Machine Learning-Based Teacher Education Student Placement Model Via Interest Profile and Diagnostic Test

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Abstract

Traditional student placement in college programs based on academic performance, interviews, and student choice may not always yield optimal results. This study proposes a machine learning-based model for teacher education program placement, integrating student interests and diagnostic test results across various specializations. Data from 208 freshmen in a teacher education institution (AY 2024-2025) were collected using a validated interest profile questionnaire and diagnostic test. Various machine learning methods were evaluated for classification performance. Results showed that most students exhibited strong interest in their chosen specialization, highlighting interest as a key placement factor. Diagnostic test performance trends further indicated that students tend to excel in their respective fields. The final placement model employed artificial neural networks, support vector machines, gradient boosting, and adaptive boosting, each achieving at least 80% classification accuracy and F1 score. This model offers a systematic and data-driven approach to optimizing teacher education student placement.

Keywords: *Student placement*, *teacher education*, *machine learning*.

INTRODUCTION

Choosing a major in college is an important step in progressing one's career plans. College programs determine most students' lives and what they become in the near future (Cuy & Salinas, 2019). In higher education institution, most students answer the question "what program should I take?" solely based on their preference, which is sometimes affected by peers, family, career opportunities, financial stability and other factors (Del Rosario, et al., 2024). This student-based placement system for college admission presents issues that may affect both the students and the higher education institution they plan to attend to. Placement systems for students taking majors in college institutions mostly rely on static criteria such as academic performance in high school, college admission test scores, college interviews, and student choice. This traditional method of placement in college is inflexible in guiding a student towards the best college pathway for them, as it overlooks the dynamics of student interest profiles and a more specific overview of student qualification.

Personal and academic interests of students are one of the key factors in choosing their desired program and specialization. Parsons (1909) asserted in his theory that students assess themselves with factors like interests, characteristics, and capabilities in mind. Hence, when students declare that they take interest in taking a certain program or specialization, they tend to be led to an in-depth assessment of themselves. As stated in the Social Cognitive Career Theory of Hackett et al. (1981) & Lent et al. (1994), the academic interests of students reflect their beliefs in their self-efficacy and how they perceive outcomes that they come up on their own. This suggests that students who pin their interest on an academic pathway, at some point reflect their own capabilities.

Despite having personal and academic interest as necessary determinants in choosing a program and/or specialization, the students' academic competencies, specifically in their preferred specialization, are matters that the current system of admission fails to consider. Some students may take interest in taking a particular specialization whilst having below average skills and knowledge in the subject area, which may lead to negative consequences later in their college years such as low to mediocre performance, irregularity, and worse attrition in the program. The current admission system emphasizes the weakness of generalization since it is not applicable to all majors (Assiri et al, 2024).

With the rising prevalence of technology in the 21st century, the use of technology in various fields is the new normal, and the use of Artificial Intelligence (AI) is also set to become a widely-used tool. AI is not particularly detrimental for human utilization: AI is used in various important fields in our society, like healthcare, providing treatment, diagnoses, and prediction of diseases (Ogaga & Zhao, 2023). Universities in the Philippines acknowledge the rampancy of AI, considering its positive and negative uses, and the ethical standards to be upheld. Central Bicol State University of Agriculture (CBSUA) - Pili Campus is one of the universities that acknowledges AI, particularly its impact on education. Research conducted based on the data from the College of Development Education (CDE) introduces the awareness of said technology, the integration of AI-assisted learning instruction/material to the teaching techniques and strategies are shown to be a prevalent case within the fourth-year batch 2024 student population of CDE.

Part of AI that is particularly relevant today is machine learning. Machine learning is a revolutionary technology that aids the multi-faceted gears of a modern society, which specifically provides advanced data analysis progressing decision making leading to better predictions, and creating newer innovations (Kozon, 2023). This said innovation covers many sectors, and education sector is not an exception to this. Enhancing student admission procedures in universities is entirely possible using machine learning. It is in this context that this research was conceptualized, with the belief that leveraging predictive analytics using machine learning, the placement system for students taking teacher education programs can be further progressed.

