPA_2, SGPA_4, SGPA_5, SGPA_8, C_XII_B, CLASS_XII_BOARD, EDU_LN, URB_RUR, NO_VALUE_ADDED_COURSE, SPOR_PSN, COC_PART_ROLE, PLACED, PLAN_ENTERPRENEURSHIP	0.92

The comparative analysis performed using families of three probability distributions as shown in TABLE III has confirmed that the classification accuracy with binomial distributions has bested the other two distributions in GLM.

B. Performance evaluation of the DL based prediction model

Looking at the TABLE III, it can be observed that the final CGPA of the students is one of the common features and student's final CGPA is highly corelated to the response variable of SUS_EMPLOYMENT. The DL based predictive model is implemented on each subset of features as given in the TABLE III. As it is a nonlinear regression problem, the performance metrics used here are MSE and MAE. The TABLE IV shows the behavior of the model using the three sets features with respect to performance losses i,e MSE, and MAE.

TABLE IV. PERFORMANCE OF THE SDL FRAMEWORK

Model- GLM based DL framework				
GLM (Distribution)	CNN-Stacked BiLSTM			
	MSE-Train	MSE - Test	MAE-Train	MAE-Test
Binomial	0.91	0.17	0.70	0.31
Gaussian	1.03	0.31	0.78	0.47
Poisson	0.92	0.41	0.71	0.56

The results shown in the TABLE IV indicate that the MSE and MAE of the proposed framework is lowest where features are selected under the Binomial family.

C. Interpretation of the most influential feature(s) in the model prediction

After receiving BTech degree in their respective domain, most of the students' desire to be employable. Nevertheless, some of them wish to pursue either higher study or become an entrepreneur after graduation. An interpretable framework called InterpretML is employed in this study to assess the impact of different predictors on students' long-term employability. The **Fig. 2** explains the global interpretability of the model using EBM.

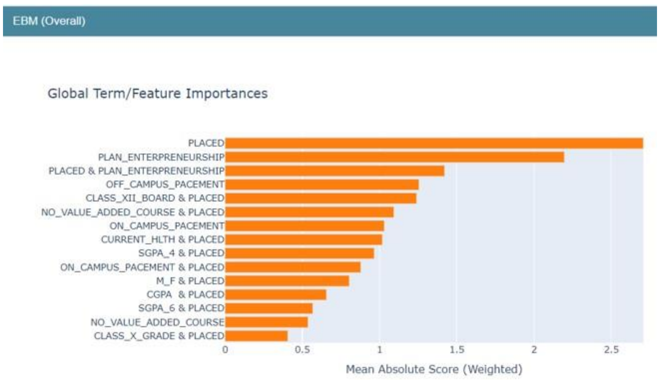

Fig. 2 Overall summary plot of EBM showing the contribution of important features on sustainable employment

As shown in the **Fig. 2**, to have long-term employability, first of all, the students must be placed. They may like to work as an entrepreneur that makes them employable for longer duration. The placement through off campus interview has better chance of long-term employment. Similarly, the result in class XII board examination has significant impact on sustainability. Likewise, number of value-added courses make the students employable for long time. In order to explain the model's prediction for a single instance of the dataset, the **Fig. 3** explains the list of predictors, positively or negatively correlated to SUS_EMPLOYMENT.

Fig. 3 Local explanation plot of EBM showing the contribution of important features (SUS_EMPLOYMENT = YES)

As illustrated by the **Fig. 3,** both the actual and predicted outcomes are aligned. The precision score provided by EBM for this specific instance is 1.0. The features with orange-coloured bars are positively correlated to sustainable employment. Whereas the other features with blue bars are negatively correlated to the response variable. The gender, class XII result, 4th semester and 5th semester SGPA and on campus placement are highly corelated with placement. Accordingly, the placement and off campus placement are positively correlated with sustainable employment. The student has no plan for entrepreneurship. Neither he/she got placed through on campus drive. Thus, these two features have no correlation with sustainable employment. Similarly excellent health and being a female engineering graduate have no direct impact on sustainable employment. However, the student who qualified class XII under central board and four value added courses in undergraduate education have better chance of long-term employability.

V. COCLUSION

In our present study, a prediction framework has been proposed to forecast employment sustainability of the engineering graduates. The input features selected by the Generalized Linear Model (GLM) based on Binomial distribution have improved the prediction accuracy of sustainable employment. The same set of features as Binomial distributions while employed in the DL based regression framework, the losses was found to be the lowest. It has been noted that the performance of the proposed framework with binomial distributions has surpassed that of the other two distributions of Gaussian and Poisson. An explainability framework is employed to find the collinearity between the response variable and the list of predictors. It has been noted that the score received by the student in class 10th board examination, Branch of engineering, SGPA, proper study environment with good Internet connectivity, a cultured and healthy family structure, participation in various extracurricular activities and high CGPA are the important factors for long-term employment. This study offers an inclusive road map that enables the application of Statistics and Deep Learning techniques to forecast sustainable employment of graduate engineers from India's Higher Education Institutions (HEI). In the future, the proposed framework would be integrated with advanced DL algorithms. The framework would help nation's educators and policy makers to improve the rate of sustainable employment among fresh engineering graduates.

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