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AMLDD: An Automated Machine Learning Framework for Depression Detection Among Undergraduate Engineering Students in India

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Abstract

Stress is a natural sentiment that impacts humans physically and mentally. It is above the physical pain that humans can bear. Stress is the main cause of depression. The research work presents an overview of stress management using Artificial Intelligence. It focuses on an experiment conducted on the IBM Cloud Platform using automated machine learning tools to detect early signs of sadness among the undergraduate students. The experimental results show that logistic regression achieved the highest accuracy of 0.861 with feature engineering and hyperparameter optimization. The presented work can be generalized to other categories to help society, especially college students aged 18 and above, and could save their lives.

I. Introduction

Stress is a natural emotion that affects humans physically and mentally [1]. It is beyond the physical pain. Stress bears fear. Stress can be positive or negative. Positive stress keeps motivating us, while negative stress can affect health for a long time. The chemical changes seen in the human body when under stress. The three hormones play an important role: Cortisol, Adrenaline, and Serotonin [2]. The first one is Cortisol, known as the "stress hormone". It is released from the adrenal glands. It affects our sleep and our immunity. We can gain weight and feel anxiety. The second one is adrenaline, which is useful for a short time because it is part of our immune system. It increases BP, blood sugar, and breathing, so it is dangerous in the long term. The third one, Serotonin, which stabilizes our mood when it dips, helps us feel less stressed.

The most stress comes from your lifestyle, including family arguments, responsibilities to your family and society, feeling alone, and sleeping less. It also comes from professional events, such as office workload, fear of deadlines, and pressure from the boss. Nowadays, stress and depression afflict many students. Students can feel stressed early due to peer pressure and expectations from parents, teachers, and society. Sometimes students are bullied by other students, which can cause them to feel stressed. Misunderstandings, arguments, or communication gaps are common causes of stress. As a result, trust issues are broken. Sometimes discrimination based on caste, religion, gender, etc., can be the reason for stress. Overthinking also causes stress in such situations.

1.1 Artificial Intelligence in stress management

Artificial Intelligence (AI) plays a key role in stress management by detecting early signs of stress and providing personalized solutions based on data and routines. An AI assistant where users can talk freely about their feelings, provides motivating messages and support as a 24/7 personal listener that doesn't judge and is always available. A custom stress management AI creates a routine based on their daily schedule, stress level, and workload. Also it suggests a proper diet plan, a healthy sleep cycle, meditation, and advice on time management [3]. Student and employee stress management AI detects stress and helps students manage career stress, exam anxiety, and depression by smartly recommending and motivating. Also, detect employee workload, reduce stress, and improve work-life balance. Multimodal Stress Analysis using AI more accurately detects stress by analyzing the user's facial expressions, voice, and physiological signals. AI helps doctors detect a patient's stress level early using data such as heart rate, blood pressure, and sleep cycle.

1.2 Research objectives

The research objectives are:

- The primary aim of this research paper is to examine how artificial intelligence can help detect the central problem of depression among college students (specifically, engineering students aged 18 and above).
- To pinpoint the most common reasons that lead to mental stress, strain, anxiety, and the most important reason, low provocation or feeling apathetic.
- To use AI-driven tools to detect early signs of sadness.
- To examine how students' lives harm mental wellness through study load, examination pressure, and time management.
- To develop an AI mental health system in colleges that encourages students to get regular sleep, play games, and exercise.
- To establish a supportive, eustress-literate environment for college students through the use of artificial intelligence.

