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Integrating Psychological Stress Indicators with Academic Data for Student Dropout Prediction: A Decision Tree and Expert System Approach

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Abstract

Student attrition remains a major problem in higher education. Although academic variables are well-established moderators, psychological wellness, especially stress, is an important but often ignored moderator. The purpose of this study is to construct prediction models for students at risk of dropping out by combining academic and psychological information. One major challenge in this field is the class imbalance of student records, which results in a significant drop in the dropout rate compared to the general population. Therefore, in this study, we employ a Decision Tree algorithm and use a Forward Chaining inference engine along with the Synthetic Minority Over-sampling Technique (SMOTE) to solve it. We employed a data set of 122 students at one institution, with psychological stress scores generated from a standardised questionnaire according to well-known symptom domains. The accuracy for the model with only a Decision Tree was 95.83%. For the stress score, integration with the FC-based attribute increased performance to 96.67%; however, this model exhibited only marginal improvement over the final model due to its very low accuracy when compared to that of SMOTE. This ensemble model performed the best with an accuracy of 97.50% and an AUC of 96.35%. This progression demonstrates that even though the introduction of psychological information is beneficial, an approach to balance data and ensure a robust prediction system is required. This article is a proof-of-concept analysis which creates an opportunity for universities to establish proactive, early-warning-driven models; yet there is a requirement for future validation studies on larger and more diversified samples.

INTRODUCTION

Education is the acquisition of knowledge and skills between teachers and students in a classroom [1]. High student success rates and low failure rates are usually the metrics that indicate good quality of higher education. One important misery index of students' failure is that when they fail to finish studying at the right time, it may cause drop out [2]. Hence, colleges and universities are confronted with the task of not only enhancing academic achievement but also reducing student attrition.

In 2022, the dropout rate of students in tertiary education sank from 5.34% to 4.02%, according to data from the Ministry of Education, Culture, Research and Technology (Kemendikbudristek). Regionally, East Java had the highest dropout rate in 2022, at 55,667 students, or 4.91% of the total. The reasons behind dropout are varied, both academically (low IPK, late completion of study) and non-academically, such as financial difficulties, social environment, and stress. Stress, in particular, has been reported as a major cause of school failure [3]. This is supported by studies from ACHA [4] and WHO [5], in which many students feel great psychological pressure in their studies. In Indonesia, data from the Center for Higher Education Studies show that students experiencing severe academic stress are 3.4 times more likely to drop out than those with low-moderate stress levels.

Due to the diverse nature of these causes, a broad-reaching strategy is required for early identification of students at risk. Artificial Intelligence and Data Mining are very promising for finding hidden patterns in both academic and non-academic data [6], [7], [8], as it helps the models to be built that allow recognition of dropout students [9], [10], [11].

Decision Tree is one of the most popular and effective data mining techniques for classification and prediction, depending upon pre-existing patterns in the data [12], [13]. According to a literature review conducted by Boran, Decision Tree was the basis of 19% studies (20 out of 109) for dropout classification and prediction [14]. Equally, review by Anaíle identified Decision Tree as a method frequently used (19.9%) together with the ones such as Naïve Bayes, KNN, Logistic Regression and Random Forest [15]. Among the many classification methods, the decision tree (DT) has been adopted based on its reliability. As a result of empirical research, DT was found to be superior to other methods by continually producing accurate and reliable results [16].

An issue that is often encountered when creating a prediction model to predict if students will drop out is the fact that classes are usually unbalanced, with more non-terminations (the majority class) than terminations (minority class). Such an imbalance can make models biased against at-risk students, resulting in poor student risk prediction. Resampling approaches, such as the Synthetic Minority Over-sampling Technique (SMOTE), can be applied to remedy this. SMOTE generates synthetic instances of the minority class to result in a balanced distribution of classes so that the model can learn stronger patterns of both classes, using improved results as it predicts accurately possible drop-outs or failures [17].

Some similar research has shown the efficiency of the Decision Tree as well. For example [18] utilized it to predict dropout students in Universitas Advent Indonesia based on the gender, age and applicant's IPK with 90% accuracy. Another research of Qurrotul [19], comparing between decision tree and naive bayes, which decision tree has a minimal better result, namely 94.44% accuracy. In addition, the comparison of the Decision Tree and Deep Learning [20] demonstrated that only 95% was obtained as the best accuracy performance by the Decision Tree model.

But if you use academic data alone, it can't represent the complex nature of why students drop out because non-academic (like being stressed) factors are very influential. To mitigate this deficiency, our study applies a Forward Chaining expert system to evaluate students' stress situations. This expert system is based on the assessment of psychological factors, including anxiety symptoms, mental fatigue, sleep disturbances and modifications in social behaviour [21], [22].

An expert system is required in this situation, as evaluation of stressors is a subjective process that needs a psychologist or a counsellor's experience. Such systems can learn and encode this knowledge in the form of rule-based if-then formulas that can be used coherently and systematically when assessing a student's condition [23].

In addition, forward chaining expert systems have the capability of representing and dealing with uncertainty and complexity in making psychological diagnosis inferences from input data, as a human expert does 24. Although the methodology of this analysis employs a self-completed questionnaire, the Forward Chaining method applies an objective structure to transforming raw subjective symptom scores into binary 'stress level' diagnostic categories and, as such, adds systematisation not afforded by simple question scores. This is especially advantageous for scalable applications where it is impractical to have a live professional interact directly with each student.

