Investigating Factors Influencing Filipino Students' Reading Literacy using Neural Network

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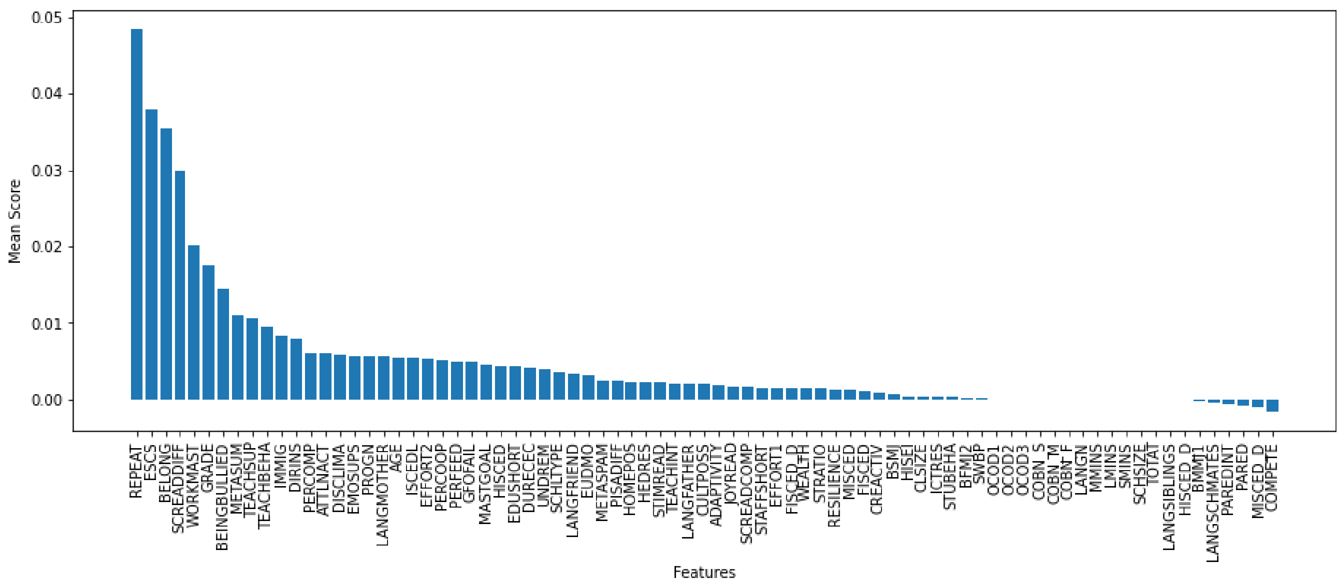


Figure 1: Feature Importance of Philippine PISA 2018 Contextual Dataset Using Neural Network

ABSTRACT

Machine learning (ML) models can help identify critical factors that influence students' reading literacy by performing classification and feature selection. A recent study [7] used a Support Vector Machine (SVM) model to classify students into high and low performing groups, with an accuracy score of 0.78. However, the model only support binary classification of students' reading literacy level. In the Philippines, where the reading literacy level of students is predominantly low level. A more fine grained categorization of low level groups is needed. Building a model with more classification levels will give insight on factors influencing these low level groups. In this study, a neural network (NN) was constructed which can classify Filipino students into four levels of reading literacy using Program for International Student Assessment (PISA) 2018 data. Reading literacy exam data of 7,233 students from the Philippines was retrieved from the PISA 2018 public dataset. This study analyzed how various features influence the model's performance on each of the reading literacy levels. Lastly, we looked into these features and their implications on improving student's reading literacy. The best model achieved an accuracy score of 0.66, while grouping students into four levels instead of two. Evaluation of factors selected by feature importance showed that a students' reading literacy level is most influenced by student-level context factors.

CCS CONCEPTS

• **Computing methodologies → Neural networks**.