II. LITERATURE REVIEW

Joshi, Lata, and Kanoongo (2022) [4] presented a study based on AI techniques such as Naive Bayes, Support Vector Machines (SVM), Long Short-Term Memory (LSTM), and Recurrent Neural Networks (RNN), Logistic Regression, and Artificial Neural Networks (ANN), which help in the detection and analysis of emotion. Liu et al. (2022) [5] primarily aim to review machine learning (ML) methods for detecting depressive symptoms in social media text data, and they found that these methods are effective but raise issues such as data sampling, generalizability, privacy concerns, and other ethical concerns. Hasib et al. (2023) [6] studied and reviewed several state-of-the-art machine learning (ML) and deep learning (DL) techniques in terms of the systematic literature review (SLR) approach for depression detection. They also highlight critical challenges identified in the existing literature that may inform future studies. Varsha et al. (2023) [7] studied finding depressed people by their comments, posts, or texts on social media. Data mining and machine learning algorithms are used for detecting a person's emotions. Six classifiers are applied to predict Depression and non-depression, and the best accuracy is obtained on a support vector machine (SVM). Aleem et al. (2022) [8] reviewed different machine learning algorithms used to detect and diagnose Depression. The ML algorithms include classification, deep learning, and ensemble. A general model for depression diagnosis, involving data extraction, preprocessing, training an ML classifier, detection/classification, and performance evaluation, is presented and discussed, along with its limitations and future research opportunities. Kumar et al. (2022) [9] studied the detection of Depression from Twitter posts using machine learning and natural language processing techniques. They analysed sentiment features and detected Depression with an accuracy of 78% using the XGBoost classifier, and achieved 89% accuracy when combining these features with N-gram, TF-IDF, and LDA using the Support Vector Machine classifier. Tahir, Waleed Bin, et al. (2025) [10] propose studio-based approaches using machine Learning and Deep Learning techniques for detecting Depression. This paper suggests that Depression can be identified using machine learning and deep learning by analysing a person's behaviour and language on social media (Twitter, Facebook, Reddit, and Instagram). Cao, Xiaoming, et al. (2025) [11]. The studies of this research paper were conducted between 2017 and 2024. In this, Depression has been identified from facial expressions. Deep learning has been used in this research paper. This system analyses face photos (facial expressions) and videos (behaviour). and identify Depression. It is divided into two parts: Special and Spital Temporal. Yan, Zhijun, Fei Peng, et al. (2025) [12] Depression is a big problem that is spreading rapidly among youth, affecting their health and life. Detection of Depression is very important. This paper uses machine learning, deep learning, and AI, focusing on data imbalance and the model's power, and employs explainable AI techniques to understand the model. Pinto, Smitha Joyce, et al. (2024) [13] Depression is a serious problem that affects people, especially youth, today. Common ways to find Depression would take more time and have a greater effect. Because of this, people are looking for easy, fast methods. Today, computers and smart tools (AI, ML, DL) are being used to help identify Depression. These tools study body signs and how people speak or write in daily life. This method is easier to use, works quickly, and is helpful in real situations. Khan, Shakir, and Salihah Alqahtani. (2024) [14] recently found that Depression is a serious mental problem in daily life and affects physical health. Between 2012 and 2023, researchers used social media to collect data to detect Depression. During this phase, machine learning techniques were used detect Depression with accuracy. They used different data sources, such as text, image, and user behaviour, for analysis. In some research, work on neural networks and image processing using a model to achieve better accuracy. In the future, this study will help researchers with important guidance and provide essential references. Ksibi et al. (2023) [15] studied depression detection using electroencephalography (EEG) by applying machine learning and deep learning techniques. EEG data are collected from the multi-modal open dataset MODMA and CNN models were trained to classify depressed and healthy subjects. Where CNN around 97 % accuracy. The study showed that a natural combination of EEG signals and demographic data improves the depression detection. Deshpande et al. (2017) [16] studied depression detection by apply natural language processing on Twitter feeds. They classified individual tweet as neutral or negative by using machine learning algorithms such as support vector machine and Naive-Bayes and their result using the primary classification including accuracy, F1-score, and confusion matrix. Patel et al. (2016) [17] reviewed the studies in depression by using neuroimaging data and machine learning methods to identify depressed patients vs. non-depressed patients and predict treatment outcomes and suggest the directions for future depression-related studies. Ghandeharioun et al. (2017) [18] studied the detection of Hamilton Depression Rating Scale (HDRS) by using machine learning algorithms on collected data from E4 wearable