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CAREER TRACK PREDICTION USING DEEP LEARNING MODEL BASED ON DISCRETE SERIES OF QUANTITATIVE CLASSIFICATION

Abstract

In this paper, a career track recommender system was proposed using Deep Neural Network model. This study aims to assist guidance counselors in guiding their students in the selection of a suitable career track. It is because a lot of Junior High school students experienced track uncertainty and there are instances of shifting to another program after learning they are not suited for the chosen track or course in college. In dealing with the selection of the best student attributes that will help in the creation of the predictive model, the feature engineering technique is used to remove the irrelevant features that can affect the performance of the DNN model. The study covers 1500 students from the first to the third batch of the K-12 curriculum, and their grades from 11 subjects, sex, age, number of siblings, parent's income, and academic strand were used as attributes to predict their academic strand in Senior High School. The efficiency and accuracy of the algorithm depend upon the correctness and quality of the collected student's data. The result of the study shows that the DNN algorithm performs reasonably well in predicting the academic strand of students with a prediction accuracy of 83.11%. Also, the work of guidance counselors became more efficient in handling students' concerns just by using the proposed system. It is concluded that the recommender system serves as a decision tool for counselors in guiding their students to determine which Senior High School track is suitable for students with the utilization of the DNN model.

1. INTRODUCTION

The K-to-12 education system is a newly implemented educational system in the Philippines, and it is the last country in Asia to implement this curriculum (Abarro, 2016). The implementation of the new curriculum in the Philippines gives additional two years of education for Senior High School to prepare the students and empower them to confidently join the labor market (Roy Montebon, 2014) even if students don't choose to go to college. The Department of Education opted for gradual implementation of K-12 that will provide Filipino students sufficient time for mastery of concepts and skills so that they will be ready for tertiary education when the time comes.

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One of the aims of the K-12 curriculum is to increase the competitiveness of students' graduates in the country, and with the current situation in the K-12 assessment, proper counseling should be conducted in the selection of appropriate careers (Gorad, Zalte, Nandi & Nayak, 2017). The guidance counselor should also determine if the student can work in a particular field. Also, it is essential for teachers to periodically monitor their students' current performance on skills to make sure that the students are learning and improving every school year. In the K-12 curriculum career tracks were categorized into four namely: academic track, sports track, arts, and design tracks, and the technical-vocational track (Gestiada, Nazareno & Roxas-Villanueva, 2017).

Moreover, there are various career options available in each track, and many career opportunities in every field offered to the students (Laguador, 2014), and this exposed students with the various factors associated with career choices. That is why student's performance evaluation plays an important role in determining the strengths and weaknesses of the student before choosing the appropriate career track.

However, in the field of educational data mining, the most important topics are about the academic performance and the socio-demographic data of the students. The students' performance is an essential part of every learning institution, and the final grades of students are generally used to evaluate students' performance. The final grades of students are based on assessment marks, major exam scores, course structure, and other extracurricular activities provided by the institution (Bin Mat, Buniyamin, Arsad & Kassim, 2014). These data such as students' grades and socio-demographic data can be extracted to provide meaningful information about the students' status on each course or subject. It is also important that these data be utilized in helping students become aware of their strengths and what needs to be improved to achieve academic success and decision making.

Hence, with the available data on education, a career track recommendation system can be used to assist guidance counselors and students in the selection of appropriate career track. This recommender system could apply methods and techniques from statistics, data mining techniques, and neural networks to the problem of making a suitable recommendation of career tracks for senior high school students. The students should be satisfied with the services offered by the institution and career guidance because students are considered as the customers. Such a system with the utilization of neural networks can also help increase student satisfaction and maintain a joint relationship between the school and the students by helping the students in the selection of the right career track in Senior High School that matches with his skills and abilities.

A lot of the junior high school students experienced track uncertainty and were left confused on making decisions about choosing which career track at the senior high school level is applicable and suits the students. There are also instances that students shift to another program after learning they are not suited for their chosen course in college. According to Bin Mat et al. (2014), many students made wrong decisions on selecting a career due to a lack of experience, support, and advice from friends, parents, relatives, and teachers, or career counseling. The number of students and the number of choices is also growing in public schools, making it difficult for advisers to spend more time counseling each student due to workload (Goyal, Kukreja, Agarwal & Khanna, 2015). Also, the problem of student retention in Senior High School, especially in higher education, can further give rise to low student contentment wherein students are shifting from one course to another and dropping out (Razak et al., 2014). Dropout incidence is a bigger concern at the collegiate level than at the secondary and elementary level due to individual-related problems such as poor academic performance, and health issues. Students are shifting to another program or strand after learning they are not suited on their chosen track or strand. This results to a waste of budget allocated by the government in State Universities for free tuition fees.

Furthermore, it is very important to help the students to increase their awareness (Durosaro & Nuhu, 2019) about the career tracks that are suitable for them, and not to just pick any course that they want (Asif, Merceron & Pathan, 2015). The students of junior high school need to select one career track from these four categories under the K-12 curriculum before entering senior high school. Career guidance should be delivered in several ways to every student so that it can help students to be more aware of selecting appropriate career tracks based on the student's overall academic performance.