KEYWORDS

reading literacy, neural networks, PISA 2018

Woodstock '18, June 03–05, 2018, Woodstock, NY

ACM ISBN 978-1-4503-XXXX-X/18/06…$15.00
https://doi.org/10.1145/1122445.1122456

ACM Reference Format:
Franz Dizon, Sidney Guaro, Syd de Ama. 2018. Investigating Factors Influencing Filipino Students' Reading Literacy using Neural Network. In *Woodstock '18: ACM Symposium on Neural Gaze Detection, June 03–05, 2018, Woodstock, NY*. ACM, New York, NY, USA, 8 pages. https://doi.org/10.1145/1122445.1122456

1 INTRODUCTION

Programme for International Student Assessment (PISA) is an international study conducted by the Organisation for Economic Co-operation and Development (OECD) where member and non-member nations can participate. It is a triennial international test given to 15-year-old students to measure their scholastic performance on mathematics, science, and reading. In the Philippines, a standardized set of examinations called the National Achievement Test (NAT) is taken by students on grade levels 3, 6, 10, and 12. Similar to PISA it tests students' academic level and knowledge on major academic subjects (Science, Mathematics, English, Filipino, Social Studies).

Prior to joining PISA in 2018 the Philippines looked to the NAT as the large scale assessment for students. Department of Education (DepEd) Secretary Briones reported that the performance of Filipino students on the NAT "gravitates towards the low proficiency levels" especially in Science, Math and English [3]. This performance is reflected in Table 1 where the target national average score of 75% in the NAT was missed every year. Given this historical performance of students in the NAT the DepEd expected that they will also not be able to perform well in PISA. Knowing that, the DepEd joined PISA to use the international large scale assessment to generate data for benchmarking and improvment of existing educational policies [6].

Table 1: National Average of Mean Performance Scores in the NAT from 2008 to 2012 [1]

Grade Level	2008	2009	2010	2011	2012
Grade 3	57.42	59.3	62.44	59.58	56.98
Grade 6	64.81	65.55	68.01	68.14	66.79
Grade 12					48.90

Reading was the focus of the PISA 2018 study. PISA defined reading literacy as "understanding, using, evaluating, reflecting on and engaging with texts in order to achieve one's goals, to develop one's knowledge and potential, and to participate in society". The 2018 PISA study had 79 participating countries and the Philippines ranked 79th in reading, with an average of 340 against the OECD average of 487. The country's poor performance in the study establishes a baseline, albeit low, relative to global standard. Putting pressure to identifying debilitating factors to the country's basic education and respond to them.

Many studies have explored factors that affect students' reading literacy in recent years. They highlight varying contextual factors [2, 5, 9–12]. There are also existing studies that used machine learning (ML) approaches to PISA datasets for classification and feature selection of impacting factors [4, 7, 18]. A recent study used SVMs to classify student data from Singapore [7]. The SVM model can categorize students to high- and low-achieving reading literacy groups with an accuracy score of 0.78. The study also presents an analysis of the top 15 contextual factors affecting classification between the two groups.

However, data from PISA 2015 for Singapore showed close numbers of 2,646 high-achieving students and 1,369 low-achieving students, Table 3 shows a different case for the Philippines. Furthermore, in PISA 2015, students from Singapore achieved the highest average mark in the reading literacy test. In contrast, data from the PISA 2018 study shows that 81.8 percent of Filipino students' scores fall under Level 1 in reading literacy. To accommodate this the DepEd even further subdivided level 1 into 3 groups (1a, 1b and 1c).

It is important to recognize the urgency of identifying other factors that influence students' reading literacy in the Philippines. This is to help address issues and gaps in the quality of basic education in the Philippines. As described, the Philippines data is unbalanced and skewed towards low level in students' reading literacy level. We argue, that a more fine grained categorization of low level groups is needed (as done by DepEd). This new categorization can be used by a Neural Network (NN) to increase classification levels and provide insight on factors influencing low level groups. If possible, improving the accuracy of classification will increase confidence on the analysis of conceptual factors.

In this study, we present a NN approach in classifying students' reading literacy level into four levels (1c, 1b, 1a, and 2). Also, we perform analysis of influential factors by calculating feature importance and feature boundaries.

2 LITERATURE REVIEW

2.1 Contextual Factors

There have been a substantial number of studies that is performed based on the PISA database to analyze the effects of different variables in the reading literacy of students. This includes the report from Department of Education (DepEd) [6]. As per contextual factors, this study reference the categories as cited in [7] which can be divided into three levels: student, family and school levels.

There are numerous studies on student-level factors that generally affect students' reading literacy. This mainly include gender, immigration status, learning time, affective domain factors [7]. Compared with native speakers, non-native speakers achieve lower reading literacy [9]. Gender is also a prominent indicator which influences students' reading performance; female score higher than male [10]. Students who are highly engaged in reading tend to spend more time on it and achieve high performance as well [11]. Family influence can also be seen as a strong element for students [2]. Among the family influence, the education levels of parents, occupational status, communications technology (ICT) resources and educational resources at home are variables in their academic success. School-level context is another reading literacy factor. Teacher's help in emotion and behavior can have a major effect on the attitude of students [5]. Additionally, students with improved economic opportunities in schools will achieve higher achievements [12].