Previous studies have confirmed that an expert system works effectively in stress detection. For example, [25] designed a web-based system by using Forward Chaining and Certainty Factor technique to detect the stress of students during the COVID-19 pandemic, which is classified as mild, moderate, and severe levels. Another research from [26] developed a similar Android-based expert system to that of the method proposed in [51] for testing stress among final year students; it attained an accuracy rate of 97.97%. However, these existing systems typically serve as isolated diagnostic tools and are not widely integrated as feature generators in a comprehensive predictive machine learning pipeline for dropout risk, an important integration that we focus on here.

Our dropout early detection model seeks to provide a more comprehensive evaluation through the mixture of Decision Tree and Forward Chaining. This is not the same as a standard incorporation of a question-scaled score into one's analysis; this is a development of a knowledge-originated diagnostic construct that can be interpreted within the logic which underpins the decision tree. The expert system provides essential information about a student's psychological status (rate of stress), which is combined with the academic data analysis through a Decision Tree.

Our methodological decisions are underpinned by particular compromises. The Decision Tree algorithm is chosen not only because of its high accuracy but for its high interpretability, which is vital in ensuring actionable findings for academic advisors—a merit that often gets lost amidst more complicated "black-box" ensemble methods or deep learning models. Forward Chaining was selected because of its simplicity and adequacy to encode deterministic expert knowledge on a diagnostic process, whereas physics-based methods, as proposed for this problem, are more suitable for manipulating uncertainty in a system. We recognize that this is a particular trade-off between interpretability and possible predictive performance.

Given the foregoing problems and related studies, in this paper, we propose a classification and prediction model of dropout students by blending a Decision Tree with Forward Chaining. A major challenge is to include the stress level as an influential factor in the dropout risk estimation. The main objective is to determine the effectiveness of this hybrid approach, which combines a rule-based product type output and an interpretable classification model, in improving the predictive performance of identifying dropout risk, particularly when evaluating students with borderline academic performances. In addition, it seeks to assess the precision of the model generated in detecting potential student dropouts.

It's been empirically shown in earlier studies that expert systems can be used to detect stress. For example [25] developed a web-based system that used Forward Chaining and Certainty Factor to monitor students' stress on the online learning level during the COVID-19 pandemic as mild, moderate, and severe. Another [26] constructed an expert system for the Android platform using a comparable approach to identify stress among final-year students with an accuracy of 97.97%. These results suggest that Forward chaining, as an expert system tool, is feasible in that facts can be systematically traced to create precise rule-based decisions.

When fused with Decision Tree and Forward Chaining, our dropout early detection model is expected to be more precise and comprehensive. The expert system also gives important input related to a student's psychological state(stress level), which is incorporated into the Decision Tree with analysis of academic data. This allows schools to develop a fuller picture of why students drop out and then focus on specific solutions.

In light of the issues mentioned above and related works, in this study, we propose a decision support system for dropout risk classification and prediction by using a Decision Tree in combination with the Forward Chaining method. An important goal is to include stress level in the automaton analysis of the risk dropout. Likewise, this research also seeks to assess the effectiveness of the regression model in predicting potential desertions.

METHODS

Data Collection

The data for this study were collected from two primary sources. The first one is academic Data**.** This dataset includes data of students in the enrollment year 2018-2020 in STTR Cepu. This multi-cohort sampling frame was deliberately constructed so that all students had time to transpire toward the conclusion of interest (graduation or dropout), and hence provide minimal right censoring bias. The data set consists of 8 attributes with Student ID (NIM), Semester IPK (IPS), Cumulative IPK (IPK), Age, Parents' Income, Number of Family Dependents and Discipline records. Student who are still enrolled beyond their cohort graduation date were excluded from the analysis to keep clear definitions of outcomes. The second one is Psychological Data**.** This dataset is about the stress of students. The stress symptoms questionnaire was developed by aggregating domains of well-known psychological constructs, such as the Perceived Stress Scale (PSS), to ensure content validity for academic stress. The diagnostic rules were developed through a structured consultation with a certified clinical psychologist specialising in student mental health. The resulting rule set indicates a consensus based on this expert input from which to operationalize the diagnostic criteria in a deterministic rule-based structure. Symptom data was self-reported by the students themselves.

Data Preprocessing

The data processing stage involved the Cleaning and Transformation. non-identifying information (name, address) was deleted. The 'Study Program' was removed to avoid overfitting and complexity. Continuous variables (IPS, IPK, Parents' Income, and Age) were recoded into a categorical format that has meaning. IPK was split using institutional academic probation standards, and other variables were discretised based on empirical quartiles. We do note that this is a tradeoff between interpretability in the Decision Tree and the loss of information granularity. This stage also included Integration. The stress level diagnoses derived from the psychological data were merged with the preprocessed academic dataset.

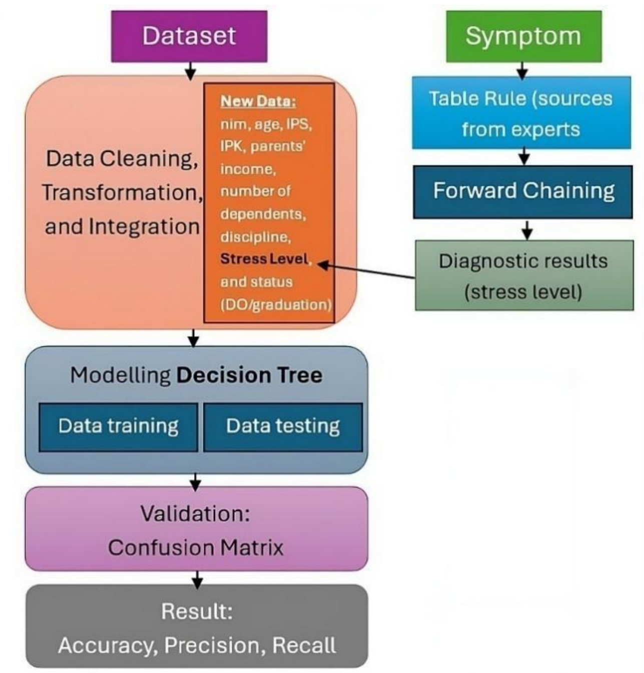

Figure 1. Proposed Modelling Method

Proposed Modelling Method

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The proposed methodology model is presented in Figure 1. This model incorporates a Forward Chaining expert system. In addition, a Decision Tree algorithm is applied to support the analysis.