By identifying the predictors through student's personal and academic interests paired with their academic competencies, machine learning algorithms can provide suggestions for students on what program or majors to take. This study is an attempt to develop a blueprint that uses machine learning algorithms to systematically place teacher education students to their appropriate programs. Specifically, this study sought to answer the following objectives: 1) Identify the interests of the first-year students in the CBSUA College of Development Education AY 2024-2025. 2) Evaluate the diagnostic test scores of the first-year students in the CBSUA College of Development Education AY 2024-2025. 3) Determine the performance metrics of various machine learning methods used in the student placement model. 4) Develop a blueprint of Machine-assisted Technology for Career and Higher Education (MATCH) placement system and its term of use using the orange data-mining application.

METHOD

This study used the qualitative method of research to provide a blueprint for the MATCH placement system. Specifically, this method was used to determine the interest profile of the respondents and their test scores in the diagnostic test, which are considered as the predictors in the study. Moreover, the same method was used in describing the performance of the various machine learning methods considered in the study along different metrics. A descriptive-developmental design was used to provide a blueprint for the MATCH placement system. Specifically, the descriptive design was used to determine the interest profiles of the respondents, their test scores in the administered diagnostic test, and the performance of the machine learning methods along various metrics. Meanwhile, the developmental design was used to develop a blueprint of machine-assisted technology for career and higher education (MATCH) placement system and its terms of use using the orange data-mining application.

For the objectives of the study to be attained, significant steps were undertaken. The researchers used a validated diagnostic test and a modified, self-made student interest profile survey. The interest profile survey consists of 35 items, designed to be answered for a duration of at most 20 minutes. The survey has 7 components, which covered personal and academic interests of the students such as child development, language and literature, scientific inquiry, folklore and tales, patterns and numbers, plants and crops and animals. On the other hand, the validated and modified diagnostic test consists of 90 items and was designed for 2 hours, inclusive of the 5-minute preparation and orientation, 15 minutes for students to check and review their answers, and an overall duration of 80 minutes to answer. There were 15-item tests for each diagnostic test component, namely: English, Filipino, Mathematics, Science, Animal Production (Biochemistry 1), and Crop Production (Biochemistry 2). The test did not include a component for the Elementary Education specialization as it covers generalized competencies. Overall, the administering of the test had a total duration of 2 hours for all items from the interest profile survey and 90-items modified diagnostic test.

The researchers proceeded to the administering of the interest profile survey and diagnostic test. The interest profile responses and diagnostic test results were then tabulated in a single comma-separated values (.csv) file and were used as the predictors for the MATCH placement system as the train data. To give meaning to the data, descriptive statistics were used. In particular, mode was used to evaluate the academic and personal interests of the students in the interest profile survey. On the other end, mean was used to describe the academic competency of the students along the different test components of the diagnostic test.

The machine learning methods considered initially in the study, namely; artificial neural networks, support vector machine, gradient boosting, adaptive boosting, stochastic gradient descent, Naïve-Bayes' model, and k-nearest neighbors, were shortlisted on the basis of their performance metrics. To provide context, a good machine learning method should have at least an 80% classification accuracy and F1 score. The shortlisted machine learning methods satisfying these conditions were then incorporated to the final blueprint for the MATCH placement system, designed to provide predictions on student placement to the different fields of specialization.

RESULTS AND DISCUSSION

Interest Profiles of first-year Students in CBSUA College of Development Education A/Y 2024-2025

This section presents the interest profiles of first year students in CBSUA College of Development Education A/Y 2024-2025. The gathered data is presented in table 1.