wristbands and from sensors in an Android phone, input data include EDA, sleep cycle, motion, phone-based communication, location changes, and phone usage to predict HDRS scores and achieved low relative error with about 4.5 RMSE and the result show that the sensor based ML methods can effectively identify depression behaviour. Campanella et al. (2023) [19] this study proposes to analyse signals obtained from the Empatica E4 bracelet using machine-learning algorithms (Random Forest, SVM, and Logistic Regression) to determine the efficacy of the abovementioned techniques in differentiating between stressful and non-stressful situations. Photoplethysmography and electrodermal activity signals were collected from 29 subjects to extract 27 features which were then fed into three different machine-learning algorithms for binary classification. Using MATLAB after applying the chi-square test and Pearson's correlation coefficient on WEKA for features' importance ranking, the results demonstrated that the Random Forest model has the highest stability (accuracy of 76.5%) using all the features. Moreover, the Random Forest applying the chi-test for feature selection reached consistent results in terms of stress evaluation based on precision, recall, and F1-measure (71%, 60%, 65%, respectively). Ahuja et at. (2019) [20] The dataset was taken from Jaypee Institute of Information Technology and it consisted of 206 student's data. Four classification algorithms Linear Regression, Naïve Bayes, Random Forest, and SVM is applied and sensitivity, specificity, and accuracy are used as a performance parameter. The accuracy and performance of data are further enhanced by applying 10-Fold Cross-Validation. The highest accuracy recorded was by Support Vector Machine (85.71%). Le Yang, D Jiang et al. (2017) [21] presented paper "Multimodal Measurement of Depression Using Deep Learning Models", where they developed a multi-modal deep learning system that combines audio, video, and text information to predict depression. This model used neural networks to analyze facial expressions, speech and responses to predict depression severity. Islam et al. (2018) [22] studied depression discovery using social network data from Facebook. They used machine literacy styles similar as Decision Tree, SVM, KNN, and Ensemble models. verbal, emotional, and temporal features were uprooted using LIWC software. The results showed that the Decision Tree model performed more than other machine literacy ways. Haque et al. Haque et al. (2021) [23] studied depression among children and teenagers from 4 to 17 years of age. The study used data from the Young Minds Matter (YMM) survey. Different machine learning models were tested, such as Random Forest, XGBoost, Decision Tree, and Gaussian Naive Bayes. The researchers mainly looked at signs like feeling sad, losing interest in daily activities, sleep problems, low energy, and suicidal thoughts. The results showed that the Random Forest model worked better than the other models for predicting depression in children. Orabi et al. (2018) [24] worked on chancing depression from Twitter posts. They used tweets written by normal addicts and tested deep knowledge models like CNN and RNN. The study tried to see if depression signs can be set up from simple textbook participated on social media. The results showed that CNN models gave better results than RNN models when the data was not truly large. Tavchioski, I., Koloski, et al. (2022) [25] Tavchioski, I., and Koloski (2022, May) shared a paper to solve the detection of early signs of depression from social media Text. They explore three different approaches to solve the challenge: fine-tuning BERT model, features construction using AutoML. They ranked 9th out of 31 teams in the competition. Their best solution, depend on knowledge graph and textual representations, was 4.9% behind the best model in terms of Macro F1, and only 1.9% behind inn terms of Recall. Squires, M., Tao et al. (2023) [26] Recent exploration shows that artificial intelligence and machine literacy are decreasingly used to support the discovery and treatment of depression. Unlike traditional individual styles that calculate substantially on tone- reported questionnaires, data- driven models dissect textbook, clinical, and neuroimaging data to identify depressive patterns more objectively. Deep literacy ways further ameliorate performance by automatically learning meaningful features from data. Several studies also punctuate the eventuality of AI- grounded models to prognosticate individual treatment response, supporting the idea of perfection psychiatry. still, limited data vacuity and lack of external confirmation remain major challenges for real- world clinical use. Amanat et al. (2022) [27] explored how deep knowledge can be used to descry depression from textbook participated on social media platforms. Their work points out that traditional opinion styles, similar as interviews and questionnaires, constantly depend on private judgment and may not always reflect a person's true emotional state. To address this issue, the authors proposed an LSTM and RNN rested model that examines the emotional meaning and terrain of written textbook. The model was tested on Twitter data and showed strong performance in distinguishing depressed from on-depressed addicts. Although the results are promising, the study suggests that farther testing on larger and further different datasets is necessary before similar systems can be used in real clinical settings.

