Application of Data Mining for the Selection Process of Prospective Students at ITTelkom Surabaya by Using the SPSS Modeler

Rokhmatul Insani, Muhammad Nasrullah, Anfazul Faridatul Azizah and Edriand Imens Raygrandi
Information System Departement, Telkom Surabaya Institute of Technology, Surabaya, Indonesia

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Abstract: In a tertiary institution, the problem of student resignation is something that often occurs, which can be due to financial factors or the ability factors possessed by students. Early detection can be carried out on prospective students who will enter to reduce this risk. A system is needed to support the New Student Admissions (PMB) process that can predict whether students will survive to graduate or will withdraw in the current semester. By using data mining techniques predictions can be made on these problems, there are various methods used to make these predictions, one of which is by using the CHAID Algorithm. Data mining is processed using the CRISP-DM (The Cross Industry Standard Process Model for Data Mining) method. To help perform data processing, the IBM SPSS Modeler 18.0 application is used.

1 INTRODUCTION

Advances in information technology are growing rapidly in all areas of life, including in the field of education. Telkom Surabaya Institute of Technology (ITTelkom Surabaya) is one of the private tertiary institutions in Indonesia, where students are the main asset that must be considered for the sustainability of the tertiary institution. However, in reality, many students resign each semester, which impacts the campus's finances. The resignation can be due to financial or ability factors possessed by students. To reduce the risk of students dropping out, early detection can be carried out on prospective students who will enter. The challenge is how to process the data so that data can produce the knowledge we need. One technique for processing a lot of data is data mining (Insani et al., 2022).

Data mining is a technique for extracting patterns from data so that you can get insight from the data (Han et al., 2012). Data mining techniques can be used to predict data based on past data. An algorithm can be used to predict these problems, namely classification. The classification method is widely used in predicting freshmen, such as the research conducted by Khoirunnisa concerning the Prediction of Al-Hidayah Vocational High School Students Entering Higher Education Using the Classification Method (Khoirunnisa et al., 2021). Research conducted by Nadiya Hijriana regarding the application of the decision tree algorithm C4.5 method for the selection of prospective university-level scholarship recipients (Hijriana and Rasyidan, 2017; Utami, 2020; Atma and Setyanto, 2018). Research conducted by Saifudin regarding the use of the classification method for the selection of prospective students for new student admissions at Pamulang University (Saifudin, 2018). Another research conducted by Sherlyn regarding predictions of potential student enrollment at Taman Siswa Teluk Betung Vocational School is web-based using the classification method (Putri, 2021).

The task of classification is to predict the output of variables/classes that have categorical or polynomial values [7]. Where to carry out classification several methods are often used, one of which is CHAID. Based on research conducted by Ardiansyah, it was found that the CHAID algorithm is one of the algorithms with the best performance applied to the research dataset used (Ardiyansyah et al., 2018). CHAID stands for Chi-squared Automatic Interaction Detector. CHAID works to estimate a single variable, known as the dependent variable, which is based on several independent variables. CHAID is an iterative technique that tests the independent variables one by one used in classification and arranges them based on the chi-square statistical significance level of the dependent variable (Ardiyansyah et al., 2018).

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In this study, the application of the classification algorithm will be carried out to classify students who are with drawing based on data on prospective new students and student data at the ITTelkom Surabaya. Data is taken from academic applications (Salal et al., 2019). The data collected included personal, education, family, and student status data, namely active or resigned. Then the two data are combined to be used as input data in the data mining process. The data active or resigned. Then the two data are combined to be used as input data in the data mining process. The data mining process uses IBM SPSS Modeler 18.0 tools. These tools have a visual interface that allows users to take advantage of statistical and data mining algorithms without programming (Insani and Soemitro, 2016). Choosing data processing tools based on several characteristics, such as user-friendliness, cost, maintenance, availability of skills, or the presence of help files (Belokurova and Piazza, 2018; Wang et al., 2019). It is hoped that this research can be used to predict whether prospective students will survive until graduation or will resign in the current semester.