The student's performance evaluation will help in the determination of the student's strengths and weaknesses before choosing a career track. It is only high time to develop a system that will assist guidance counselors in completing the performance evaluation of students. Moreover, it could be beneficial for the teachers and counselors to have a decision tool that empirically shows the academic performance analysis of students (Grewal & Kaur, 2015), and recommended career track for the students. The developed method can also provide the students with quality and convenient support services, and with the utilization of certain algorithms, career-track-related decisions will be supported and deduced.

This paper aims to design and develop a neural network-based career track for junior high school students using Deep Neural Network (DNN). The algorithms that were used in this study will give an update about the progress of students in each subject every grading period. While providing grades and early predictions on the future academic performance of students, the utilization of DNN in the developed system will classify the prediction results of academic achievement to determine which Senior High School track is suitable for the students. This developed system will provide students with recommendations in choosing a career track that is appropriate to their skills and abilities. The results of the prediction will help the teachers and guidance counselor to interpret information and apply it to their students' situation in selecting career track by using the DNN algorithm approach.

2. LITERATURE REVIEW

In this section, literature related to student academic performance prediction and classification is reviewed.

The researchers discussed the implementation of the additional two years in the Philippine high school system. As part of the program, students are set to choose one track from ten academic strands. With several factors to consider, the selection of a career path may be difficult for a student. The researcher proposed a study that aims to create a tool that will guide students in choosing a particular career track using Social Cognitive Career Theory (SCCT) and the analytic hierarchy process (AHP). To identify the factors in considering the selection of career, the researchers used the SCCT, whereas the AHP was used in ranking the career tracks according to these factors. Evaluation of the tool in terms of design, navigation, and utility was also conducted on more than 150 Grade 10 students using pilot testing (Gestiada, Nazareno & Roxas-Villanueva, 2017).

Meanwhile, the selection of the right course in formative years is a very important decision as students' future depends on this one decision. The student by himself is not mature enough to decide his early life. The selection of wrong courses means a mismatch between student aptitude, capability, and personal interest. Also, the faculty or parents have neither the required knowledge nor experience. Since there is no other reliable source generally available that can guide a student towards the most suitable direction, the recommender system has been evolved to provide students' guidance in selecting a right course. This paper proposes feasible predictions for students' course selection based on final marks and choice of job interest (Grewal & Kaur, 2015). To find structure and relationship within the data, the clustering technique was used, and it is said the technique can work on unsupervised data.

A proposed career recommender system using Fuzzy logic was presented which aims to help not only the guidance counselor but most especially the Senior High School students to guide them in considering numerous factors associated with their decision on what career they will pursue. In dealing with choosing the student attributes from numerous factors, a feature selection technique is appropriate to use to remove irrelevant features that affect the performance of the proposed fuzzy-based system. In this paper, different filter methods are used to select the best attributes (Natividad, Gerardo & Medina, 2019; Razak et al., 2014; Qamhieh, Sammaneh & Demaidi, 2020; Sulaiman, Tamizi, Shamsudin & Azmi, 2019). After selecting the best attributes, these are now used as crisp inputs. The result of the experiment shows a reasonable result for making decisions (Alzhrani & Algethami, 2019). It is concluded that the proposed career recommender system for students assists students in their career decision. The proposed system for students is also very timely and will be one of the significant researches works in the new era of the education system in the Philippines.

In another study of Okubu et al. (2017) about students' performance prediction, the researchers show a method that will predict students' final class marks using a Recurrent Neural Network. For this purpose, the learning logs from 937 students who attended one of six courses by two teachers were collected. Nine kinds of learning logs are selected as the input of the RNN. The researchers carefully examine the prediction of final class marks, where the training data and test data are the logs of courses conducted in 2015 and 2016, respectively (Tai-Nghe, Drumond, Krohn-Grimberghe & Schmidt-Thieme, 2010) The study shows that observing the weight values of the trained RNN helps identify the important learning activities when it comes to obtaining a specific final class mark.

According to the study of Rafanan et al. (2020), the artificial neural network approach can be used in predicting the career strand of incoming senior high school students. The K-12 program gives additional two years in the students' basic education, and these ancillary years allow senior high school students to take courses under the core curriculum and the track of choice. Each student must select one track to pursue that can equip him/her with skills to prepare for the future. Prediction of choice of a career track in senior high school is advantageous for educational institutions since it gives insights that can help them develop vital programs beneficial for students learning in school. In this study, the applied artificial neural network (ANN) to predict the career strand based on the students' grades in five major subjects. Different ANN models have been considered and compared. In training and testing the models, a sample of 293 student data information was used (Nazareno et al., 2019). The highest accuracy recorded among all the models was 74.1%.

A neural network called the Deep Neural Network model was proposed in another study that shows students which class category it belongs to. This study provides knowledge to the institution so that proper remedy can be offered to the potential failing students. A comparison with existing machine learning algorithm which uses the same dataset with the proposed model (Bendangnuksung & Prabu, 2018). With larger dataset records and features, a DNN can achieve higher accuracy and will outperform the other machine learning algorithm (Vijayalakshmi & Venkatachalapathy, 2019). Two hidden layers are implemented Relu and Soft-Max activation function. The prediction of students failing is effective, with an estimated 85% accuracy, and outperforms other machine learning algorithms inaccuracy.