III. Methodology

a. Data collection and pre-processing

The data for this study were obtained from a Kaggle repository titled "Student Depression Dataset". The dataset includes 16,698 students from across India.

Data preprocessing has been performed to remove null, redundant, and irrelevant features. After preprocessing, the final list contains only 1,153. The students were selected based on certain criteria. Eligibility criteria include students aged 18 or older. Students pursuing an Engineering (B. Tech) degree from any Indian college. On the other hand, the exclusion criteria include students under 18 and those not pursuing Engineering (B. Tech) at any Indian college. The sample size was filtered to maintain consistency in the study and to avoid bias from adding students from different academic backgrounds or age groups.

b. Feature Engineering

Data analysis and feature engineering have been performed on the IBM Cloud Platform to select the most suitable parameters.

Table 1. Feature description

Features	**Importance**
Age	age group(18-34) of students
City	Data includes multiple cities of India.
Profession	Student
Academic Pressure	The level of academic stress rated on the scale of 1-5.
CGPA	Cumulative grade point : 5.08 to 10.
Study Satisfaction	It identify whether a student is satisfied with their studies; it ranges from 1 to 5.
Sleep duration	There are four categories: less than 5 hours, 5-6 hours, 7-8 hours, and more than 8 hours.
Dietary habits	Dietary habits with three parameters: unhealthy, moderate, and healthy.
Degree	B. Tech (Bachelor of Technology).

IV. Experimental design

The experiment has been conducted on the IBM Cloud Platform using the IBM Watson machine learning framework. AutoML is suitable for this dataset, which consists of structured tabular data with a moderate number of samples and includes numerical, categorical, and binary variables.

IBM AutoML is an automated machine learning framework provided by IBM Cloud Pak for Data. It systematically evaluates multiple model pipelines using cross-validation and ranks them based on performance parameters such as accuracy. In this experiment, IBM AutoML was used to build a reliable, unbiased model for the early detection of depression among engineering students in India, ensuring high accuracy, transparency, and consistent results. The dataset was ingested from a Comma-Separated Values (CSV) file, and an AutoML experiment was configured with depression as the prediction column. In Binary Classification, the prediction type is defined with 1 indicating the positive class (depressed students). The AutoML configuration interface is shown in Figure 1. When the experiment commenced, AutoML automatically read the dataset, split the data, preprocess the data, select models, and optimize, all within a structured workflow.