2.2 Philippine Literacy Levels

DepEd's report summarizes that Filipino students received an average score of 340 points in Overall Reading Literacy, lower than the OECD average of 487 points [6]. DepEd noted that Filipino students can understand the main theme profoundly, recognize the literal meaning of sentences or short passages, and make a single connection on average between several neighboring pieces of data. Furthermore, only 1 out of 5 Filipino students achieve at least the minimum proficiency level. Due to the fact of data imbalance, this study primarily focus on the analysis of Level 1 Filipino students.

2.3 Machine Learning Approaches

Machine learning approaches have been applied to PISA dataset in different countries. [4, 7] used SVM for the feature selection of contextual factors. They provided analysis for binary classification of reading and mathematics literacy levels (low and high). In expounding the categories, [18] compared NN and Decision Trees algorithms and Discriminant analysis for analyzing six, three, and two levels of mathematics literacy. The results shows that NN has the best performance in six, three, and two categories having an accuracy of 44.2%, . 68.2%, and 81.7% on 6186 student of all countries in PISA 2012 dataset.

3 DATA ANALYSIS AND PREPOSSESSING

The raw data comes with 105 variables to classify the reading proficiency level of every student involved in the reading assessment. The raw data also comes with 7233 rows. The list of variables are shown on appendix B. This set of variables was also been used by Dong & Hu to classify whether a student in Singapore is high-achieving student or a low-achieving student using SVM models [7].

3.1 Missing and invalid cells in the data set

Invalid cells of data, mostly represented as NaN, are abundant in the data set. Columns with more than half the samples having NaN values where removed, which results in removing 26 columns in our data set. The remaining NaN cells in the data set are imputed using Sklearn's KNNImputer. The KNNImputer estimates the NaN cells using the mean value from its nearest neighbors found in the data set [15].

3.2 Number of students on each level

Majority of students in the Philippines who participated in the PISA assessment are categorized as Level 1 in the reading proficiency category. Having majority of the samples skewed on being a Level 1 student, it may not provide much of an insight, specially when used under machine learning models. Therefore, in this study, reading proficiency levels defined by Philippines' Department of Education (DepEd) will be used to make the numbers of students on each level more evenly distributed. Since majority of the students are under Level 1, DePed decided to furthur divide it into 3 levels, namely levels 1C, 1B, 1A [6]. Mapping of score points to proficiency levels, together with number of students per level, are shown on Table 2. For the purposes of this study, levels 2 and above are only categorized as level 2, because if not, the machine learning model might have a hard time classifying various numbers of student levels. The final resulting of students per level is shown on table 3.

It can be observed on table 3 that majority of the samples are categorized as level 1b. With this, it can be noticed that the dataset is imbalanced. Imbalanced dataset tends to make the machine learning models concentrate on optimising overall accuracy resulting to disregarding the minority classes in favor of the majority classes [14]. To deal with the problems of having an imbalanced data, SVM-SMOTE(Support Vector Machine-Synthetic Minority Over-sampling TEchnique) is used. It performs over-sampling of the minority class in the borderline region defined by an SVM classifier [14]. By using SVM-SMOTE, the number of samples on each level in the dataset is now at 2932.

Table 2: Categorization of Student's Reading Proficiency based from DepEd [6]

Level	Score Points on the PISA scale	Number of Students
6	698 and above	0
5	626 to 697	2
4	553 to 625	69
3	480 to 552	334
2	408 to 479	937
1A	335 to 407	2932
1B	262 to 334	1914
1C	less than 262	1045

Table 3: Number of students per level before SVM-SMOTE is applied

Levels	Number of Examples
1c	1045
1b	2932
1a	1914
2 and above	1342

3.3 Data Normalization using Zero Mean and Unit Variance Technique

To further help the Machine Learning models, like Artificial Neural Networks, it is normal to scale each columns of the data set to have a value closer to zero as the minimum and one as the maximum. In the case of this study, a technique called zero mean and unit variance for normalization is used. The Zero Mean and Unit Variance technique for normalization was used instead of the more common 0-1 scaling because this technique is less prone to outliers data [13][17].