2 RESEARCH METHODS

In data mining processing it is known as CRISP-DM (The Cross Industry Standard Process Model for Data Mining). CRISP-DM is a consortium of companies established by the European Commission in 1996 (Abbott, 2014), CRISP-DM provides a standard process for data mining that can be applied to common problem-solving strategies in businesses or research units (Fadillah, 2015). The stages in CRISP-DM can be seen in Figure 1 below:

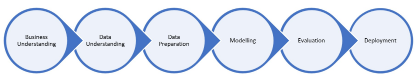


Figure 1: CRISP-DM.

2.1 Business Understanding

The first stage is to understand the goals and needs from a business point of view and explain the benefits of data mining with data that is by the case studies taken. Then determine the boundaries of the cases taken to be used as formulas in data mining problems.

2.2 Data Understanding

In this second stage, data collection is carried out which is then followed by a process to gain in-depth knowledge about the data and identify data quality. Understanding the data can be done by checking the Data Summary. Data Summary can show the distribution of data, and oddities in data that must be resolved at a later stage. Problems that are usually in data such as missing values, outliers, spikes, and high cardinality, must be identified before being resolved in the next stage. Data visualization can provide a better picture when compared to data summary.

2.3 Data Preparation

This stage produces a dataset as input at the modeling stage. By paying attention to the results obtained at the data understanding stage, several methods will be carried out to clean the data so that the resulting model is good. This stage includes attribute selection, data cleaning, and data transformation.

2.4 Modeling

This stage is carried out by selecting and applying various modeling techniques and adjusting several parameters to obtain optimal results. At this stage, the selection of modeling techniques or algorithms to be used, model development, and assessment of the resulting model are carried out.

2.5 Evaluation

At this stage, the model has been formed and an evaluation is carried out on the quality of the model for the data generated, as well as whether the model has achieved the initial goals that have been set. At this stage, the interpretation of the results of the data mining modeling that has been carried out is carried out.

2.6 Deployment

Use the command At this stage, the knowledge that has been obtained is carried out by applying the method and will be represented to the user.

3 RESULTS AND DISCUSSION

Based on the method used there are several stages in data mining processing, namely:

3.1 Business Understanding

In this study, the data to be processed is student data in the academic section. Where students are the most important asset of a tertiary institution. The challenge that must be faced by every tertiary institution besides getting prospective students who are on target is how to maintain existing students, so they do not withdraw. Withdrawal can be caused by various reasons such as financial problems or academic problems faced by the student (Kristanto et al., 2020). Therefore, we need a system to conduct early detection of prospective students in the PMB process so that students can survive attending lectures until they graduate.

Data mining is an information extraction process to find important patterns in piles of data so that it becomes knowledge. With data mining, universities can see the character of prospective students who will be owned and can make predictions in the future to avoid the risk of students withdrawing in the current semester.

Based on the need for the application of data mining for tertiary institutions, the purpose of data mining at ITTelkom Surabaya is to classify student data to determine the characteristics of students who withdraw in the current semester. Based on this data, can be used to conduct early detection of prospective new students who will enter college. In addition, if a prospective student is found to have the same characteristics as a student who is withdrawing, then the institution can carry out certain treatments for the prospective student.

3.2 Data Understanding

To carry out the data understanding stage, in this study software was used, namely SPSS Modeler 18. The input data used came from academic data from IT-Telkom Surabaya students. The input data consists of 21 variables which can be seen in Table 1.

Table 1: Input Data Variable.

