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An Automated Machine Learning Approach for Early Identification of At-Risk Maritime Students

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ABSTRACT

Machine Learning (ML) presents a significant opportunity for the field of education, including Maritime Education and Training (MET). The benefits of ML have yet to be fully realized within MET. By utilizing ML-powered methods into maritime education, institutions can better prepare future seafarers while providing accurate, state-of-the-art education tailored to individual student needs. Early identification of areas for improvement can help students and teachers enhance educational outcomes within MET. This study presents the potential of ML approaches for predicting future performance as well as for identifying at-risk maritime students at the initial stages of their degree program. By enabling early identification, institutions can more efficiently plan and execute instructional strategies.

Keywords: Machine learning, Performance prediction, Maritime education, Learning analytics

INTRODUCTION

Machine Learning (ML) and Artificial Intelligence (AI) have facilitated data-backed decision-support system for educators across all domains (Chen et al., 2020). It involves training models on data to make predictions or decisions without the need for human intervention. Nowadays ML methods are being used for objective analysis of learners' performance (Alkadri et al., 2021), providing adaptive learning content to the students (Edwards et al., 2018), even psychological evaluation of learners (Liu et al., 2020) in a variety of contexts.

A novel application of ML and AI in education includes identifying students who may need extended supervision or are at-risk of dropout, i.e., identification of at-risk students during the early stages of their studies (Chui et al., 2020; Waheed et al., 2020; Xing & Du, 2019). ML algorithms are a perfect fit for this purpose especially due to their inherent capacity to identify patterns and trends in students' data along with making predictions based on the data (Chen et al., 2020). These characteristics enable ML algorithms to be used for monitoring students' development and analysing the present and predicted performances in a specific learning context. However, there is a lack of literature employing these methods in the maritime education context.

Maritime education, or more specifically seafaring education is generally divided into two separate streams, i.e., engineering and navigation. Maritime Education and Training (MET) providers offer educational components to prospective seafarers satisfying the International Convention on Standards of Training, Certification and Watchkeeping for Seafarers (STCW, 2011). Depending on the country or administration, universities may offer maritime degrees (e.g., Bachelor's in Marine Engineering or Bachelor's in Nautical Science etc.) that include relevant course components along with on-the-job training at sea and a few post-sea study components (*IAMU*, 2023). With the increasing demand for quality education as well as for workplace-relevance of seafarers' training, it has become crucial to understand which factors affect the learning trajectory of seafarers during the early stages of their degree education.

This study demonstrates an application of ML enabling early prediction of specific courses that instructors at maritime institutes may use to identify areas where their students need improvement. By providing instructors with targeted insights into students' strengths and weaknesses, this system can help them tailor their teaching approaches and offer additional support where necessary. Ultimately, this can help maritime degree students to succeed in their studies and prepare them for successful careers in the maritime industry.

RELATED STUDIES

Studies related to the application of ML in differing educational contexts ranging from administration, instruction and learning have increased significantly over the past few years (Chen et al., 2020). A recent review by Luan & Tsai (2021) identified a wide spectrum of ML applications in educational context ranging from diagnosis (e.g., introverts, extroverts), prediction (e.g., dropout, performance), intervention (e.g., plan-making intervention, value-relevance intervention), prevention and recommendation (e.g., personalized learning paths, learning contents). In addition, state-of-the-art AI tools have been employed in safety-critical industries, e.g., in surgical training for performance categorization as well as for real-time feedback (Alkadri et al., 2021; Yilmaz et al., 2022), in assessing mental workload during pilot training (Jiang et al., 2022) as well as a few prospective use cases in maritime simulator training (Tusher et al., 2022).

Type of Variables and Methods Used

In learning context, varying ML algorithms are operationalized such as logistic regression, decision trees, Artificial Neural Networks (ANN), Support Vector Machines (SVM), Bayesian networks, gradient boosting machine, K-nearest neighbour along with other available methods (von Gerich et al., 2022). However, manual data pre-processing to utilize these algorithms require substantial computing and human resources if done manually. In such cases, automated machine learning (AutoML) is being utilized as a low-cost alternative where the steps of building the ML model such as data pre-processing, feature engineering, model selection and tuning is automated (Feurer et al., 2015; He et al., 2021). This method is already being used in a plethora of contexts which includes predicting academic performance (Tsiakmaki et al., 2021) and evaluation of simulator training exercises in healthcare domain (Smith et al., 2022).