4 EXPERIMENTS

4.1 Neural Network Architecture

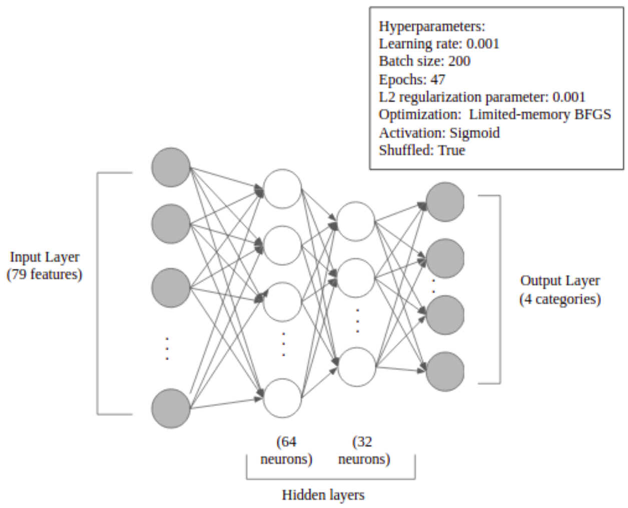


Figure 2: Neural Network Architecture for Filipino students' Reading Literacy Levels

Figure 2 shows the NN architecture used to classify the reading literacy of Filipino students. The NN architecture consists 79 input features, 2 hidden layers each having a size of 64 and 32 neurons correspondingly, and 4 output nodes. The activation function used in the hidden and output layers is sigmoid. Additionally, the hyper-parameters is set as seen in the Figure.

4.2 Training

The dataset is split to 80-20% for the train and test sets. Afterwards, the train set is split to 80-20% for the train validation sets. The samples assigned to each sets are 7505, 2346, and 1877 respectively.

In choosing the hyperparameters, number of layers, and nodes, several parameters are selected as candidate in which Grid Search is performed. Before the selection, there are propositions that are considered:

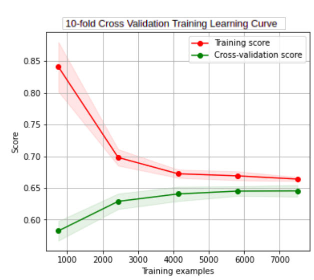
- The batch size multiplied to the number of epochs must not go further beyond the number of training samples. This causes the model to look at the seen samples causing to overfit.
- The model is constrained to the given data, limited on the real dataset. Adding other student data from different country may cause mixed analysis.
- L2 regularization and learning rate is set to be optimal at all of the combinations of the parameters.

Table 4: Train Test Score of Different Parameters

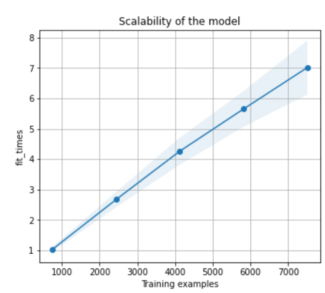
Parameters	Train Score	Test Score
solver: lbfgs, hidden layer sizes: 512, 256, 128, 64, activation: tanh	90	59
solver: lbfgs, hidden layer sizes: 64, 32, activation: tanh	86	57
solver: lbfgs, hidden layer sizes: 512, 256, 128, 64, activation: relu	68	64
solver: lbfgs, hidden layer sizes: 64, 32, activation: relu	72	64
solver: lbfgs, hidden layer sizes: 512, 256, 128, 64, activation: logistic	64	64
solver: lbfgs, hidden layer sizes: 64, 32, activation: logistic	69	66

Table 4 shows the different accuracy in test train set according to the set parameters. Parameters with no changes in the test set are disregarded. In this study, the parameters solver: lbfgs, hidden layer sizes: 64, 32, activation: logistic are chosen as they provide the best accuracy among the rest of the combination.

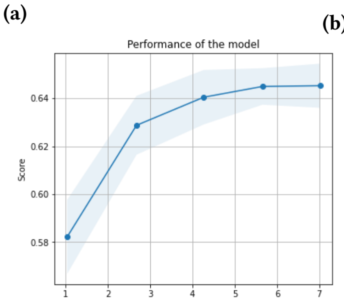
4.3 Model Evaluation



(a)



(b)



(c)

Figure 3: Learning Curve

In Figure 3a the 10-fold cross validation set has an accuracy of 63%. Figure 3b shows the time required by the model to train with various sizes of training dataset. Figure 3c shows how much time was required to train the models for each training sizes. Figure 3b and 3c fit_times unit are in seconds and the time required to train the model is 7 seconds.