Forward Chaining for Stress Level Assessment

The Forward Chaining approach was employed in stress level classification of students (low, moderate and high) corresponding to their self-reported symptoms. This approach was selected for its ease of use and applicability to diagnostic purposes [27]. Well, it starts with facts (the symptoms) and adds a chain of expert-authored rules to arrive at a conclusion (stress level diagnosis). The diagnosis that is obtained is inserted as a new feature in the academic dataset.

The steps for this process are: (1) Students were asked to answer a group of questions, which included whether they had difficulty sleeping, felt agitated easily, lacked appetite and were too anxious; (2) Rule-based diagnostic IF-THEN statements were developed by psychological experts (IF symptom1 AND symptom2 AND symptom3 THEN high stress, IF symptom1 AND symptom4 THEN moderate stress, IF only symptom1 THEN low stress); (3) Reasoning Process: The student's questionnaire entries are read by the system, and then the expert rules are utilized to predict his stress level. For example, if a student showing symptoms as 1 and 2 and 3 then the system return stress level is "High." (A diagram of this process is given in Fig. 2 of your article); (4) Dataset Integration: The last stress level prediction is then added as a new feature in the main academic dataset and this latter is taken as input for the next phase.

Figure 2. Forward Chaining Reasoning Process

Illustration:

Input: A student exhibits symptoms 1, 2, and 3

Applicable rule: "IF symptom1 AND symptom2 AND symptom3 THEN high stress"

Inference result: Stress level: High

Decision Tree for Dropout Prediction

Decision tree model and validation for the severe class imbalance present in this data (\textasciitilde15\% dropout rate) SMOTE was used. SMOTE was then applied only to the training data (with k=5), after train/test partitioning, in order to avoid any data leakage to the test set. We recognize the danger of SMOTE producing unrealistic synthetic samples; however, it was required to enhance model sensitivity.

The Decision Tree algorithm was applied to the combined dataset. The model was applied in Python with scikit-learn. Grid search and 5-fold cross-validation on the training set were used to determine approach-specific best hyperparameters that optimize performance versus generalization. The hyper-parameters tuned were criterion='gini', max_depth=4, min_samples_split=5, and min_samples_leaf=2.

The modelling and validation process was designed for robustness: (1) Data Splitting: The data were initially divided into a stratified 80% train set and 20% hold-out test set. A stratified split was employed to maintain the distribution of different classes for both sets; (2) Model Development and Validation: Grid search with a 5-fold cross-validation was conducted in the training set for robust hyperparameter tuning. The best/most consistent model was subsequently retrained using the optimal hyperparameters on the full training set and rigorously tested against the hold-out 20% set to provide metrics of generalisation such as accuracy, precision, recall, F1-score and AUC.

RESULT AND DISCUSSION

In this part, the results of our study are illustrated from the process of data preprocessing to the performance evaluation for this combined model. It combines student psychological characteristics and academic information to make more complete and accurate predictions of potential drop-outs. This research used 122 data points of the students at STTR Cepu. One should mention that in this dataset we observed a heavy class imbalance, 18 students (14.8%) as dropouts and 104 students (85.2%) as graduates an important aspect for model building and testing. The dataset comprised two main components: academic data and psychological data.

Academic Data: The academic dataset consisted of fields such as Student ID Number, Name, Gender, Age, Address, Email ID, Semester IPK (IPS), Cumulative IPK (IPK), and Parental Income No.of Dependents, Discipline and Graduation Status (Dropout/Graduated).

nim	name	gender	age	adderss	email	IPS	IPK	Parental	Numbe	Discipl	Graduati
20150001	CLARA DWI ANGGRAINI (Keluar	P	23	Kedungnongko Rt 2 rw	dwi030392@gm	0.86	1.12	1	1	70	0
20150003	ACHMAD CHABIB AKBAR ALMAD	L	23	Ds Kentong Rt 05 Rw 0	chabibur212@g	4	3.47	1	1	100	1
20150004	AHMAD RIGAN MUSTOFA	L	24	Desa purwosari Dukuh	ahmadriganmu	4	3.45	2	1	100	1
20150006	ANNAS FIGAR SYAHYA (Keluar)	L	23	Des. Jeruk, kec. Randu	Figarannassyah	1.12	2.4	1	1	70	0
20150007	ARDANA TUNGGA DEWI	P	23	Desa Sumber RT:05 RV	ardanatd@gmai	4	3.54	1	1	100	1
20150008	ARYO RONGGO WIBOWO (Kelu	L	22	Jl Raya Randublatung k	aryoronggo77@	0.34	0.86	2	1	70	0
20150010	DODY RISQI CRYSTYAWAN	L	24	Ds biting Dk mlawu Rt	dodyydod84@g	3.63	3.3	1	0	90	1
20150011	ELA DWI OKTAVIANI	P	24	Jln.nglajo lr.04 no.29,F	elaviani48@gm	4	3.61	1	3	100	1
20150012	ELIZABETH DEVI RAHMAWATI	P	24	Jl.Jendral Sudirman Ga	elizabethdevi90	3.63	3.3	2	2	97	1
20150013	FAIZAL MAYONG KURNIAWAN	L	25	004 RW 004 Kec.	faizalmayong24	3.63	3.24	2	1	97	1
20150014	FARKHAN SYAEFULLAH	L	25	Jl Ronggolawe Timur Sl	aant.cru@gmail	4	3.06	1	5	100	1
20150015	IING CANTIKA NINGRUM	P	23	Desa Sidorejo 014/003	iingcantika27@	4	3.46	1	2	100	1
20150017	JOKO SETIAWAN	L	23	Ds. Temurejo RT 02 RV	setiawanjoko35	4	3.48	1	1	100	1
20150018	KARUNIA FAJAR WIMUKTI	L	23	ledok rt 03/rw01	muktigendut0@	3.63	3.32	1	3	90	1
20150019	KHAFIDZ AKHMAD SUYUDI	L	23	Batokan rt26 rw04 kec	khafidzsuyudi@	4	3.44	1	4	100	1
20150020	KURNIA SETIYA DEWANTORO	L	24	Jalan duku no 74 RSS k	kurniasetyadew	4	3.37	1	4	100	1