Scope of This Study

Recent literature reviews (2020-2022) related to the application of ML in differing educational contexts include identifying the influential factors to predict academic success (Alyahyan & Dustegor, 2020); students' performance prediction in e-learning platforms (Albreiki et al., 2021; Ouyang et al., 2022); various use cases of educational data mining in humanities and social science fields (Charitopoulos et al., 2020), in K-12 education (Du et al., 2020); identification of gaps and remedies of applying ML methods in performance prediction (Sekeroglu et al., 2021) as well as in exam preparation (Kaddoura et al., 2022). However, the lack of evidence in literature related to ML applications in maritime education context forms the scope of this study.

METHOD

This study employed an AutoML platform, *DataRobot (datarobot.com)* for identifying at-risk maritime students based on their early exam grades, i.e., to predict their final graduation grades based on their initial semester exam grades. DataRobot facilitates the analysis of data through a number of models and proposes the best model for deployment based on performance metrics.

Data Collection

We collected a pseudo-anonymous dataset of all exam results of a 4-years Bachelor's in Marine Engineering program consisting of a 3-phase, 08 semester course plan, i.e., (a) *phase 1*: two-year pre-sea training (with 04 semesters), (b) *phase 2*: one-year on-the-job training at sea (with 02 semesters) and (c) *phase 3*: one-year post-sea study (with 02 semesters). Each student of this program takes a total of 45 different courses (see **Figure 1**) during the first two-year of *phase 1* and receives a BSc in marine engineering degree with a final GPA (grade point average) after four (04) years upon the completion of *phase 3*. It is crucial to note for the analysis that the number of *phase 3* graduates in a given year is lower than the number of *phase 1* graduates due to the staggered completion of required on-the-job training placements in *phase 2*.

A total of 416 samples of *phase 1* graduated students and 137 samples of *phase 3* graduated students from three (03) consecutive batches of a maritime institute are included in the analysis (see Table 1).

Model Performance

Based on the properties of the data, 09 different ML models are operationalized by DataRobot. The best performing model was selected based on their RMSE (Root Mean Square Error) and R-Squared values of validation and cross-validation samples (see **Table 2**).

1st semester courses		2nd semester courses		3rd semester courses		4th semester courses	
English	ENG_1	Applied Physics-II	AP-II_2	Leadership and Principles Management	LPM_3	Turbocharger and Scavenging Technology	TST_4
Applied Physics-I	AP-I_1	Applied Mathematics-II	AM-II_2	Maritime Environment and Technology	MET_3	Engineering Watch keeping	EWK_4
Applied Mathematics-I	AM-I_1	Maritime Legislation	ML_2	Marine Internal Combustion Engines-III	ICE-III_3	Applied Mechanics	AMC_4
Marine Internal Combustion Engines-I	ICE-I_1	Marine Internal Combustion Engines-II	ICE-II_2	Shafting, Propeller and Steering Technology	SPST_3	Control Engineering-I	CE-I_4
Workshop Process & Materials	WPM_1	Marine Boilers and Steam Engineering	MBSE_2	Naval Architecture	NA_3	Refrigeration and Airconditioning Technology	RFAT_4
Ship Structure and Construction	SSC_1	Pump and Pumping Technology	PPT_2	Applied Heat	AH_3	Machine Drawing-II	MDR-II_4
Basic Electro-Technology	BET_1	Basic Electronics	BE_2	Machine Drawing-1	MDR-I_3	Power System Protection	PSP_4
English Sessional	ENS_1	Physics Sessional	PS_2	Electrical Machines	ELM_3	Applied Mechanics Sessional	AMCS_4
Basic Electro-Technology Sessional	BETS_1	Basic Electronics Sessional	BES_2	Electrical Machines Sessional	ELMS_3	Power System Protection Sessional	PSPS_4
Hand and Power Tools Sessional	HPTS_1	Maritime English & Communication Skill	MECS_2	Machine Tools Sessional	MTS_3	Maintenance of Main & Auxiliary Machineries	MMAM_4
Computer Fundamentals and Application	CFA_1	Basic Maritime Safety & Security	BMSS_2	Welding Technology	WLT_3	Basic Oil & Chemical Tanker Cargo Operation	OCTC_4
		Basic Maritime Safety & Security Sessional	BMSSS_2				

Figure 1: All pre-sea courses in phase 1 (total 04 semester).

Table 1. Details of students.

Student batches	Number of phase 1 graduated students	Number of phase 3 graduated students
A	156	39
B	119	62
C	141	36
Total	*416*	*137*

Table 2. Ranking of best performing ML model.