Table 1. ***Interest profiles of first-year students in CBSUA's College of Development Education***

Specializations	Interest Profiles							Academic Interest
	A	B	C	D	E	F	G	
BEED	**152***	90	65	105	72	45	39	Child Development
BSED 1A	113	**118***	74	84	53	39	37	Language and Literature
BSED 1B	147	115	**168***	99	77	65	60	Scientific Inquiry
BSED 1C	109	80	56	**115***	45	46*	32*	Folklore and Tales
BSED 1D	111	76	72	71	**155***	52	33	Patterns and Numbers
BTVTED ACP	**54***	49	29	37	20	52	26	Child Development
BTVTED AP	**62***	44	47	43	24	46	54	Child Development

LEGEND:
A – Child Development
B – Language and Literature
C – Scientific Inquiry
D – Folklore and Tales
E – Patterns and Numbers
F – Plants and Crops
G - Animals
** - Modal Score*

As gleaned from table 1, the academic interest of Bachelor of Elementary Education (BEED), Bachelor of Secondary Education (BSED) Majors in english, science, filipino, and mathematics correspondingly characterize their field of specializations, which is in child development, literature, environment, language, and patterns and numbers respectively. Conversely, the academic interests of Bachelor of Technical-Vocational Teacher Education (BTVTED) students majorly lies in child development, but does not deviate that much from their expected interest in animals and crops which are their second most dominant interest as gleaned in table 1.

According to the theory of Parsons (1909) as cited in the article of Katy Jordan (2019), systematic approach on self-assessment is important in understanding people's traits, characteristics, and interests with occupational requirements. Interest profile surveys help to assess themselves, based on their interests, skills, capabilities, and values. Students' differences should be understood, the differences in the field of specialization for future teachers matter a lot, so appropriate matching of individuals and their fields is necessary. Furthermore, in-depth self-assessment plays an important role in determining academic interest. Self-efficacy and outcome beliefs jointly give rise to interests while interests promote recognition of career choice goals which increase the likelihood of choice actions. Students must assess their academic interest thoroughly by determining the skills and ability they possess. It was mentioned in Social Cognitive Career Theory, an individual's academic interests at any point in time are reflective of his or her concurrent self-efficacy beliefs and outcome expectations. An individual's occupational interests is also influenced by his or her occupationally-relevant abilities, but this relation is mediated by one's self-efficacy beliefs (Hackett et al., 1981, Lent et al., 1994, Lent and Brown, 2019, and Pham et al., 2024).

It is important to note that in order to determine the academic interests of students, an assessment or survey should be implemented rather than only stating their preferred programs. Predictors will help the students to identify their academic interests through a diagnostic test.

While academic interest is considered in placing the students in their respective specialization, it is also important to note in this discussion how significant it is to include the diagnostic test scores as a major predictor in the placement system to assess if they have adequate skills, abilities, and capabilities to place the students in teacher education institutions.

Diagnostic Test Scores of the First-Year Students in the CBSUA College of Development Education A/Y 2024-2025

This section presents the mean diagnostic test scores of the first-year students across different specializations within the CBSUA College of Development Education A/Y 2024-2025. The diagnostic test administered is divided into 6 components: ENG (English), SCI (Science), FIL (Filipino), MATH (Mathematics), CROP (Crop Production), and ANIM (Animal Production). The gathered data is presented in figure 1. The performance patterns of each groups across test components vary slightly, which emphasizes the difference of individual strengths and weaknesses of each target variable within this study.

Students from the BEED program displayed great performance in the Filipino test component as all specializations do, while having poor performance in both mathematics and crop science with mean scores of 3.67 and 3.39, respectively.

BSED 1A students, who specialize in English, garnered highest mean score in their corresponding test component (English) and has also performed well in Filipino. This suggests that students from this program excels in language and literature regardless of the medium. Same can be said to their language program counterpart, the Filipino majors (BSED 1C), which also achieved highest performance in their respective test component and had note-worthy performance in English garnering a mean score of 6.29 points. In contrast, they perform quite poorly in mathematics and animal science component, respectively.