Figure 3. Initial academic data

Psychological Data: Psychological evaluation was based on a questionnaire designed by taking cues from existing psychological paradigms, except that it was not validated against any standard instrument such as the PSS. The survey was based on 60 symptoms of stress obtained through expert consultation and literature search.

Form_Responses

Timestamp	Name	NIM	email	Sudden, i	Difficulty slee	Excessive fatigu	Being easily irrita	Loss of motivation	Difficulty cor	Increased heart ra	Frequent fe
22/07/2025 11:46:59	Ella Dwi Oktaviani	2015001	Dewi67@gma	no	no	no	no	no	no	no	no
22/07/2025 12:27:18	Muhammad Anif Fir	2355001	Aniffirman6@	yes	no	no	yes	yes	no	no	no
22/07/2025 12:28:32	Artikha Putri Nirmal	2355002	artikaa5262@	yes	yes	yes	yes	yes	yes	yes	yes
22/07/2025 12:32:59	Cevin Eris Setiawan	2155000	cevintok123@	no	yes	no	no	no	no	no	no
22/07/2025 12:39:44	Muhammad narul hi	2455000	Baliyanto287(	no	yes	no	no	no	no	no	no
22/07/2025 12:57:46	nayla fitriani	2455001	naylafitriani61	no	yes	no	no	no	yes	no	no
22/07/2025 13:10:41	Fikha Aulia	2355003	fikhaauliaa05	yes	yes	yes	no	no	yes	no	yes
22/07/2025 13:11:28	Denni figo	2155000	dennifigo1@g	no	yes	no	no	no	no	no	no
22/07/2025 13:13:13	Nur Azizah	2355001	anurazizah37	no	yes	yes	no	yes	yes	no	no
22/07/2025 13:29:15	Bintang putra nagar	2355001	putranbintang	no	no	yes	no	yes	no	yes	yes
22/07/2025 13:29:57	Amelia Tiani	2355001	ameliatiani80	no	no	yes	yes	no	no	no	no
22/07/2025 14:14:10	Ervian febrianto	2155000	febriantoervia	no	no	no	no	no	no	no	yes
22/07/2025 14:49:24	Dewi Nuraeni	2455000	dewinuraeni0	yes	no	no	yes	yes	yes	no	yes
22/07/2025 15:15:37	Ika Putri Mu'alimah	2455001	ikaptri245@g	yes	no	yes	no	yes	yes	no	yes
22/07/2025 15:34:29	Nabila Belva Fawnia	2255000	nabilabelvafa	yes	yes	yes	no	yes	yes	no	yes

Figure 4. Student Psychological Data

Student Stress Diagnosis Using Forward Chaining

The Forward Chaining method was employed to diagnose student stress levels (categorized as mild, moderate, and high) based on self-reported symptoms. The rule-based system utilized a deterministic inference engine with a 'first-match' conflict resolution strategy, though it lacked explicit mechanisms for handling uncertainty or ambiguous symptom presentations.

Rule Formulation: Diagnostic rules were structured as IF-THEN statements derived from psychological literature and expert consultation. For transparency, a sample rule is shown where the presence of symptoms {J2, J3, J4, J6, J9, J10, J12, J15, J16, J22, J23, J25, J27, J28, J29, J33, J54, J57, J59} leads to a 'Moderate' classification, though we note the system's limitation in handling partial matches (e.g., J121 missing) through confidence weighting.