No.	Variable	Explanation
1	PRODI	Student Major Data
2	NIM	Student ID Number
3	NAMA	Student Name
4	ANGKATAN	Student Intake
5	TAHUN_MASUK	Student Entry Year
6	PEND_AYAH	Father's Last Education
7	KERJA_AYAH	Father's Occupation
8	GAJI_AYAH	Father's Salary
9	PEND_IBU	Mother's Last Education
10	KERJA_IBU	Mother's Job
11	GAJI_IBU	Mother's Salary
12	UMUR	Age of Student at Admission
13	GENDER	Student Gender
14	ASAL_KOTA	City of Origin of Students
15	ASAL PROVINSI	State of Origin of the Student
16	NILAI_SMA	Total High School Grades
17	STATUS_SMA	High School status whether public or private
18	JURUSAN_SMA	Student Majors
19	TAHUN_LULUS SMA	High School Graduation Year
20	PEBAYARAN PMB	Payment Status in Full/Credit
21	STATUS_MHS	Student Status is Active / Inactive

The input data is 1831 data with 1749 active student data and 82 inactive students. An example of input data that will be analyzed can be seen in Figure 2 below: In the process of understanding the data using SPSS Modeler 18.0 tools. The following describes the process of understanding the data carried out in this study (Wendler and Gröttrup, 2016) as Figure 3. The process of understanding the data uses 3 nodes, namely: Node 1 (Source Excel) is used to enter research data that will be checked for data quality, node 2 (Filter) is used to select what variables the data will be audited and node 3 (Audit Data) is used to check data quality. Following are the results of checking the quality of the input data that will be used in modeling as Figure 4.

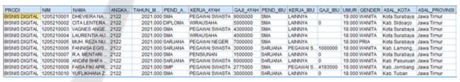


Figure 2: Example of Input Data.

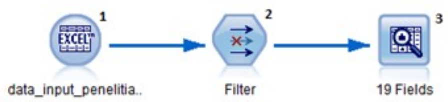


Figure 3: Process of Understanding Data with SPSS Modeler.

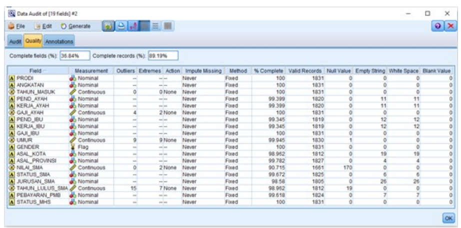


Figure 4: Data Understanding Results.

Based on the results above, it is found that some data is still empty, data with extreme values, and some incomplete data. In the next stage, the input data will be transformed and cleaned to form a dataset that is ready to be modeled.

3.3 Data Preparation

This stage is useful for cleaning data and forming datasets. From the results of the analysis that was carried out at the stage of understanding the data, it was found that there were still incomplete data. At this stage, transformation is also carried out according to the data requirements in the modeling. The transformation was carried out using the SPSS Modeler 18 software, which can be seen in the image below as Figure 5.

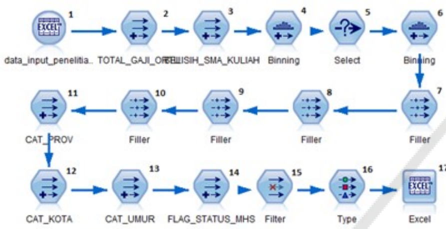
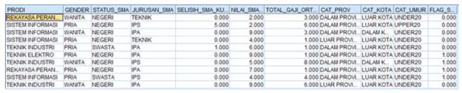


Figure 5: Data preparation process with SPSS Modeler.

The data preparation process involves 17 nodes, namely: Node 1 (Source Excel) is used to enter research data to form a dataset, node 2 (Derive) is used to add new variables based on existing variables, this node is used to add up father's salary and salary mother, Node 3 (Derive) is used to calculate the difference between college admission and senior high school graduation, node 4 (Binning) is used to simplify data. The data that will be generated will have a range of 1 to 10. This is done so that the data is easier to read, this node is used to simplify SMA values, node 5 (Select) is used to select data, this node is used to select parental salary data that is more from 0, node 6 (Binning) is used to simplify parental salary data, nodes 7-10 (Filler) this node is used to change the value of a variable, this node is used to change categorizing SMA majors data into 4 categories, namely IPA, IPS, Engineering, Non-Engineering. Node 11 (Derived) is used to categorize the origin of the province into and outside the province of East Java, Node 12 is used to categorize the origin of the city into and outside the city of Surabaya, Node 13 is used to categorize the age to be under 20 or over 20 years, Node 14 is used to categorizing student status data into 0 (for withdrawing students) and 1 (for active students). Node 15 (Filter) is used to select which variables will be included in the dataset. Node 16 (Type) is used to determine the type of variable that will be input in the next stage. Node 17 (Export Excel) is used to form datasets in excel format which will be processed at a later stage. The following is the dataset generated in the data preparation process as Figure 6.