Table 5: Training Classification Report

	precision	recall	f1-score	support
Level 1c	0.79	0.82	0.81	2345
Level 1b	0.58	0.54	0.56	2345
Level 1a	0.58	0.58	0.58	2345
Level 2	0.77	0.80	0.79	2345
accuracy			0.69	9380
macro average	0.68	0.69	0.68	9380
weighted average	0.68	0.69	0.68	9380

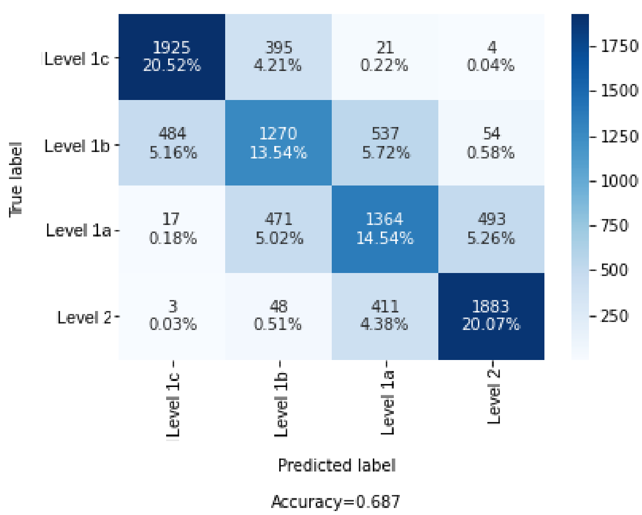


Figure 4: Confusion Matrix of Train Set

Table 5 and Figure 4 shows the classification report for the train set of the model for Philippine PISA 2018 contextual dataset. In the report, the model achieved an accuracy of 69% with Level 1b and Level 1a category having the lowest accuracy. Table 5 shows the f1-score of Level 1b and Level 1a, 56% and 58%.

Table 6: Test Classification Report

	precision	recall	f1-score	support
Level 1c	0.77	0.78	0.77	587
Level 1b	0.54	0.52	0.53	587
Level 1a	0.57	0.57	0.57	587
Level 2	0.76	0.77	0.76	587
accuracy			0.66	2348
macro average	0.66	0.66	0.66	2348
weighted average	0.66	0.66	0.66	2348

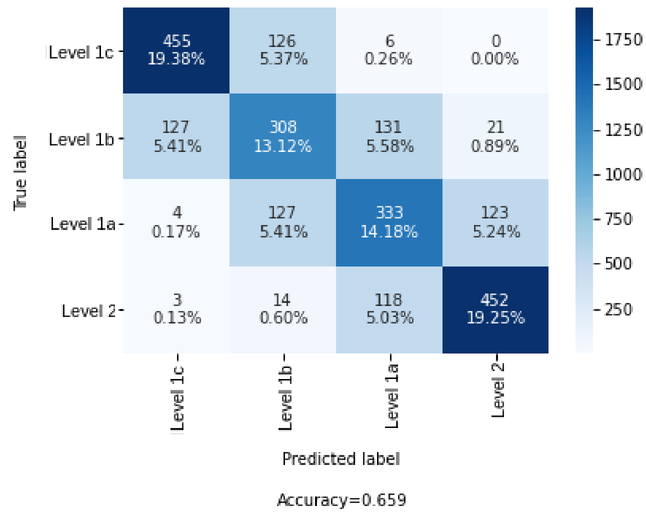


Figure 5: Confusion Matrix of Test Set

Table 6 and Figure 5 shows the classification report for the test set of the model for Philippine PISA 2018 contextual dataset. The report shows that the accuracy of the model achieved 66%, and the lowest accuracy is the same categories as in the train set. In Table 6, the f1-score of Level 1b and Level 1a are 56% and 58% respectively.