Table 1. List of Stress Symptoms

Symptom Code	Symptoms	Symptom Code	Symptoms
J1	Sudden, intense feelings of anxiety	J31	Nausea/vomiting
J2	Difficulty sleeping or insomnia	J32	Weight gain or loss
J3	Excessive fatigue for no reason	J33	Cold hands and/or feet when discussing your final project
J4	Being easily irritated or angry for no reason	J34	Cold sweats while working on your thesis
J5	Loss of motivation to study, work, or engage in activities	J35	Slow body responses
J6	Difficulty concentrating	J36	Waking awake at night
J7	Increased heart rate or blood pressure	J37	Lack of activity throughout the day
J8	Frequent feelings of hopelessness	J38	Frequent anxiety about thesis-related matters
J9	Changes in eating patterns, such as overeating or undereating	J39	Muscle tremors and/or restlessness while working on your thesis
J10	Feeling overwhelmed by responsibilities	J40	Carelessness
J11	Frequent feelings of helplessness or loss of control	J41	Excessive consumption of certain foods or drinks
J12	Sudden, unexplained crying or anger	J42	Abnormally aggressive behavior
J13	Frequent muscle pain or headaches	J43	Decreased quality of work done
J14	Loss of interest in activities you used to enjoy	J44	Dry mouth
J15	Tendency to avoid responsibilities	J45	Stomach discomfort
J16	Increased consumption of caffeine or other stimulants	J46	Anxiety about meeting your thesis supervisor
J17	Unexplained or unreasonable fear	J47	Feeling helpless or frustrated
J18	Frequently feeling lonely even when surrounded by others	J48	Feeling bored with life
J19	Decreased productivity or performance	J49	Inability to make decisions about college
J20	Desire to be alone for long periods of time	J50	Panic-proneness
J21	Loss of self-confidence	J51	Frequent crying
J22	Drastic mood swings in a short time	J52	Suicidal thoughts
J23	Difficulty making decisions, even about simple things	J53	Loss of time orientation/frequently being late/missing schedules
J24	Feelings of dissatisfaction with what has been achieved	J54	Experiencing periods of confusion
J25	Reluctance to talk about your thesis	J55	Feeling tense
J26	Feeling tired when waking up in the morning	J56	Forgetfulness
J27	Studying seems difficult	J57	Loss of interest in physical appearance
J28	Daydreaming when alone	J58	Looking gloomy
J29	Difficulty thinking or feeling somewhat slow	J59	Pacing up and down
J30	Loss of enthusiasm for anything	J60	Constant procrastination

Diagnosis Distribution: Analysis of the 122 students revealed 48% were diagnosed with mild stress, 39% with moderate stress, and 13% with high stress (Figure 5). This distribution is noteworthy as it indicates that over half of the student population experiences moderate-to-high stress levels, establishing a substantive basis for including psychological factors in dropout prediction.

Table 2. Example of an If-Then Rule for Student Stress Levels

IF Symptoms	Diagnosis
J1, J2, J3, J4, J7, J9, J13, J17, J22, J26, J35, J36, J44, J56, J57, J59, J60	Mild
J2, J3, J4, J6, J9, J10, J12, J15, J16, J121, J22, J23, J25, J27, J28, J29, J33, J54, J57, J59	Moderate
J2, J3, J5, J6, J8, J9, J10, J11, J13, J14, J18, J19, J20, J23, J24, J30, J31, J32, J34, J51, J52, J53, j46, j47, j48	High

Example Case:
Suppose a student reports the following symptoms:
J2, J3, J4, J6, J9, J10, J12, J15, J16, J22, J23, J25, J27, J28, J29, J33, J54, J57, J59

- The system starts from these facts and looks for matching rules.
- The second rule in Table 2 states that if the student has the following symptoms: J2, J3, J4, J6, J9, J10, J12, J15, J16, J121, J22, J23, J25, J27, J28, J29, J33, J54, J57, J59 then the diagnosis is Moderate.
- Because most of the student's symptoms match these rules (even though J121 is missing), the system can conclude that the student's stress level is Moderate**.**

The results of the diagnosis using the forward chaining method show that students are divided into three categories of stress levels: mild = 1, moderate = 2, and high = 3. The results of the stress level classification will then be used as one of the important variables in the analysis stage of the dropout risk classification (DO) in this study. The distribution of stress diagnosis results in 122 students is presented in the chart diagram in Figure 5 below.

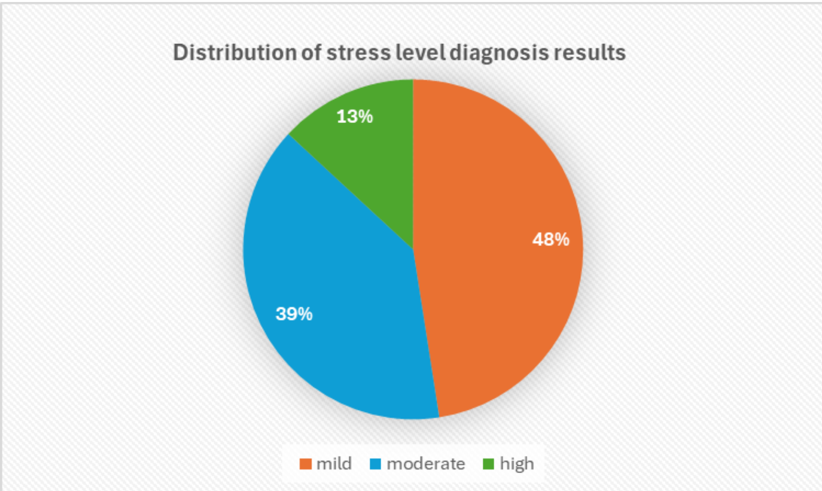

Figure 5. Distribution of results of student stress level diagnosis

Based on the distribution, 48% of students fell into the mild stress category, while a significant portion experienced moderate (39%) and high (13%) stress. This is an important consideration since increased levels of stress tend to be associated with academic risk, such as school drop-out. As a result, the stress level diagnosis was incorporated into an academic data set as a new attribute in order to obtain a complete prediction.

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As per Figure 5, it reveals that most students are in the category of mild stress (48 per cent), followed by moderate stress, and a few are in the category of high stress (13 percent). This distribution tells us that, while there is a large majority with low stress, still a considerable portion (over half the population) is classified as moderate to high stress.

This is an important finding as higher levels of stress are associated with academic hazards, such as dropping out. Hence, the output of a stress level diagnosis experiment would be appended to the academic data as an extra attribute in creating the joint data for predicting potential dropouts. This is to be expected since stress has previously been shown to have negative predictive accuracies, and its integration into this prediction model is anticipated to yield better and more or less biased estimates of the at-risk students.