Moreover, the study of Piad et al. (2016) predicted the employability of IT graduates using nine variables. First, different classification algorithms in data mining were tested making logistic regression with an accuracy of 78.4 is implemented. Based on logistic regression analysis, three academic variables directly affect; IT_Core, IT_Professional, and Gender identified as significant predictors for employability. The data were collected based on the five-year profiles of 515 students randomly selected at the placement office tracer study.

Several kinds of research in the educational field that involve Data mining techniques are (Hamsa, Indiradevi & Kizhakkethottam, 2016) rapidly increasing. The researcher applied Data Mining techniques in the field of education that aims to discover hidden knowledge and patterns about students' performance. This work aims to develop students' academic performance prediction model, for the Bachelor and Master degree students in Computer Science and Electronics and Communication streams using two selected classification methods; Decision Tree and Fuzzy Genetic Algorithm. The resultant prediction model can be used to identify students' performance for each subject (Jauhari & Supianto, 2019).

Thereby, the lecturers can classify students and take early action to improve their performance. Systematic approaches can be taken to improve the performance with time. Due to early prediction and solutions being done, better results can be expected in final exams (Hasan et al., 2018). The students can be able to view their academic information and updates in school. Moreover, the results from the decision tree algorithm made more students at risk class, which makes lecturers decision to take more care of those students. Results from the fuzzy logic algorithm give more past students considering those who are in between risk and safe, to a safe state that gives students mental satisfaction.

Furthermore, another study about the use of a classification model for predicting the suitable study track for school students was presented by researchers. Researchers said that one of the most important issues in academic life is to assign students to the right track when they arrive in the end of the basic education stage (Al-Radaideh, Ananbeh & Al-Shawakfa, 2011). The main issue in the selection of an academic track in basic Jordanian schools is the lack of useful knowledge for students to support their planning. A decision tree classification model was developed to determine which track is suitable for each student. There are set of classification rules that were extracted from the decision tree to predict (Al-Barrak & Al-Razgan, 2016) and classify the class label for each student. A confusion matrix is built to evaluate the model (Varade & Thankanchan, 2021) where the 10-fold Cross Validation method was used for accurate estimation of the model. The overall accuracy of the model was 87.9% where 218 students were correctly classified out of the 248 students.

In the polytechnic system, a student must take the elective subjects at least three subjects to complete their study. The researchers decided to use the Decision Tree method for predicting students' performance in the elective subjects. The elective subjects were chosen based on their interest and first come first serve. The results of the final examination for elective subjects affect the future of the students, and it is important to predict whether the students will pass or fail in the final examination. To obtain the necessary information about students' profiles, the literature survey was used. The researcher of this paper uses data mining which is the decision tree method for the prediction of the student's performance in each elective subject (Sulaiman, 2020; Khasanah & Harwati, 2017). This research is focused on the ICT students who select DBM3033 as an elective subject, and the two phases involved were preprocessing the data and mining the data. The RapidMiner software is used in the data mining process.

Classification technique is applied for decision tree method. Some attributes are collected from the students' database record to predict the final grade in DBM3033. From the experiments, the average training accuracy is 71.11% and the accuracy for the testing data is 77.50%. Therefore, it looks like the accuracy is still in the good range. The research findings showed that students whose results are weak in both SPM Mathematics and DBM1033 are predicted as fail in final examination for DBM3033 (Sulaiman, Shibghatullah & Rahman, 2017).

According to the researches, the data mining techniques can be applied to predict and analyze students' academic performance based on students' academic records and forum participation. This paper explained that educational institutions can use educational data mining for extensive analysis of students' characteristics (Rizvi, Rienties & Khoja, 2019; Abu Zohair, 2019; Mhetre & Nagar, 2018). Three different data mining classification algorithms (Naïve Bayes, Neural Network, and Decision Tree) were used and applied in the dataset. The prediction performance of three classifiers was measured and compared. It was observed that the Naïve Bayes classifier outperforms the other two classifiers by achieving an overall prediction of 86%. While the two classifiers achieved 82% and 79% for the DT classifier. This study help teachers to improve student academic performance (Mueen, Zafar & Manzoor, 2016).

3. PROPOSED WORK AND METHODOLOGY

3.1. Proposed approach

This section, it shows the processes to the methodology used in this study. This includes data collection, data pre-processing, data cleaning, model building, model evaluation, and interpretation. The first and foremost step is to identify the data and collect the dataset required for the study.

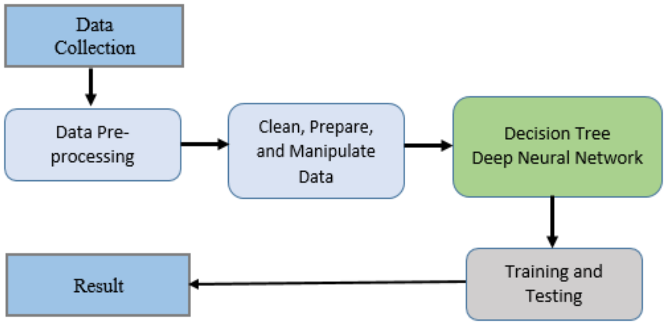

Fig. 1. System Model Architecture

Figure 1 shows the system model architecture. The class marks of students in each subject and their socio-demographic data were collected. After the required data is gathered, the raw data must be pre-processed to achieve the proper format and remove the unnecessary or inconsistent data that may affect the performance of the model. The efficiency and accuracy of the algorithms depend on the correctness and quality of the data collected. The next step is to use the two well-known classification techniques which are Decision tree and Deep Neural Network. These two techniques were used to classify students' academic performance according to the Senior High School academic track. Moreover, the researcher discussed the data pre-processing and strategies performed in this study.