4.4 Feature Importance

Feature importance and feature boundary is calculated using permutation importance [8] and LIME [16]. In this study, features with high importance is identified to have a high mean score as compared to the other features. This is represented by the first 12 features. In Figure 1, REPEAT (See Appendix B for list of feature boundary values) mostly affect the reading literacy of the students, with a normalized value of lesser than or equal to -1.28 for levels not 1c, not 1b, 1a, and 2 (See Appendix A for list of feature boundary values). What follows after are the following with the normalized values: ESCS of greater than 0.03 but lesser than or equal to 0.66 for levels not 1c, not 1b, 1a, and 2; BELONGING of lesser than or equal to -0.83 for levels 1c, 1b, 1a, and not 2; SCREADDIFF of greater than 0.94 for levels 1c, 1b, not 1a, and not 2; WORKMAST of lesser than or equal to -0.76 for levels 1c, 1b, 1a, and not 2; GRADE of less than or equal to -0.18 for levels 1c, 1b, not 1a, and not 2; BEINGBULLIED of greater than 0.45 for levels 1c, 1b, 1a, and not 2; METASUM of lesser than -0.89 for levels 1c, 1b, not 1a, and not 2; TEACHSUP of lesser than -0.94 for levels 1c, 1b, not 1a, and 2; TTEACHBEHA of lesser than 0.11 for levels 1c, not 1b, not 1a, and 2; IMMIG of lesser than -0.69 for levels not 1c, not 1b, 1a, and 2; and DIRINS of greater than -0.81 for levels not 1c, not 1b, not 1a, and 2.

Features that have no impact on the model are OCOD1, OCOD2, OCOD3, COBN_M, COBN_F, COBN_S, LANGN, MMINS, SMINS, SCHSIZE, TOTAT, lANGSIBLINGS, and HISCED_D.

On the contrary, factors that negatively affects the classification of the model with an normalized mean value are as follows: COMPETE of lesser than or equal to -0.71 for levels 1c, 1b, 1a, and 2; MISCED_D of greater than 0.43 for levels not 1c, not 1b, not 1a, and

2; PARED of greater than 0.00 but lesser than or equal to 0.32 for levels not 1c, not 1b, 1a, and 2; LANGSCHMATES of greater than 0.01 for levels not 1c, 1b, 1a and 2; and BMMJ1 of greater than 0.01 for levels 1c, not 1b, 1a, and not 2.

It is also discernible that student-level factors such as learning time (MMINS LMINS , SMINS), family-level factors such as parents' occupation, place of birth, language at home (COBN_S, COBN_M, COBN_F ,LANGN, MMINS) and school-level factors such as school size (SCHSIZE) and total number of teachers (TOTAT) scored zero (0) influence/effect on the student's reading literacy.

Further, the graph provides a more stabilized data from features 22-32 (dominantly-student-level factors) and features 33-48 (dominantly-family-level factors).

5 DISCUSSION

This study examines the contextual factors of level 1 students on a fine-grain analysis, and level 2-6, relabelled as level 2. The analysis was performed on 7232 Filipino students' answers in PISA 2018 dataset. In this study, the NN model on 4 categories, levels 1c, 1b, 1a, and 2 achieves an accuracy of 66% having the lowest classification on level 1b and 1a. The results may imply that the dataset of levels 1b and 1a have a marginal distinction. In comparison with the study of [7][4], the accuracy is low compared to the SVM models which achieved greater than 70% accuracy. However, this study classifies 4 categories having level 1 on a fine grain analysis. This may weigh the performance of the model as compared to the 2 categories classification of the SVM models.

In relation to the factors, the feature importance ranking classifies the following features with high importance in the model selection: For the student-level factors: REPEAT, BELONGING, BEINGBUILLIED, GRADE, WORKMAST, METASUM, IMMIG, PERCOMP For the school-level factors: TEACHSUP, TEACHBEHA, DIRINS For the family-level: ESCS.

The ranking shows that features stated by [7] are different on the high importance features for Philippine 2018 contextual dataset. This may suggest that there are other feature-sets to correctly discern reading literacy of Filipino students. Additionally, the top features, according to the model, are dominated by student level factors indicating that people who studies Filipino students' reading literacy may focus on the student level factors. Despite the ranking, the accuracy percentage may affect the analysis and may appear differently on models with higher accuracy.

6 CONCLUSION

The objective of this study is to investigate the features impacting the reading literacy of Filipino students. Initially, the study identifies that NN can be used as a tool for feature analysis of the dataset. The results shows that the model can classify Filipino students reading literacy on 4 categories at 66% accuracy. Furthermore, from the model, it is found out that the student-level contextual factors of Philippine PISA 2018 contextual dataset significantly affects the reading literacy of the student.