BSED 1B students who specialize in science performed relatively well in science test component, having a mean score of 4.26 which is the highest across all specializations. They also perform proficiently in Filipino (7.6) and English (6.56). Moreover, science majors seem to struggle most with the mathematics test component having a mean score of 3.21, which is the lowest among all specializations.

BSED 1D students surprisingly performed below average in their corresponding test component (mathematics) with mean score of 3.71 and only third highest in the test component, but were consistently at par in their performance in some other test components. However, they scored the lowest in the English test component (6.05) and second lowest in the crop production component (3.61).

BTVTED students who specialize in agricultural crop production excel in both science and crop production test components with highest mean scores across specializations of 4.8 and 4.73, respectively. Similarly, BTVTED students who specialize in animal production also excel in science and crop production with mean scores of 4.06 and 4.31, respectively. Both specializations in BTVTED performed consistently in the other test components. On a general note, it can be observed that these students excel most at language and literature whilst ailing in STEM subjects.

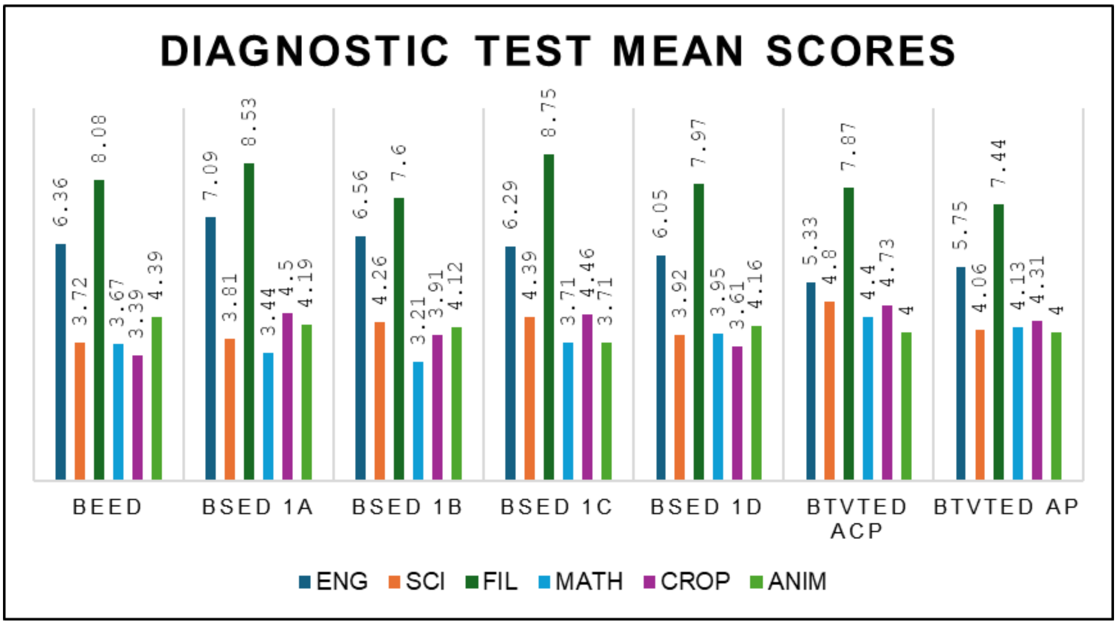

Figure 1. Mean scores of the different specializations in the different test components.

Legend: BEED – Bachelor of Elementary Education
BSED 1A – Bachelor of Secondary Education Major in English
BSED 1B – Bachelor of Secondary Education Major in Science
BSED 1C – Bachelor of Secondary Education Major in Filipino
BSED 1D – Bachelor of Secondary Education Major in Mathematics
BTVTED ACP – Bachelor of Technical-Vocational Teacher Education Major in Agricultural Crop Production
BTVTED AP - Bachelor of Technical-Vocational Teacher Education Major in Animal Production