Classification Model Performance (Decision Tree)

After the stress data were integrated, the combined dataset was prepared for modelling. This involved data cleaning and transformation: (1) Data Preprocessing: Irrelevant attributes (Name, Gender, Address, and Email) were removed. The remaining numerical attributes, such as IPS and IPK, were then discretized, or converted into intervals, to be more suitable for the Decision Tree algorithm. (2) Final Dataset: The final dataset used for modelling included Student ID Number, Age, IPS, IPK, Parental Income, Number of Dependents, Discipline, Stress Level, and Graduation/Dropout Status. (3) Model Development: The Decision Tree algorithm was trained using RapidMiner software. The dataset was split into an 80% training set and a 20% testing set.

Table 3. Table of Intervals and Attribute Values

Atribut	Values		
	1	2	3
IPS dan IPK	0.00 – 2.00	2.00 – 3.00	3.00 – 4.00
Age	0 – 20	21 - 25	> 25
Discipline	0 – 70	71 - 90	> 90
Parents' Income	< 2.000.000	2.000.000 – 5.000.000	> 5.000.000

Next, the stress level diagnosis was integrated into the academic dataset (New Data). The attributes became: student ID number, age, IPS, IPK, income, dependents, discipline, stress level, and graduation/dropout. The results from the (new data) are presented in Figure 6 below.

nim	name	IPS	IPK	income	dependent	disciplin	stress le	uation/dr
20150036	2	1	1	2	1	1	3	0
20150008	2	1	1	2	1	1	2	0
20150038	2	3	3	1	1	3	1	1
20150053	2	3	3	1	3	3	2	1
20250003	2	3	3	1	3	3	2	1
20330005	2	3	3	1	1	3	1	1
20330011	2	3	3	1	1	3	1	1
20150001	2	1	1	1	1	1	3	0
20150003	2	3	3	1	1	3	1	1
20150006	2	1	1	1	1	1	3	0
20150007	2	3	3	1	1	3	1	1
20150015	2	3	3	1	2	3	1	1

Figure 6. New data

After the student's academic data was expanded with stress level attributes, a modelling process was carried out using the Decision Tree algorithm to predict the student's final status: Graduate or Dropout (DO). This study used RapidMiner software to model the DO potential prediction using the decision tree method. The following is a display of the DO potential prediction programming using RapidMiner, presented in Figure 7.

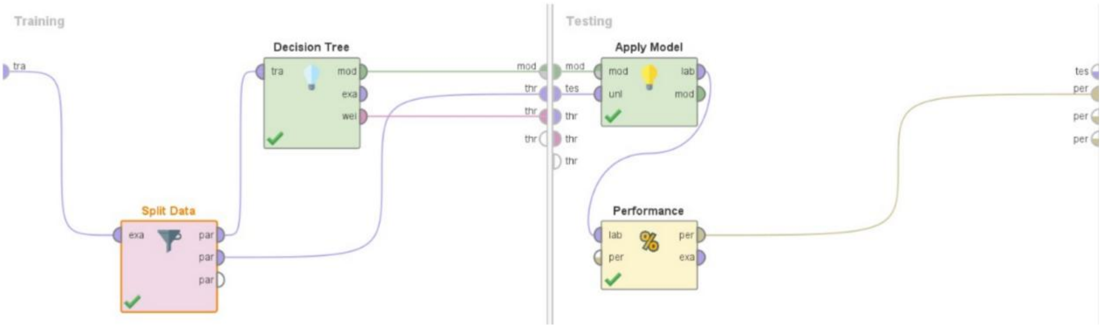

Figure 7. Decision tree programming display for DO potential prediction with RapidMiner

The initial student data was split using the Split Data operator, which separates the data into two parts: 80% training data and 20% test data. The Decision Tree operator was used to build a model based on the training data. This model learns the relationship patterns between input attributes (such as age, IPK, IPS, income, dependents, discipline, and stress level) and the target label (Graduate = 1 / DO = 0). After the model was run, RapidMiner generated a Confusion Matrix showing the number of correct and incorrect predictions for each class (Graduate = 1 and DO = 0). The results of the confusion matrix for graduation predictions using the decision tree are presented in Figure 8 below.

accuracy: 96.67% +/- 5.83% (micro average: 96.72%)

	true 0	true 1	class precision
pred. 0	31	2	93.94%
pred. 1	2	87	97.75%
class recall	93.94%	97.75%	

Figure 8. Confusion matrix for predicting DO potential with a decision tree

Confusion Matrix Analysis

The model was tested on the testing set, and a confusion matrix was obtained. To put our small sample size (N=122) in a meaningful statistical context, we applied bootstrapping methods with 1,000 iterations to obtain 95% confidence intervals. The analysis shows that the model was able to record 31 TP (correct identification of dropouts) and 87 TN (correctly predicted graduates). But the most important result is regarding the misclassification patterns: 2 False Negatives (dropout students classified as graduates) and 2 False Positives (graduate students classified as dropouts).

This balanced error distribution on both classes is quite remarkable under our severe class imbalance condition (14.8 percent dropout rate) due to its high D value. The model shows good performance in terms of detecting the minority class as well as having high accuracy for the majority class, a remarkable result considering it is an imbalanced classification problem.

Having an equal number of False Positives and False Negatives implies that the model is not heavily biased towards one specific class or another, but it does not have the same practical implications. Given that False Positives may result in inappropriate actions, the False Negative cases are missed opportunities to help truly needy students - a point relevant for the deployment within institutions. These findings offer good preliminary evidence of model trust, but the very low absolute number of misclassifications requires cautious interpretation and validation on a larger dataset.