Future works could improve the analysis of the Philippines PISA 2018 contextual dataset by increasing the accuracy of the model. This can be achieved by looking directly at the data separation for levels 1b and 1a. Increasing the samples in the dataset, by involving additional Filipino students in future PISA examination, could provide a more direct distinction among the categories hence improving the accuracy.

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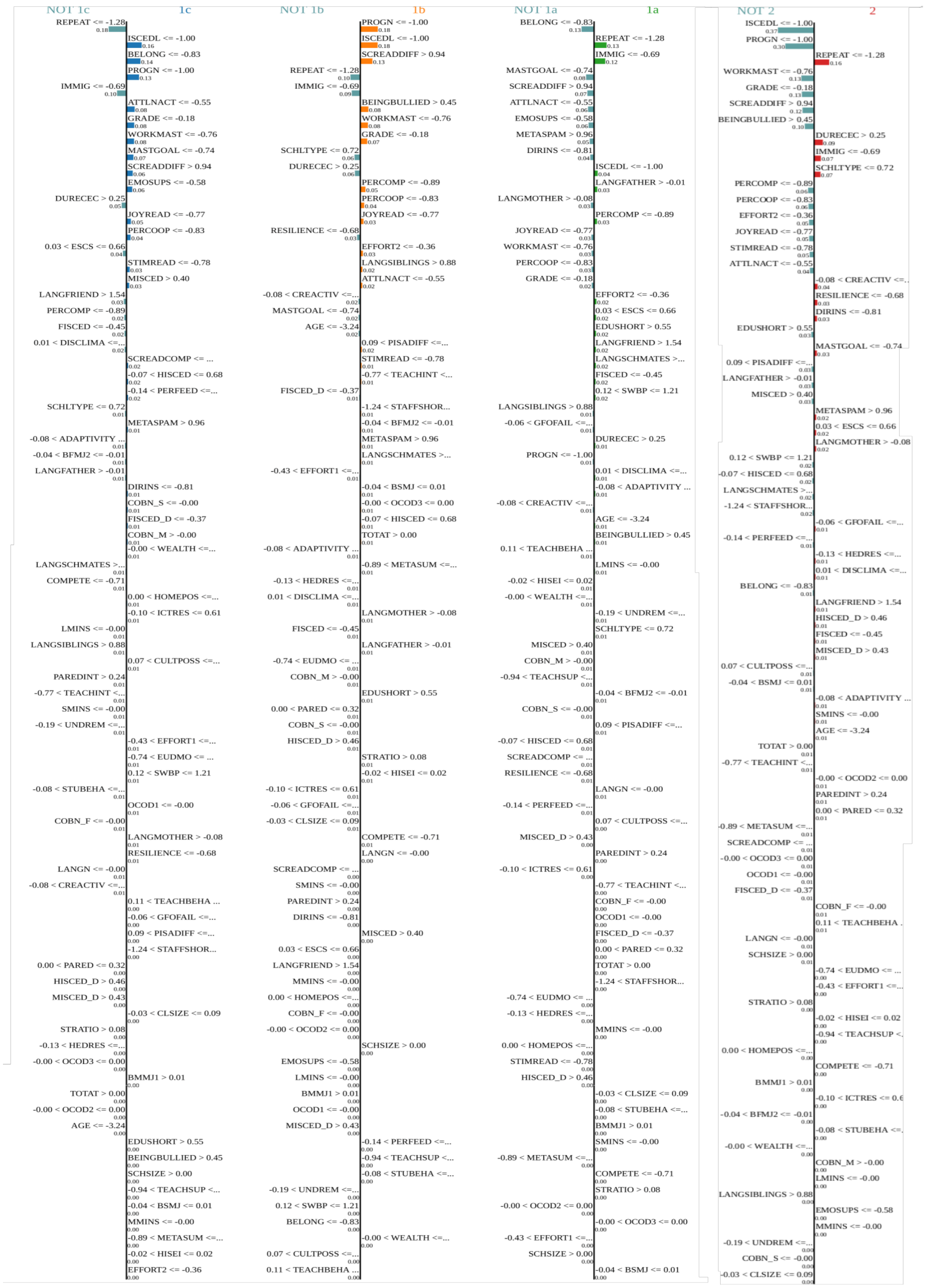
A FEATURE BOUNDARY