3.2. Methodologies

3.2.1. Data Collection

Table 1 shows the initial data collected from the student during the data collection process. The grades of student for each grading period and their final average in each subject were collected and used in the creation of the DNN and Decision tree model.

Tab. 1. Collected Data from Students

No	Attributes
1	Student Name
2	Track
3	Sex
4	Age
5	No. of Siblings
6	Salary Bracket of Parents
7	Occupation of Mother
8	Occupation of Father
9	Place of Birth
10	Name of Region
11	Subject Grades

The gathered response from the students about their socio-demographic data contained the following: Name, Age, Sex, Place of Birth, Name of Region, Number of Siblings, Occupation of Mother, Occupation of Father, Family Salary Bracket, and Academic Track. In the collection of data, the researcher ensured that ethical procedures were properly performed before, during, and after the actual data gathering. Class scores of students and socio-demographic data were collected through an online structured questionnaire. Concentrating on the required data, the names of the respondents were removed so that no student can be identified in this study.

3.2.2. Data Cleaning

The collected datasets were downloaded and organized in an excel sheet. During the data pre-processing, the researcher cleaned and replaced the students' data with appropriate data. The cleaning of data was carefully applied to make it suitable for the model. All null values found were removed so that it would not be difficult for the predictive model to learn.

3.2.3. Normalization

Normalization is an essential step in data pre-processing because it transforms data in a way that the data have similar distributions. In this paper, the researcher ensured that input requirements are prepared for Deep Neural Network and Decision tree algorithms. The student's attributes with text data were converted into numerical values. Then, normalization is applied by scaling each attribute and grades of students in each subject between 0 and 1. In this study, the min-max type of normalization is adopted in which it scales every feature value between its minimum (0) and maximum (1). The validation accuracy of the model increases after applying the normalization.

3.2.4. Data Preprocessing

Feature engineering is used in the selection or creation of variables in a dataset to improve the prediction results. It is a process of transforming collected data into features that will act as inputs to the machine learning models.

The two important parts of this data pre-processing were variable transformation and feature creation. The features were created by extracting the data in a variable, removing the unused features (such as names of students, occupation of parents, and region). Fine-tuning of hyper-parameters was also applied in this study, and it was used to find the best combination of parameters for the predictive model. The data-preprocessing procedures were conducted in this study after the grades and socio-demographic data were gathered. The steps and strategies are as follows.

[a] To begin with, all the grades in eleven subjects were normalized such that it less one. This means that the grades in each subject are all divided by 100 so each grade varied within the same range from 0 to 1.

[b] While all categorical data were converted into indexes. For example, Male was assigned as 1, and Female was assigned as 0.

[c] The Place of Birth has a high correlation to the Region, and it is because the student's birthplace is where their family stays.

[d] The occupation of the mother and the occupation of the father has a high correlation with the salary bracket of the family. The income of their parents is defined by the occupation and contributes to the Salary Bracket of the Family unless they also have other sources of income.

[e] In addition, the region was dropped since most of the respondents all come from the same region which is CALABARZON 4A.

[f] Place of Birth could be a factor for a student's upbringing and choice of academic track/strand but inclusion in this would require more data from different schools in the country to prove the claim.

[g] Furthermore, the salary bracket of the family is taken over the occupation of the mother and the father since this has few numerical categories compared to the number of occupations taken from the survey, and the salary bracket is more reasonable to use in the model as discussed in [a].

Tab. 2. Student related attributes

No.	Attributes	Category	Frequency
1	**Student ID**	Student ID No.	1500
2	**Track**	STEM	500
		HUMSS	500
		ABM	500
3	**Sex**	Male	465
		Female	1035
4	**Age**	18yrs old	171
		19yrs old	502
		20yrs old	465
		21yrs old	337
		22yrs old	21
		23yrs old	4
5	**No. of Siblings**	0	91
		1	324
		2	417
		3	300
		4	168
		5	107
		6	38
		7	22
		8	12
		9	13
		10	8
6	**Salary bracket of Parents**	1 – Poor (<9250)	30
		2 – Low Income (Between 9250–19040)	891
		3 – Low Middle Income (19040–38080)	432
		4 – Middle Income (38040–66640)	83
		5 – Upper Middle Income (66640–114240)	58
		6 – Upper Income (114240–190000)	6
7	**Subject Grades**	Filipino, English, Mathematics, Science, Social Science (AP), Technology and Livelihood Education, Edukasyon sa Pagpapakatao, Music, Arts, Physical Education, and Health	1500

Table 2 shows the final attributes and descriptions of student records. Each student's socio-demographic and academic record had the following attributes.