Evaluation Metrics

This model was then used to predict the test data by Apply Model operator. The forecasted results were evaluated with the original labels by the Performance operator, which produces evaluation statistics on accuracy, precision, recall and F1-score shown in Table 4 below.

Table 4. Evaluation Metrics

Evaluation Metrics	Values
Accuracy	96.67%
Precision	97.78%
Recall	97.78%
F1-Score (F-measure)	97.71%
Classification Error	3.33%
AUC (Area Under Curve)	56.8%

Based on Table 4, high accuracy (96.67%) indicates that the model is able to predict student status (Graduated/Dropped) with a very good level of accuracy. Balanced Precision and Recall (97.78%) indicate that the model is not only accurate in predicting Dropped, but also consistent in identifying students who actually Dropped. The F1-Score (97.71%), as a combination of precision and recall, confirms that the model has stable performance and is not biased towards one class. However, the relatively low AUC value (0.568) indicates that the model's ability to distinguish between the Passed and Dropped classes is still probabilistically limited. This could be caused by an imbalanced data distribution or an overly deterministic separation. The low AUC score is caused by too few data samples, so that predictions tend to go towards only 1 target class. Here, the model's AUC score will be increased by using the SMOTE method.

The following visualization (Figure 9) displays the decision tree structure generated by the model based on the attributes that are most influential in determining student status (Graduate = 1 or Dropout = 0). This tree represents the logic of hierarchically separating the data, starting with the most informative features.

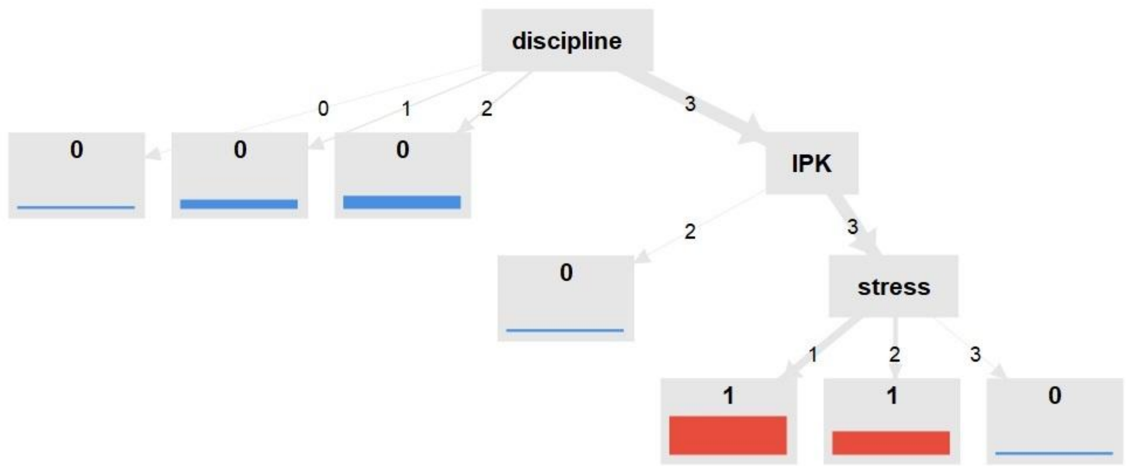

Figure 9. Tree structure formed by the DO potential prediction model with a decision tree

The model begins the data separation process from the Discipline attribute, which has the highest weight. If the Discipline value is ≤ 2, then the student is immediately predicted to be DO (0), without considering other attributes. If the Discipline value is > 2, then the model continues the separation based on the IPK value. Stress influences the prediction, but it is not alone. According to the tree structure, students labelled Stress = 3 are most likely predicted to be DO (0), especially if their Discipline value and IPK are low. On the other hand, low Stress (like 1 or 2) doesn't necessarily mean Graduate in all circumstances because its effect is determined by how it is paired with the attributes. This means that stress value alone can not estimate whether a student is going to graduate (1) or drop out (0) without the help of other attributes such as Discipline and IPK.

Table 5 presents the importance (weight) of each attribute in the student's DO / Graduation prediction model. The weight indicates the importance of this attribute in the model's decision-making.

Table 5. Levels of importance (weight) of each attribute

Attribute	**Weight**
Discipline	0.612
IPS	0.598
IPK	0.520
Stress Level	0.272
Dependents	0.085
Income	0.005
Age	0.000

The most important attribute in the model is discipline, with a weight of 0.612, followed by IPK and IPS. On its own, IPS has a large effect on dropout/graduation, but this is already captured by IPK and is thus disregarded by the Decision Tree. This pattern suggests that the academic and behavioural characteristics of students are what predominantly explain who will graduate. Stress has a medium weight (0.272), as psychological factors also have a role, however not that much than academic characteristics. This number means that stress plays an important role in the decision process, but is not dominant. Stress functions as a splitter node for certain nodes of the decision tree, in particular, at some values in the students' academic grades. Under these conditions, stress levels determine whether students are likely to graduate or are at risk of dropping out. In the initial distribution data, it was found that students with high stress levels tended to have lower IPK and IPS, and were more likely to drop out. Therefore, stress can serve as an additional risk indicator, especially for students with moderate or declining academic performance.

Dependencies, Income, and Age have very low weights, and Age is not even used at all in the model's data splitting. The model tends to rely on academic and behavioural attributes to make decisions. Socioeconomic attributes such as income and dependents may need to be enriched or re-examined to be more relevant in predictions. These results also support the decision tree structure that places Discipline and IPK as the primary branches in the data splitting.