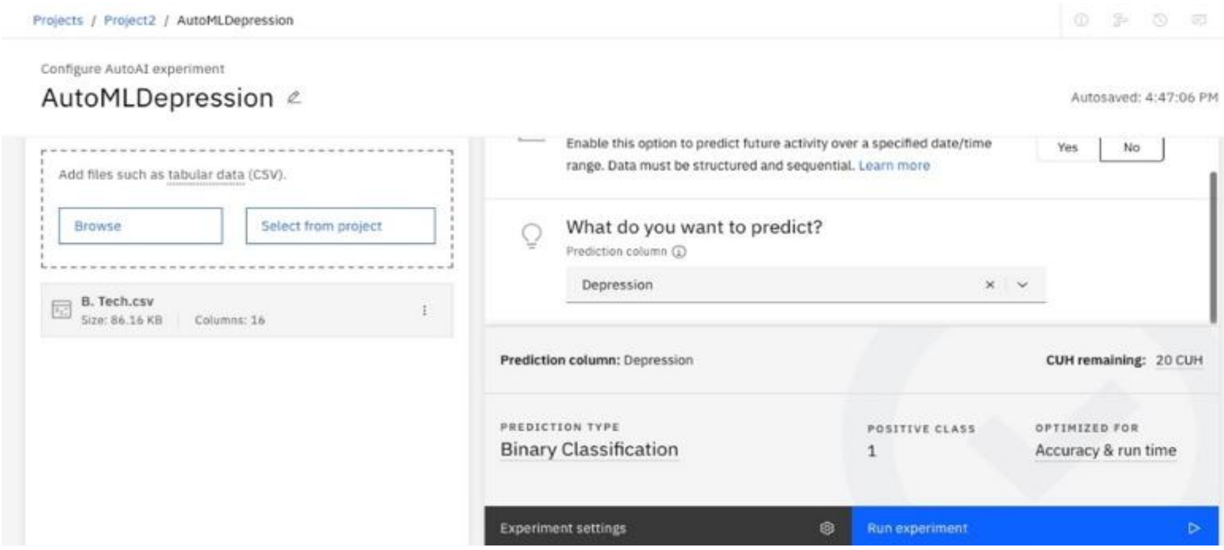

Figure 1. AutoML experiment configuration for depression prediction

V. Result and discussion

This section will discuss the model building, experimental results, and their analysis. The progress of model selection is shown in the IBM Cloud Platform-based AutoML (Automatic Machine Learning) interface immediately after completing the experimental setup. The progress map is shown in Figure 2 below. AutoML performs model selection by choosing suitable algorithms for the dataset. In this case, the models are Logistic Regression and SVM (Support Vector Machine). After that, AutoML applies feature engineering and hyperparameter optimisation to improve model performance. The model generates multiple pipelines (P1-P8) and automatically evaluates them. These steps show that AutoML executes the complete ML process without any manual intervention.

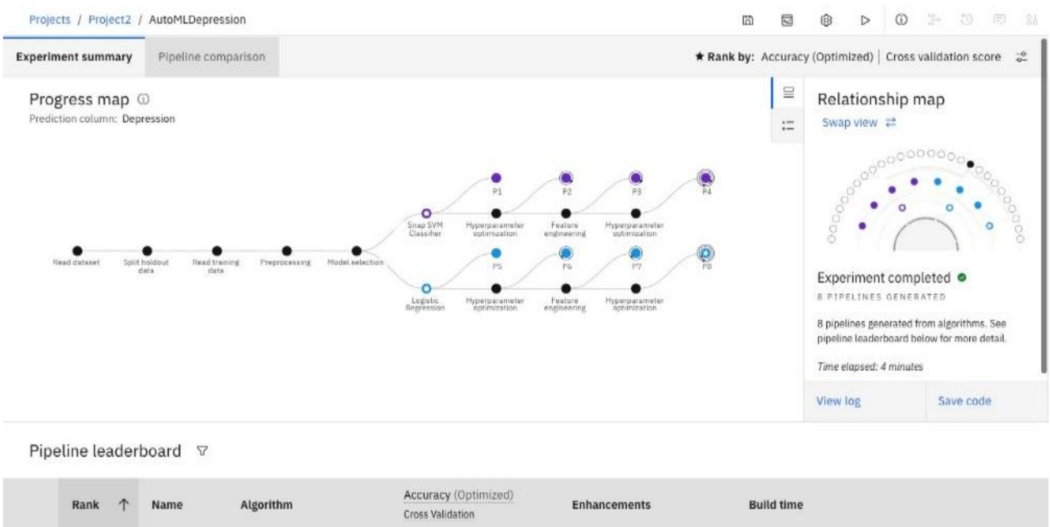

Figure 2. AutoML progress map showing pipeline generation process

The relationship among the different models has been evaluated and depicted in Figure 2. This map shows the different approaches used by AutoML before the final model selection. The pipeline generation view shows how different models are built step by step.