The dataset is comprised of 1,500 undergraduate degree students and then were categorized into three academic tracks (STEM, HUMSS, and ABM) which consisted of 500 (33.34%), 500 (33.33%), and 500 (33.33%) students. In table 2, the final dataset or attributes were applied in the creation of the DNN and Decision Tree model.

3.2.5. Made Learning Model

For the model construction, a deep neural network and decision tree method has been used.

Studen No	FIL	ENG	MATH	SCI	AP	TLE	EP	MUSIC	ARTS	PE	HEALTH	Age	Sex	Siblings	SalaryBracket	STRAND
502	78.75	76.8125	76.25	77.375	77.6875	76.9375	81.0625	81	80.8125	80.125	79.8125	21	F	4	Low Income	HUMSS
503	77.5	77.5625	78.5	77.5625	78.1875	77.5	82.1875	79.625	80.25	79.0625	79.875	20	F	1	Low Income	HUMSS
238	84	83.125	83.25	83.75	83.125	83.625	82.5	87.0625	87	86.6875	86.0625	21	F	2	Low Middle In	ABM
198	81.9375	84.3125	84.8125	84.9375	84.0625	84.125	82.5625	90.875	90.25	90.5625	89.8125	19	F	2	Low Middle In	ABM
181	85.25	84.0625	83.375	84.5625	80.875	81	82.9375	85.125	85.5625	86.1875	86.9375	21	M	3	Low Income	ABM
491	85.25	84.0625	83.375	84.5625	80.875	81	82.9375	85.125	85.5625	86.1875	86.9375	19	M	2	Low Middle In	ABM
832	86	86.0625	84.625	85.875	84.4375	84.9375	83.3125	85.4375	85.6875	86.375	86.6875	19	F	2	Low Income	HUMSS
199	83.0625	84	84.4375	82.9375	83.1875	84.0625	83.375	90.875	90.8125	89.9375	90.25	19	F	2	Low Middle In	ABM
228	85.5625	84.875	85.8125	87.125	86.125	84.8125	83.4375	86.625	86.875	87.125	88.25	21	F	5	Low Income	ABM

Fig. 2. Sample of input variables for the first 9 students

Figure 2 shows the format of the final dataset used in the training and testing of the model. From the dataset collected 70 percent of the data was utilized for training, and 30 percent of the data is reserved for testing. The DNN and Decision Tree algorithms were applied to the dataset and results are noted and observed.

3.2.6. Deep Neural Network and Decision Tree

A Deep Neural Network is described as a kind of machine learning with multiple hidden layers between the input and output layers. The neurons in the neural network are used for the processing of information, which is interconnected to sense the propagation of signals. These networks of neurons become useful when applied in solving problems of prediction and classification (Oancea, Dragoescu & Ciucu, 2013). The architecture of a deep neural network which consists of an input layer, hidden layer, and output layer is shown in Figure 3. The number of layers and number of neurons in each layer were also discussed in the next page.

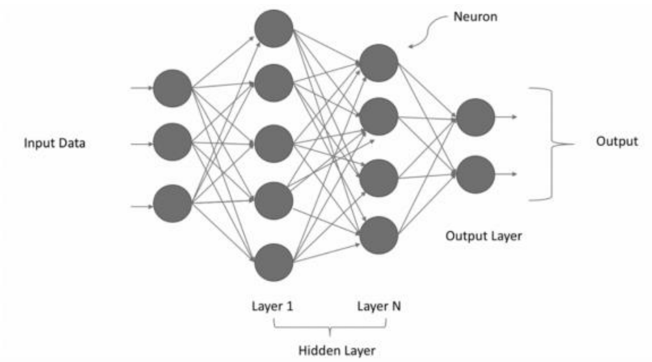

Fig. 3. Deep Neural Network Architecture

In this study, the Deep Neural Network is employed in the model to perform the classification (Sarvepalli, 2015) and prediction of a career track for students. According to Yi et al. (2017), DNN aims at transforming the data towards a more abstract and innovative element. All neurons of input layers are fed to the neurons of hidden layers to process the input, while outputs are obtained from the output layer. The hyperparameters used in this study were sigmoid activation function, epochs, input layer consists of 8 nodes, hidden layers which consists of 8 nodes, while the final layer consists of 3 nodes. These hyperparameters obtained were used by the researcher to establish the DNN predictive model.

The sigmoid activation function was used because it exists between 1 to 0, and this activation function is especially utilized for the model that can predict the probability as an output. Since the probability of anything exists only between the range of 0 and 1, sigmoid is the right choice. While the 4000 epochs for the DNN model are determined during the training phase, the final number of epochs used was taken due to high and consistent accuracy. Moreover, the number of layers was more on experimentation, the first layer is usually the number of features the researcher wants to feed the model, the number of the second layer should be at least greater than the first layer then the addition of hidden layers.

Finally, the final layer in Deep Neural Network algorithm consists of three nodes i.e., [ABM], [HUMSS], and [STEM], and each has a percentage for the recommendation of the academic strand. The highest percentage the student obtained from the three strands was the one recommended for the student, but students are free to choose which career track to pursue in senior high school. The guidance counselor can use the result to guide and evaluate their students in the selection of career track.