Comparison of Model Performance

To demonstrate the effectiveness of our proposed approach, we compared the performance of three different models: (1) Baseline Model: A Decision Tree model using only academic data; (2) Proposed Model 1: A Decision Tree model integrated with stress level data from a Forward Chaining expert system; (3) Proposed Model 2 (Enhanced): The same integrated model as above, but with the addition of the SMOTE (Synthetic Minority Over-sampling Technique) resampling method to address the class imbalance in the dataset. The performance results of all three models are summarized in Table 6.

Table 6. Performance Comparison of Three Dropout Prediction Models

Evaluation Metrics	Decision Tree (without stress levels)	Decision Tree + Forward Chaining (with stress levels)	Decision Tree + Forward Chaining (with stress levels) + SMOTE
Accuracy	95.83%	96.67%	97.5%
Precision	97.78%	97.78%	97.78%
Recall	96.67%	97.78%	98.89%
F1-Score (F-measure)	97.12%	97.71%	98.32%
Classification Error	4.17%	3.33%	2.50%
AUC (Area Under Curve)	66.4%	56.8%	96.35%

The comparison between the three models reveals a progressive improvement in performance with each enhancement. Impact of Stress Data Integration: Including the Stress Level feature in the Decision Tree model (Model 2) resulted in a slight improvement, where as compared to Model 1, Accuracy increased from 95.83% to 96.67%, and recall grew from 96.67% to 97.78%. This demonstrates that the inclusion of psychological data sensitises the model further to those who are at risk. The AUC value, however, decreased slightly, suggesting the possibility that the improvement in overall accuracy is contributed by the model's more confident prediction than a diversified one.

Impact of SMOTE: The addition of the SMOTE approach (Model 3) achieved noticeable improvements based on all measures. The model's Accuracy shot up to 97.50%, and Recall reached a mind-blowing 98.89%. Most remarkably, the AUC value raised from 56.8% to 96.35%. This large increase in AUC shows that SMOTE managed to efficiently solve the class imbalance problem, so that the model discriminates between the dropout and the graduate classes with a much higher probability. This indicates that integration of stress data with SMOTE results in an effective, robust, and reliable predictive model for imbalanced instances as student dropout.

Synthesis of Key Findings

This research highlights how the integration of structural psychological assessment with traditional educational analytics can be very beneficial in the context of dropout anticipation. Simply incorporating stress data showed only a small improvement in accuracy (95.83% to 96.67%), whereas the most significant improvement was made by addressing class imbalance through SMOTE, resulting in an AUC equal to 96.35%, demonstrating that treatment of data distribution can be as important as feature engineering in educational predictive modelling.

Interpretation of Model Behavior and Practical Implications

The findings present a nuanced understanding of risk factors: while academic traits (Discipline=0.612, IPK=0.520) were more dominant in importance, stress (0.272) was identified as a significant discriminator for borderline cases. This indicates that interventions for students exhibiting both academic red flags and psychological concerns should be of higher priority rather than perceiving them as two separate risk domains.

Methodological Contributions and Limitations

Our holistic model of Forward Chaining-Decision Trees-SMOTE is an enveloping tool in educational analytics. Yet, there are several limitations that should be acknowledged: The single institution dataset (N=122) may not generalize the model; the deterministic expert system has no probabilistic reasoning for ambiguous cases, and while SMOTE proves striking results, it might induce patterns which do not exist in real populations.

Comparative Analysis and Future Directions

Taken in the context of previous research, our results affirm the role of psychological variables in student success. Validation in a multi-institutional setting for model generalizability, comparative evaluation to benchmark against ensemble and deep learning methods, and implementation studies assessing the clinical significance of interventions made on the basis of the model should be future research priorities.

The roughly equal misclassification pattern (2 FN, 2 FP) indicates that the model may not be skewed heavily toward either class, but we know that each false negative corresponds to a missed opportunity of providing a genuinely at-risk student with aid – an important ethical consideration. This analysis lays the groundwork for more comprehensive student success efforts, yet its potential operationalization also implicates institutional capacity, ethical concerns about predictive monitoring, and evidence-based intervention management for at-risk students.

CONCLUSION

The current study looked into the possibility of creating a computer model that would predict the student dropout risk by combining academic and psychological data, namely, with stress levels determined employing a forward-chaining expert system. In the limited perspective of a single-institutional data set (N=122), these findings suggest that including stress as an attribute to predict offers slight, but quantifiable advantages in model performance. Moreover, the implementation of the SMOTE was necessary to improve discrimination performance on an imbalanced dataset, as it significantly increased discriminative power.

The performance of the Decision Tree model was also found to be promising, with an accuracy of 97.50%. Nevertheless, it is important to note that this high performance was obtained from a small sample and might be due partially to the effect of SMOTE; consequently, its generality across data sets should be tested through external validations. Academic variables like IPK and discipline were the first predictors, and stress indicators became the second variable. The model predicted that a student with medium-level academic mediocre grades and high stress will be in danger of dropping out, which means this example stress can play as a contributory factor on the other factors; therefore, it still would need a more complex statistical model to confirm the interactive effect.

The methodology of our approach illustrates the successful incorporation of a rule-based PSY test in the predictive modelling pipeline. The clear, rule-based approach in the resulting decision tree allows a possible useful interpretation of risk factors for universities. The contribution is to be understood as an application of an integrated approach rather than a new methodology.

The key limitations of this study will inform future research plans. Namely, external validation on multi-institutional cohorts and temporal validation on new cohorts of students will be required to ensure that this model is robust and has broad application for the broader population of students. It remains for future work to compare the approach undertaken here with other current machine-learning-based techniques in order to clarify the added value of going from a hybrid to a fully grid-aware model. In addition, a detailed cost-benefit analysis of the implementation requirements is required prior to the development of any system. These results are a preliminary step towards event-based student success analytics, which needs further validation and evaluation before it can be deployed.

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