B LIST OF PREDICTOR VARIABLES USED

Variable	Description
EFFORT1	How Much effort in test
EFFORT2	How much effort invested
OCOD1	Mother's occupation code
OCOD2	Father's occupation code
OCOD3	Self's occupation code
GRADE	Grade compared to modal grade in country
AGE	Student's age
PROGN	Unique national study program code
COBN_S	Country of birth
COBN_M	Mother's country of birth
COBN_F	Father's country of birth
LANGN	Language at home
ISCEDL	Educational attainment level
MISCED	Mother's educational attainment level
FISCED	Fathers's educational attainment level
HISCED	Highest educational attainment of parent
PARED	Alternate definition of HISCED
MISCED_D	Alternate definition of MISCED
FISCED_D	Alternate definition of FISCED
HISCED_D	Alternate definition of HISCED
PAREDINT	Alternate definition of PARED
BMMJ1	Mother's occupational status
BFMJ2	Father's occupational status
HISEI	Parent's highest occupational status
LANGMOTHER	Language spoken with their mother
LANGFATHER	Language spoken with their father
LANGSIBLINGS	Language spoken with their siblings
LANGFRIEND	Language spoken with their friend
LANGSCHMATES	Language spoken with their schoolmates
IMMIG	Immigration status
DURECEC	Duration in early childhood education
REPEAT	Grade repetition
BSMJ	Student's expected occupational status
MMINS	Learning time per week in mathematics
LMINS	Learning time per week in language
SMINS	Learning time per week in science
TMINS	Learning time per week in total
FCFMLRTY	Familiarity with concepts of finance
SCCHANGE	Num. of school changes
CHANGE	Num. of changes in educational biography
STUBMI	Body mass index of student
ESCS	Economic, social and cultural status
UNDREM	Meta-cog.: understanding/remembering
METASUM	Meta-cog.: summarising
METASPAM	Meta-cog.: assess credibility
ICTHOME	ICT resources available at home
ICTSCH	ICT resources available at school
HOMEPOS	Home possessions
CULTPOSS	Cultural possession at home
HEDRES	Home educational resources
WEALTH	Family wealth
ICTRES	ICT Resources
DISCLIMA	Disciplinary climate in test language lessons

Variable	Description
PERFEED	Perceived feedback
EMOSUPS	Parents' emotional support
STIMREAD	Teacher's stimulation of reading
ADAPTIVITY	Adaptation of instruction
TEACHINT	Perceived teacher's interest
JOYREAD	Joy/Like reading
SCREADCOMP	Self perception of competence
SCREADDIFF	Self perception of difficulty
PISADIFF	Perception of difficulty of PISA test
PERCOMP	Perception of competitiveness at school
PERCOOP	Perception of cooperation at school
ATTLNACT	Attitude towards school activities
COMPETE	Competitiveness
WORKMAST	Work mastery
GFOFAIL	General fear of failure
EUDMO	Eudaemonia: meaning in life
SWBP	Subjective well-being: Positive Effect
RESILIENCE	Self resilience
MASTGOAL	Master goal orientation
GCSELFEFF	Self-efficacy regarding global issues
GCAWARE	Awareness of global issues
ATTIMM	Attitude towards immigrants
INTCULT	Interest in learning other cultures
PERSPECT	Perspective-taking
COGFLEX	Cognitive flexibility/adaptability
RESPECT	Respect for people from other cultures
AWACOM	Awareness of intercultural communication
GLOBMIND	Global-mindedness
DISCRIM	Discriminating school climate
BELONG	Sense of belonging to school
BEINGBULLIED	Experience of being bullied
ENTUSE	ICT use outside of school (for leisure)
HOMESCH	ICT use outside of school (for school work)
USESCH	Use of ICT at school in general
INTICT	Interest in ICT
COMPICT	Perceived ICT competence
AUTICT	Perceived autonomy related to ICT use
SOIAICT	ICT as a topic in social interaction
ICTCLASS	Subject-related ICT use during lessons
ICTOUTSIDE	Subject-related ICT use outside lessons
SCHSIZE	School size
CLSIZE	Class size
SCHLTYPE	School ownership type
EDUSHORT	Shortage of educational material
STAFFSHORT	Shortage of educational staff
TOTAT	Total number of all teachers at school
STRATIO	Student-teacher ratio
CREATIV	Creative Extra-curricular activities
STUBEHA	Student Behaviour hindering learning
TEACHBEH	Family wealth
TEACHSUP	Teach support in test language lessons
DIRINS	Teacher-directed instructions