Moreover, the Decision Tree classifier is also used for the prediction of the academic track of students and compared the result of validation accuracy to DNN results. A decision tree is a flow-chart-like tree structure, where each internal node is denoted by rectangles, and leaf nodes are denoted by ovals. All internal nodes have two or more child nodes. All internal nodes contain splits, which test the value of an expression of the attributes. Arcs from an internal node to its children are labeled with distinct outcomes of the test. A class label is associated with each leaf node (Pal, 2011). Moreover, the decision tree algorithm is beneficial in data mining when it comes to handling a variety of textual, numeric, and nominal types of documents (Li & Zhang, 2011). This method can be used in datasets with a large number of errors and missing values. In this study, the maximum depth of the tree is three. One of the focuses of this study is to determine which Senior High School track is suitable for the students. The system provides the students a recommendation in choosing a career track based on their academic performance in each subject. The result of the prediction of which career track to choose can assist guidance counselors to interpret information and apply it to their students' situations in the selection of career track using the Deep Learning algorithm. This study helps students have a better insight into their future performance and make informed decisions by recommending a suitable strand under an academic track.

3.2.7. Tools and Techniques

The Python programming language was used in creating and testing of the DNN and Decision Tree model, while the Google Colaboratory serves as the Integrated Development Environment which helps in analyzing and visualizing the dataset. Python is a powerful general-purpose programming language. It is a mature and rapidly growing platform for scientific investigation and numerical computation, and Python hosts a large number of open source libraries as well as almost all general purpose machine learning libraries that can be used to train the deep learning and decision tree models. Moreover, Colab Notebooks are Jupyter notebooks that are useful in for generating and presenting data science projects in an interactive manner, and it supports variety of programming languages such as Python.

Table 3 shows the output of the Deep Neural Network model and the prediction of students' academic track.

Tab. 3. Final Output of the DNN Model for the first 11 students

Student No	ABM	STEM	HUMSS
0	67.65	1.47	30.88
1	28.82	64.75	6.43
2	28.82	64.75	6.43
3	75.69	23.2	1.1
4	28.82	64.75	6.43
5	8.86	5.14	86
6	28.82	64.75	6.43
7	8.86	5.14	86
8	28.82	64.75	6.43
9	75.69	23.2	1.1
10	67.65	1.47	30.88

The results of prediction were classified according to the Senior High School academic track and is presented in this table. The exact parameters used in this DNN model were grades of student in each subject, sex, age, number of siblings, and salary bracket of parents.

3.3. Evaluation metrics

To evaluate the prediction model 5-fold cross-validation was used, and the percentage split method is applied. In the percentage split method, the dataset training set (70%) is used to train the model while the remaining 30% is for testing the model. A comparison of validation accuracy between Neural Network and Decision Tree was tested to ensure the highest prediction or classification could be achieved in this study. Moreover, the training set was divided into 5 disjoint sets of approximately equal size. The 5-fold cross-validation of data is an iterative process in which the process was repeated five times and then the accuracy of the predictive model is computed.

To compare the prediction model, the Root Means Square Root was used. This evaluation metric is a standard deviation of the errors that occur when a prediction of the academic track is made on a collected dataset. The $\boldsymbol{RMSE}$ evaluation metric is the same as MSE (Mean Squared Error) but the value of its root is considered while determining the accuracy of the predictive model as in the following equation:

$$\boldsymbol{RMSE} = \sqrt{\left(\frac{\Sigma(\hat{Y}_i - \mathbf{Y}_i)^2}{\boldsymbol{n}}\right)} \tag{1}$$

where: $\hat{Y}_i$ and $\mathbf{Y}_i$ are the predicted and targeted values, and $\boldsymbol{n}$ is the total number of records.

The smaller the $\boldsymbol{RMSE}$ values the better as it is an indication of a good prediction of the target values. Generally, the simpler and easier model to interpret is preferred if the compared predictive models have no significant difference (Obsie & Adem, 2018).

4. RESULTS AND DISCUSSIONS

Table 4 illustrates the performance of DNN and Decision Tree methods after the testing process. As the results indicate, the two predictive models performed reasonably well in classifying and predicting the academic strand of the student.

Tab. 4. Prediction result of two algorithms

Prediction Methods	Accuracy %	MSE	RMSE
Decision Tree	0.7889	0.5844	0.7644
Deep Neural Network	0.8311	0.4555	0.6749

Table 4 shows that the Deep Neural Network method produced the more accurate prediction results, in which 0.8311 accuracy, 0.4555 MSE, and 0.6749 RMSE values were obtained with the 5-fold cross-validation test. While Decision tree method obtained a 0.7889 accuracy, 0.5844 MSE, and 0.7644 RMSE respectively. The parameters used in DNN and Decision tree model were grades in each subject, sex, age, number of siblings, and salary bracket of parents. The input layer in DNN model consists of 8 nodes, and hidden layers consists of 8 nodes, while the final layer consists of 3 nodes. The Decision Tree model has a maximum depth of three. Moreover, tree depth is the number of splits a tree can make before making a prediction.

Figure 4 shows the graph of the testing accuracy and loss from the predictive model. The loss in this graph is a value that represents the summation of errors in the predictive model. This measures how good or bad the model is performing. It is important to note that if the errors are high, then the loss will be high, which indicates that the predictive model does not perform well. Otherwise, the lower it is, the better the model works when it comes to predicting the academic strand of the students.