On a general note, it can be captured in the data that these students perform well in language and literature but are ailing at subjects related to STEM. The structure of the Philippine education system may explain the profound impact on this particular student performance. The K-12 program emphasizes language and literature, fostering skills in these areas from an early age. Courses related to the Filipino language and literature are comprehensive and take precedence in the curriculum compared to STEM subjects, which are often perceived as more challenging and less engaging as cited by DepEd in their 2024 report on 21st century literature curriculum. This curricular focus leads to enhanced aptitude and interest in language and literature. Moreover, the educational mindset among some Filipino students may also contribute to the discrepancy in performance between language arts and STEM disciplines. The PISA 2018 report indicates that only 31% of Filipino students possess a growth mindset, which is critical for tackling challenges in complex subjects like math and science. Many students may feel intimidated by the perceived difficulty of STEM subjects, resulting in a preference for languages and humanities, where they experience greater confidence and success as stated by an article by SciDev (2022).

Performance Metrics of Various Machine Learning Methods Used in the Student Placement Model

The development of an effective student placement model relies heavily on the selection and evaluation of appropriate machine learning methods. Hence, the performance metrics of these methods play a pivotal role in determining their suitability for the model, as each metric provides unique insights such as the overall correctness of predictions (accuracy), the ability to correctly identify positive outcomes (precision), and the capacity to minimize false negatives (recall or sensitivity). Analyzing the performance metrics of these algorithms can greatly help developers in identifying the optimal model for accurately predicting student placements while addressing the inherent trade-offs in classification tasks. To achieve this, we administered a 70-30 train-test data split in the orange data mining application to gauge the performance of the model in specific metrics. Table 2 shows the performance along the classification accuracy and F1 score of the machine learning methods identified in this research.

Table 2. ***Performance metrics of various machine learning methods considered in the study***

Model	Classification Accuracy	F1 Score
Artificial Neural Network	0.846	0.845
Support Vector Machine	0.832	0.828
Gradient Boosting	0.812	0.811
Adaptive Boosting	0.803	0.803
Stochastic Gradient Descent	0.784	0.781
Naïve Bayes	0.654	0.663
k-Nearest Neighbors	0.452	0.450

It can be gleaned from table 2 that in terms of classification accuracy, artificial neural network performed best with CA=0.846. This means that for every 100 data points, the model can correctly place at least 84 students to the most appropriate program in the TEI. This is followed by support vector machine, gradient boosting, adaptive boosting, and stochastic gradient descent which by theory can accurately place at least 83 students, 81 students, 80 students, and 78 students respectively to their appropriate program for every 100 data points. All these aforementioned methods performed over the machine learning threshold of 80% classification accuracy. Conversely though, Naïve Bayes' model and k-nearest neighbors performed under the threshold, each only having a classification accuracy of 0.654 and 0.452 respectively. This means that they can only correctly place at least 66 students and 46 students respectively to their appropriate program for every 100 data points. This may be caused by the high dimension of the data set to which kNN is sensitive at, while Naïve Bayes' model is sometimes compromised when the number of predictors is too high with respect to the number of instances.

F1 score is another metric which gives insight on the performance of a machine learning method by combining its precision and recall scores. Higher F1 score means more predictive power, as the model can perform better predictive accuracy on each class individually rather than considering overall performance like the usual classification accuracy as a metric. As gleaned in table 2, artificial neural network remained atop in terms of F1, with an overall performance of 0.845. This further means that the predictive capacity of the model is good (falling in the 0.8 to 0.9 range), and that it can correctly identify true positives by at least 84% and can minimize the prevalence of false positives and negatives by at most 15%. Similarly with CA, artificial neural network is followed by support vector machine, gradient boosting, adaptive boosting, and stochastic gradient descent, with respective F1 scores of 0.828, 0.811, 0.803, and 0.781 respectively. All these are also categorized as good models except for stochastic gradient descent, which can already be categorized as an average model (falling into 0.5 to 0.8 range). On the other end, Naïve Bayes model is also an average model (F1=0.663), but k-nearest neighbors can already be considered a poor model having only a 0.450 F1 score.