PRODI	GENDER	STATUS_SMA	JURUSAN_SMA	SELISIH_SMA_KU...	NILAI_SMA...	TOTAL_GAJI_ORT...	CAT_PROV	CAT_KOTA	CAT_UMUR	FLAG_S...
REKAYASA PERAN...	WANITA	NEGERI	TEKNIK	0.000	2.000	3.000	DALAM PROVI...	LUAR KOTA	UNDER20	0.000
SISTEM INFORMASI	PRIA	NEGERI	IPS	5.000	2.000	6.000	DALAM PROVI...	LUAR KOTA	UPPER20	0.000
SISTEM INFORMASI	WANITA	NEGERI	IPA	0.000	9.000	3.000	DALAM PROVI...	DALAM K...	UNDER20	0.000
SISTEM INFORMASI	PRIA	NEGERI	TEKNIK	0.000	4.000	1.000	LUAR PROVI...	LUAR KOTA	UNDER20	0.000
TEKNIK INDUSTRI	PRIA	SWASTA	IPA	1.000	6.000	1.000	DALAM PROVI...	LUAR KOTA	UNDER20	0.000
TEKNIK ELEKTRO	PRIA	NEGERI	IPA	0.000	9.000	1.000	DALAM PROVI...	LUAR KOTA	UNDER20	1.000
TEKNIK INDUSTRI	WANITA	NEGERI	IPS	0.000	5.000	8.000	DALAM PROVI...	DALAM K...	UNDER20	1.000
REKAYASA PERAN...	PRIA	NEGERI	IPA	0.000	7.000	1.000	DALAM PROVI...	LUAR KOTA	UNDER20	1.000
SISTEM INFORMASI	PRIA	SWASTA	IPS	0.000	4.000	4.000	DALAM PROVI...	LUAR KOTA	UNDER20	1.000
TEKNIK INDUSTRI	WANITA	NEGERI	IPA	0.000	9.000	6.000	LUAR PROVI...	LUAR KOTA	UNDER20	0.000

Figure 6: Results of the Data Preparation Process.

Based on the results above, several variables will be processed using Data Mining, namely: Study Program, Gender, High School Status, High School Major, High School College Difference, Total Parent Salary, Province Category, City Category, Age Category, and Student Status Flag.

3.4 Modeling

This stage is the core stage in the data mining process, namely the application of the algorithm by the case studies taken. This process requires input in the form of datasets generated in the previous process, then modeling using data mining algorithms is carried out as Figure 7.

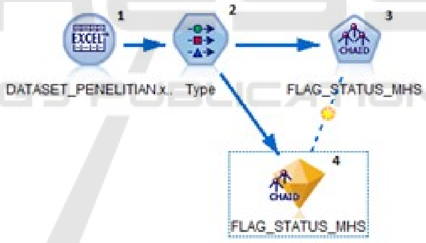


Figure 7: Process Modeling with SPSS Modeler.

This modeling process involves 3 nodes, namely Node 1 (Source Excel) is used to enter the research dataset that has been obtained from the previous stage and will be modeled, Node 2 (Type) is used to determine the type of variable that will be the input or output variable at the next node, Node 3 (CHAID) is an algorithm used in classifying the character of prospective students who will register on the campus. Node 4, which is golden in color is the result of the algorithm used in the form of a tree diagram.