Rank	Model name	RMSE		R Squared	
		validation	cross validation	validation	cross validation
1	Light Gradient Boosting on Elastic-Net Predictions	0.0702	0.0668	0.8956	0.8909
2	Light Gradient Boosting on Elastic-Net Predictions	0.0617	0.0697	0.9195	0.8784
3	Elastic-Net Regressor (mixing alpha = 0.5 / Least-Squares Loss)	0.0642	0.0741	0.9129	0.8629

In addition to the accuracy measures (e.g., RMSE, R-squared values), we refer to the lift chart (see Figure 2) to assess the model performance. The lift chart depicts actual and predicted final GPA scores in 10 bins. Each bin includes an equal number of observations and shows prediction performance by comparing the average actual and predicted final GPA. Here, we see that the actual and predicted values for each bin fit well, indicating a good predictive performance of the selected models. We also observe that overfitting is not

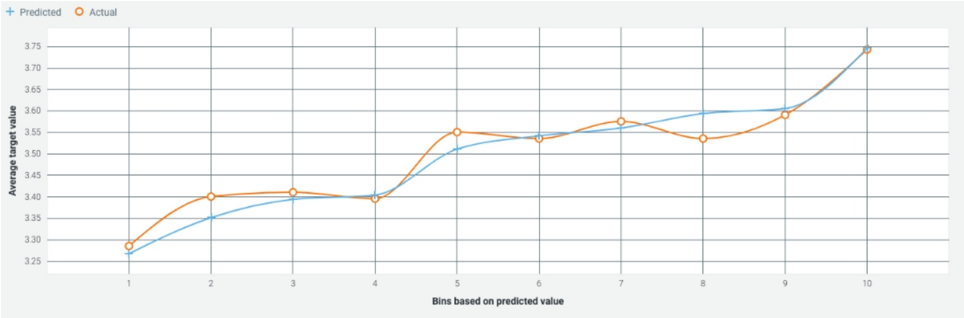

Figure 2: Lift chart.

an issue in the model since the actual and predicted curves intersect four (04) times (see **Figure 2**).

Therefore, we utilized the model *Light Gradient Boosting on ElasticNet Predictions* for estimating the feature effects (i.e., semester courses) on the final GPA as well as differing inter-connected association of features.

Subsequently, the K-Means Clustering algorithm was utilized to analyze the data in an unsupervised manner, without any predetermined target variables (e.g., final GPA). This approach allowed the identification of natural patterns and groupings within the data, which potentially provide useful insights into the students' scores.

RESULTS

Identification of Feature Impact and At-Risk Students

The analysis suggests that Engineering Watchkeeping (EWK_4) and Control Engineering-I (CE-I_4) from 4th semester, Basic Electro-Technology (BET_1) and Workshop Process & Materials (WMP_1) from 1st semester are top four (04) subjects in decreasing order of importance with the highest feature effect on the final GPA. In addition, Applied Heat (AH_3) from 3rd semester, English (ENG_1) from 1st semester, Applied Physics (AP-II_2) from 2nd semester and Applied Mechanics Sessional (AMCS_4) from the 4th semester bear the least feature effect on the final GPA (see **Figure 3**). While the actual values in the figures are based on the given data, the predicted values are generated by the best performing ML model. Therefore, the tight coupling between the actual and the predicted values of the feature effect on the target (final GPA) depicts good model fit (see **Figure** 3b, 3c, 3d). On the other hand, partial dependence takes the effect of all features into account.

The K-Means Clustering revealed four (04) clusters where students scoring an average of 62.22, 61.86, 55.89 and 64.66 in EWK_4, in CE-I_4, in BET_1 and WPM_1, respectively, are at-risk of scoring the lowest in their final GPA (see **Figure 4**a, 4b, 4c & 4d).