While classification accuracy is already a good metric in itself, it sometimes does not give a clear picture as to how well a model performs specifically when there is an imbalance in the outcome variables from the train data, which is in fact the case in this study. Hence, we use F1 score to shortlist our potential models in the MATCH placement system. In this case, we systematically chose only the models with good predictive capability in terms of F1; that is, artificial neural network, support vector machine, gradient boosting, and adaptive boosting.

The Blueprint of the Machine-Assisted Technology for Career and Higher Education (Match) System and its Terms of Use

After evaluating the performance metrics of the various machine learning methods considered in the study, the researchers made a model workflow using Orange to provide a blueprint of Machine-Assisted Technology for Career and Higher Education (MATCH) system, the baseline for a student placement system in CBSUA College of Development Education. Figure 2 shows the blueprint for the application.

The “CSV File Import” widget in figure 2 serves as the input portal of the MATCH system, where the comma separated values (.csv) file containing the test data will be uploaded. The .csv file shall now be referred to as the “test file”, which shall be the repository of the interest profile and diagnostic test (now referred as the MATCH test) results per domain for every teacher education program applicant. The data for each unique applicant shall be encoded in a unique row. The columns in the test file shall consist of the following, with corresponding column headers:

- “Name” column – this is where the name of each unique teacher education program applicant will be encoded.
- “S1 to S35” columns – this corresponds to the 35 interest profile indicators incorporated in the match test, with each statement having its unique columns. S1 shall correspond to statement 1 in the interest profile, S2 for statement 2, so on and so forth. In these columns, the responses of the applicants will be recorded. There will only be two valid data in these columns; code “1” when they agree they are described by the statement and “0” otherwise.
- “Eng” Column – this is where the english component test score of the teacher education program applicant will be encoded. The scores shall be in the range of 0 to 15.
- “Crop” Column – this is where the crop production component test score of the teacher education program applicant will be encoded. The scores shall be in the range of 0 to 15.
- “Math” Column – this is where the mathematics component test score of the teacher education program applicant will be encoded. The scores shall be in the range of 0 to 15.
- “Animal” Column – this is where the animal production component test score of the teacher education program applicant will be encoded. The scores shall be in the range of 0 to 15.
- “Fil” Column – this is where the filipino component test score of the teacher education program applicant will be encoded. The scores shall be in the range of 0 to 15.
- “Science” Column – this is where the science component test score of the teacher education program applicant will be encoded. The scores shall be in the range of 0 to 15.

The “Prediction” widget provides a placement decision for each teacher education program applicant using the pattern obtained from the gathered train data for every classification model shortlisted in this study. These shortlisted models can be found in the MATCH system as shown in figure 2, namely: “ANN” widget for artificial neural network, “SVM” widget for support vector machine, “GB” widget for gradient boosting, and “AdaBoost” widget for adaptive boosting. The admission decision for an applicant in a program of a teacher education institution (TEI) using the MATCH system shall be based on the placement simulation shown in the prediction widget. Notice, however, that since there are four machine learning methods incorporated in the MATCH system, there may be times when the applicant classification from each of these models may be different. In this context, the following guidelines shall be followed for each scenario.

- When all four (4) machine learning methods have a conclusive program classification, that is, when ANN, SVM, GB, and AdaBoost simulated the same program, the TEI shall strictly place the applicant in the program suggestion simulated from the MATCH system.
- When majority of the models suggest a specific program classification, that is, when there’s a 3-1 or 2-1-1 split in the model classification, the TEI shall consider the major program

classification as the first choice of placement for the applicant. The other programs suggested by the MATCH system shall serve as an alternative program for the applicant. While it is advised that the major program classification shall be followed, the applicant shall still be given the chance to choose which program they'll subject themselves into provided that the program choice is one of the programs rendered in the system. When the student quota for a program has already been met, the TEI may consider this as a meritorious reason to decide on the placement of an applicant in another program, provided that it is still part of the rendered classification from the MATCH system.