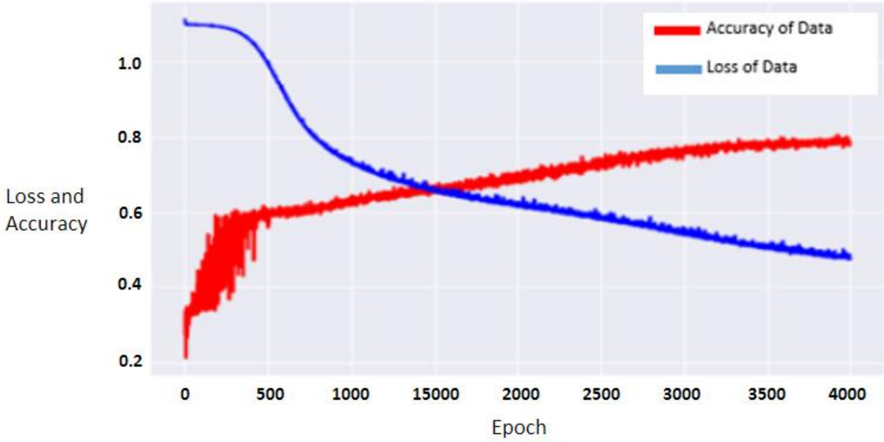

Fig. 4. Accuracy and Loss Graph

In this figure 4, the loss data is decreasing and we can see the expected behavior of the learning process even if it has slight ups and downs. The loss decreases over time, so the predicted model is learning. While accuracy in the graph describes the percentage of test data that are classified correctly, the higher it is, the better the predictive model becomes. With the proposed deep neural network, it was able to achieve an accuracy of 83.11% in predicting the academic strand of a student. Great accuracy with low loss means that the model made low errors on a few data and is considered as the best case.

A comparison-based study is also made to Nazareno et al.'s (2019) proposed model. The researchers used and suggested an Artificial Neural network model in predicting the career strand of incoming senior high school students. The parameters used in this proposed ANN model were grades in Filipino, English, Math, Science, and Technology and Livelihood Education. The DNN and Decision tree predictive models used in this study were compared with their ANN prediction accuracy. The prediction accuracy of the three models is calculated and recorded. Table 5 shows the result of the comparison of accuracy.

Tab. 5. Comparison of Accuracy Among Different Techniques

Classifier	Accuracy
Artificial Neural Network	74.1%
Decision Tree	78.89%
Deep Neural Network	83.11%

The table shows that the accuracy of our predictive model Deep Neural Network is 83.11%, while other techniques got an accuracy of 78.89% for Decision tree and 74.1% for Artificial Neural Network. Also, the ANN value is less than the decision tree value, which is why it can be concluded that DT and DNN work better than the other model when it comes to predicting performance and classifying students' academic strands. Moreover, the two predictive models (Decision Tree and Deep Neural Network) have been compared to one another using the ROC index performance measure.

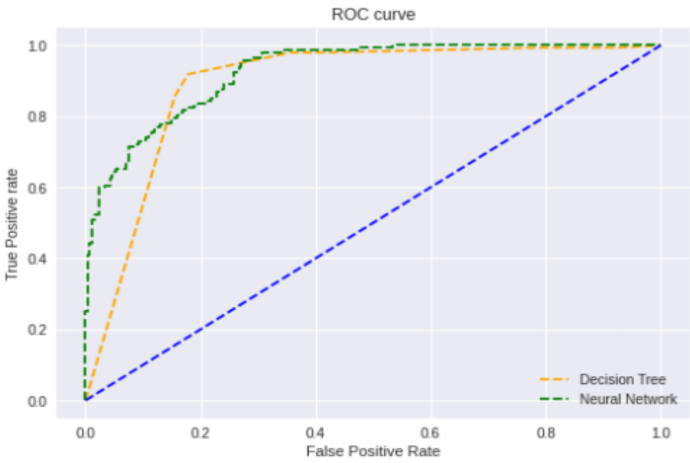

Fig. 5. DNN and DT ROC index

Figure 5 shows that DNN model has the highest ROC index that is equal to 0.9271. While the decision tree model got an accuracy of 79%. This means that the DNN model is much better than the DT model when it comes to predicting the performance or academic strand of students. In addition, the Deep Neural Network is more versatile compared to the Decision Tree model in most cases. The DNN provides percentages which is more useful for the recommender setup, where the Decision Tree gives a specific academic strand of choice. This means that DNN performed well in predicting the academic strand of students using the same attributes. Moreover, all the data used during the training phase came from the real-life values which actual student grades and their response from the surveys. The researcher split the test set into 20-80 and 30-70 portions into 5-folds where the researcher determined which parameters and features to use that provides the highest accuracy.

4.1. Confusion Matrix

The researcher used the confusion matrix to determine the accuracy of strand prediction. This summarizes the number of correct and incorrect predictions made by the model in a tabular format. The actual value and predicted value are indicated in the table below. The performance of the model is also evaluated using the accuracy, precision, and recall performance metrics. Accuracy is a proportion of the total number of correct predictions of a strand, while Precision indicates the proportion of correct positive observations. The recall is a proportion of positives correctly predicted as positive.