3.5 Evaluation

Based on the CHAID algorithm used, several important variables can be used for classification, therefore in the modeling process, only the 4 most important predictors are used, namely SMA majors, SMA grades, SMA status, and parent's salary as Figure 8.

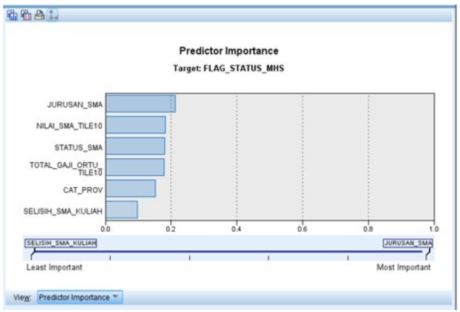


Figure 8: The Most Important Predictor of the Modeling Process.

After knowing the 4 most important predictor variables, then resetting the variables that will be input to the data mining process is carried out. After that, modeling is carried out again according to the input. Based on the 4 input variables used, a tree diagram is obtained as follows Figure 9.

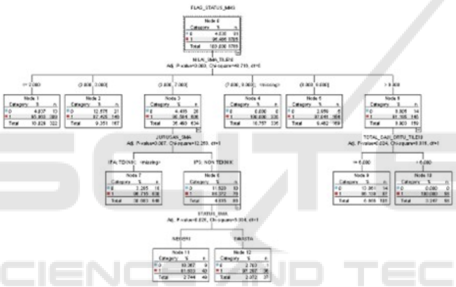


Figure 9: Tree Diagram of CHAID Algorithm Results.

Based on the resulting tree diagram, the classification table for the characteristics of ITTelkom Surabaya students is obtained as follows Table 2.

Table 2: Input Data Variable.

Classification	Node	Characteristics
Rule 1	1	SMA value ≤ 2 (from range 1-10)
Rule 2	2	SMA score between 2-3 (from 1-10 range)
Rule 3	3, 7	High school grades between 3-7 (from 1-10 range) and majoring in Science or Engineering
Rule 4	3, 8, 11	High school grades between 3-7 (from 1-10 range), majoring in Social Sciences or Non-Engineering and Public High School status
Rule 5	3, 8, 12	High school grades between 3-7 (from 1-10 range), majoring in Social Sciences or Non-Engineering and Private High School Status
Rule 6	4	High school score between 7-8 (from 1-10 range)
Rule 7	5	High school score between 8-9 (from 1-10 range)
Rule 8	6, 9	High school grades > 9 (from 1-10 range) and parents' total salary ≤ 6 (from 1-10 range)
Rule 9	6, 10	High school grades > 9 (from 1-10 range) and parent's total salary > 6 (from 1-10 range)

Based on the classification in the Table 2, the following is the percentage of students who withdrew.

Based on Table 3, shows that most students withdraw from a trough in the 4th classification with a percentage of 18.367% with high school grade characteristics between 3-7 (from range 1-10), coming from social studies or non-engineering majors and state high school status.

Table 3: This caption has one line so it is centered.

Classification	Resign	Active
Rule 1	4,037%	95,963%
Rule 2	12,575%	87,425%
Rule 3	3,285%	96,715%
Rule 4	18,367%	81,633%
Rule 5	2,703%	97,297%
Rule 6	0%	100%
Rule 7	2,959%	97,041%
Rule 8	13,861%	86,139%
Rule 9	0%	100%

4 CONCLUSIONS

Based on research that has been conducted using the CHAID algorithm to classify prospective students who will enter the ITTelkom Surabaya, it can be concluded that as many as 18.367% of students who resign have high school grade characteristics between 3-7 (from the range 1-10), comes from the Social Sciences or Non-Engineering major and State Senior High School status. Meanwhile, the characteristics of parents' salary did not have much effect on the number of students who withdrew. With these characteristics, it is hoped that the institution can pay more attention to students with these characteristics so that they can survive until they graduate from college.

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