- When there's a 2-2 split in the classification, that is, when two machine learning methods rendered a program and the other two models rendered another program, the TEI shall give the applicant the choice which program to choose. In the case where the applicant's program of choice already met the student quota, the TEI may consider this as a meritorious reason to place the applicant to the other program.
- When the four (4) machine learning methods have an inconclusive program classification, that is, when pairwise each method suggested different programs, the TEI shall give the student to choose which program to take. However, when the student quota for a program has already been met, the TEI may consider this as a meritorious reason to decide on the placement of an applicant in another program, provided that it is still part of the rendered classification from the MATCH system.
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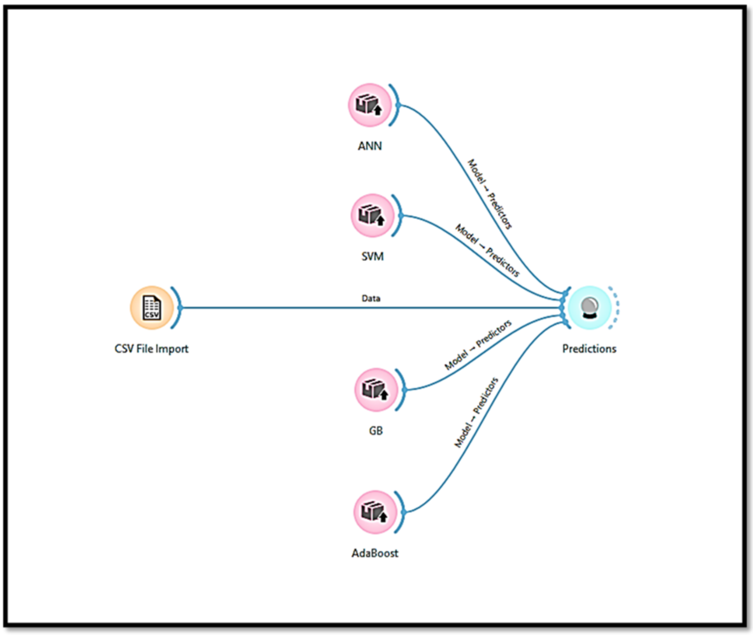

Figure 2. The blueprint of the MATCH model made from Orange workflow.

To ensure data robustness and refined classification metrics of the MATCH system, it is highly suggested that the data for every admission runs in every academic year be included in the train data. When the TEI plans or decides to terminate the offering of a teacher education program, the accumulated train data must be cleaned in such a way that all rows classified as the terminated program will be deleted. This is to ensure that the MATCH system will not render a classification in favor of the terminated program in the next admission run. On the other end, should the TEI plan or decide on adding a new curricular offering, train data for the proposed program shall be gathered following the methodology specified in this study.

CONCLUSION

The evaluation for the interest profile of the respondents indicates that their academic interest in their respective fields of specialization is a significant factor in placing students in their respective fields of specialization. The diagnostic test scores of the respondents reinforces the idea that students may excel or not in their respective fields. Moreover, as the data shows an observable trend in the mean scores of respondents in the different test components, the researchers suggests that a standardized test be used instead of a modified diagnostic test. The accuracy, precision and recall of a machine learning method play a pivotal role in developing the model for student placement. After having performance metric diagnosis for each model, three models were excluded from consideration. The Naïve Bayes' model and k-nearest neighbors both performed under the acceptable threshold, each having a relatively low classification accuracy and F1 score. On the other hand, the stochastic gradient descent despite having a higher classification accuracy was also excluded due to an F1 score less than the acceptable 80% threshold. Machine learning can be leveraged to make placement models for the students, deviating from the traditional placement methods used by colleges and universities. The blueprint for the Machine-Assisted Technology for Career and Higher Education (MATCH) can provide a more personalized, effective, and efficient student placement in teacher education institutions. The researchers strongly suggest the implementation of the MATCH placement model to systematically place students in their right fields in teacher education, thereby helping them secure an industry-ready future.

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