Tab. 6. Confusion Matrix for DNN

	ABM (Actual)	**STEM (Actual)**	**HUMSS (Actual)**	**Classification Overall**	**Precision**
ABM (Predicted)	108	3	36	147	73.469%
STEM (Predicted)	3	135	9	147	91.837%
HUMSS(Predicted)	7	18	131	156	83.974%
Truth overall	118	156	176	450	
Recall	91.525%	86.538%	74.432%		

Table 6, shows the actual and classifier results. There are 147 students from ABM and STEM strands, and it is observed that 108 students were predicted correctly under the ABM strand, while the STEM strand predicted 135 students out of 147 students under the STEM strand. Moreover, there are 156 students in the HUMSS strand and 131 students are predicted correctly. The overall accuracy of the DNN model is 83.11%.

Tab. 7. Interpretation of Values in Cohen's Kappa Statistics

Values	Interpretation
Smaller than 0.00	Poor Agreement
0.00 to 0.20	Slight Agreement
0.21 to 0.40	Fair Agreement
0.41 to 0.60	Moderate Agreement
0.61 to 0.80	Substantial Agreement
0.81 to 1.00	Almost Perfect Agreement

Cohen's Kappa Statistic is also used to measure the inter-rater agreement for categorical items (ABM, STEM, HUMSS). The Cohen's Kappa value for this study has a 0.746% value which means that there is a substantial agreement as shown in Table 7.

4.2. Comparative Analysis of Significant Parameters

The original parameters or attributes used in the model were Grades, Age, Siblings, Sex, and Salary Bracket of parents. This achieved an accuracy of 83.11% in the prediction of strands for the DNN model. The table shows the comparative analysis of significant parameters and their corresponding accuracy.

Table 8 below shows 10 model cases having different combinations of parameters and determine which parameter made a significant effect on the performance of the model used in the system. Case 9 and 10 got the lowest accuracy of 59.11% and 62.32% with the combination of the following attributes: Grades in 11 subjects, age, sex, number of siblings, salary bracket of parents, region, and subject groupings. Comparing Case 3 and 4, Case 3 has an accuracy of 82.44% with the following attributes: Grades, Age, and Sex. While Case 4 has achieved an overall accuracy of 80.66% with attributes Grades, Age, Sex, and Number of Siblings.

Another comparison was made between Case 3 and 5, and it shows that predictive accuracy increased after removing the number of siblings and replacing it with the salary bracket of parents attribute in Case 5 with an accuracy of 82.66%. Moreover, it is observed that the most important attributes were the grades of the student, and the combination of Age, Sex, Number of Siblings, and Salary Bracket of Parents with an accuracy of 83.11%. The difference of accuracy results between the two cases 1 (Original) and 6 is only a small percentage.

Tab. 8. Comparative analysis of best attributes

	Grades in 11 subjects	Age	Sex	No. of siblings	Salary Bracket of Family	Region	Subject Groupings (4 groups)	Accuracy
Original	✓	✓	✓	✓	✓	X	X	83.11%
Case 2	✓	X		X	X	X	X	79.33%
Case 3	✓	✓	✓	X	X	X	X	82.44%
Case 4	✓	✓	✓	✓	X	X	X	80.66%
Case 5	✓	✓	✓	X	✓	X	X	82.66%
Case 6	✓	X	✓	X	✓	X	X	83.09%
Case 7	X	X		X	X	X	✓	63.55%
Case 8	✓	X	✓	✓	✓	X	X	81.55%
Case 9	✓	✓	✓	✓	✓	✓	✓	59.11%
Case 10	✓	✓	✓	✓	✓	✓	X	62.32%

5. CONCLUSION AND FUTURE WORKS

The researcher successfully collected the grades and socio-demographic data of the students following the strict compliance and requirements by the University's Data Privacy Rules. The two models (Decision Tree and Deep Neural Network) have been compared to one another using the ROC index performance measure, and classification accuracy. The DNN model has the highest ROC index that is equal to 0.9271 and has an accuracy of 83%. While the decision tree model got an accuracy of 79%. To solve the mismatch of students in selecting academic strand and help students in deciding which career track to pursue in Senior high school. The grades in each subject and socio-demographic data of students are the attributes used in the Deep Neural Network model. This is a new development in terms of larger parameters as compared to the existing studies. This study is the first to utilize more data to train the model. The study can be more processed if the dataset can be increased from different geographic locations of the Philippines which can probably make the Machine Learning model better than what the researcher has achieved.

This study shows that it is possible to predict and classify the academic performance of the students. It is also concluded that the DNN technique can be used efficiently in classifying students' academic performance in junior high school. With the utilization of an algorithm, the work of the guidance counselor became more efficient in handling students' concerns and providing a remedy to the student who is undecided in selecting a career track.

For future works, the development of an online career track recommender system was recommended so that counselors can have a decision tool in guiding their students in the determination of which Senior High School track is to pursue and suitable for them. Having an online viewing of grades and recommended career track for students can be helpful to the students who are undecided in career track selection. Furthermore, the development of an online recommender system with the utilization of an algorithm serves as an awakening factor for education agencies to be in line with the government's view of globalization and competitiveness in the 21st century or today's information age.

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