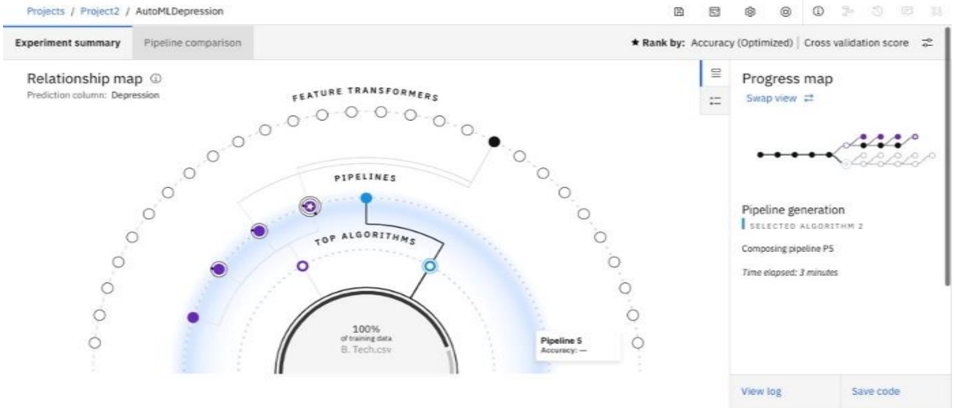

Figure 3. AutoML experiment configuration for depression prediction

The pipeline leader board is shown in Figure 4 below. Every pipeline was evaluated using cross-validation accuracy, and the AutoML system automatically ranked them based on optimized performance. All pipelines initiated during the experiment were represented on the pipelines leader board as shown. On the progress leader board, the highest accuracy was consistently achieved by Logistic Regression-based pipelines. A cross-validation accuracy of 0.861 included both feature engineering (FE) and hyperparameter optimization (HPO).

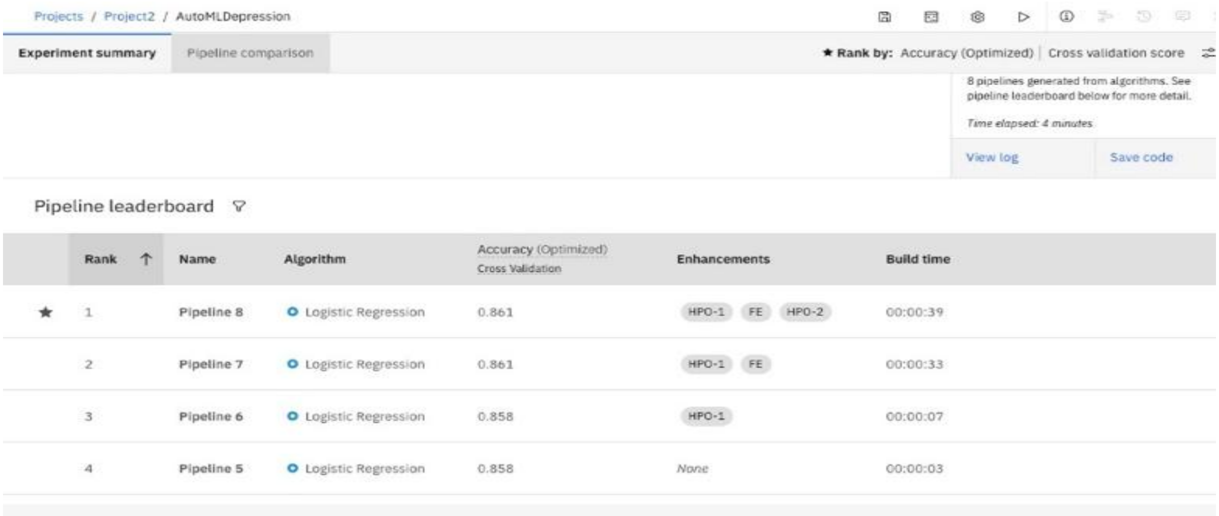

Figure 4. Pipeline leaderboard with accuracy comparison of generated models

6. CONCLUSION AND FUTURE DIRECTION

Among the college students (focused on those 18 years and above), depression due to academic load, ruthless competition among scholars, and more expectations affect students' psychological health. They suffer many consequences, including physical and mental effects and behavioral changes. The number of suicides in India is very large. The AutoML model was applied to a dataset of 1153 samples, achieving 0.861 accuracy with the Logistic regression model. The proposed AutoML model can detect stress at early stages. This study is highly beneficial for college students aged 18 and above and could save their lives.

More cognitive diseases can be addressed in the future from the collected dataset. Deep learning techniques can be applied to yield more efficient results. The dataset may be further expanded to generalize this study in other domains.

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