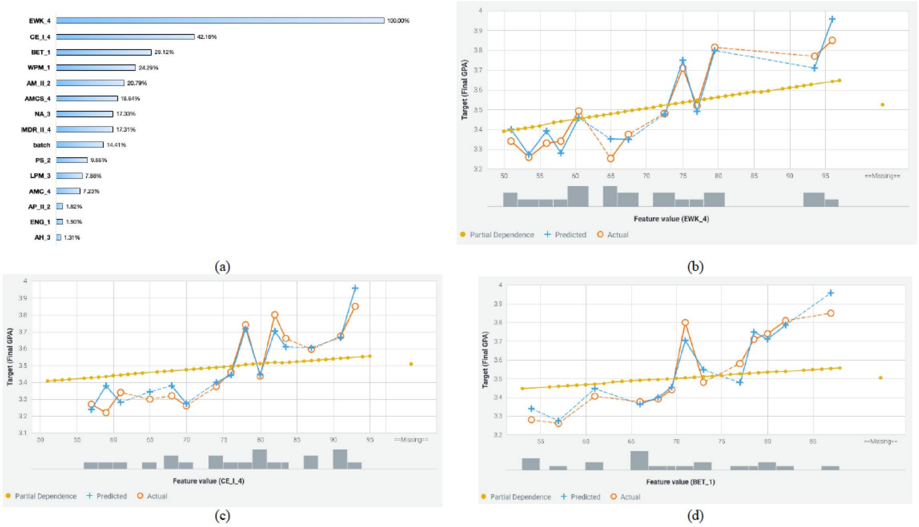

Figure 3: Feature impact on final GPA (a) along with feature pair association for top three features (b, c and d).

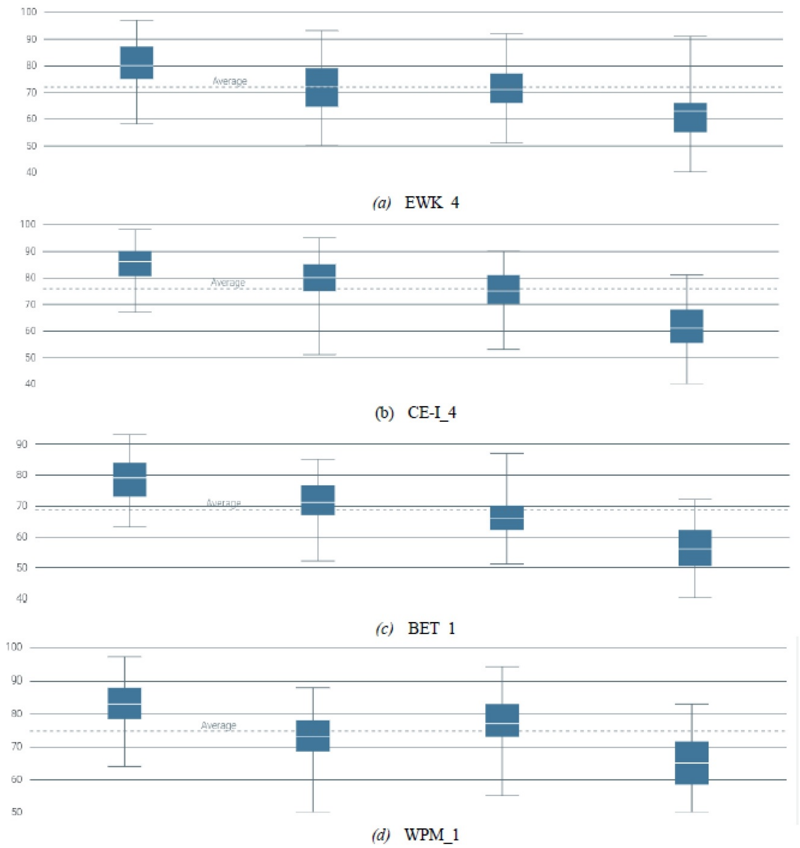

Figure 4: Cluster analysis of top four (04) features [(a) EWK_4; (b) CE-I_4; (c) BET_1; (d) WPM_1] in four different clusters.

DISCUSSION

The study suggests that ML techniques hold promise for enhancing maritime education. Specifically, the utilization of such tools may aid in the early detection of students who may struggle in their coursework and potentially achieve lower GPAs in their final assessments. This research carries significance for both academic institutions and industry stakeholders in the maritime domain.

The results identified four (04) different courses (i.e., two courses from 4th semester and two courses from the 1st semester) which have the highest feature effect in the final GPA of a marine engineering degree program. In addition, the cluster analysis identified specific groups of students taking those four courses who may need extensive care at an early stage. Courses with the least feature effect indicate that a they hold less power in predicting the final GPA. It is important to note that a few courses are left out of analysis by the AutoML program either due to their duplicating effect or for minimal feature effect. Nevertheless, these courses could still be important; for example, the English course from 1st semester holds low feature effect (1.90%) in predicting overall GPA but it bears crucial significance for overall professional success as seafarers (Shi & Fan, 2021). This instance conforms with the findings of Zawacki-Richter et al., (2019) highlighting the importance of human intervention and critical reflection in utilizing automated decision-support systems in education. Thus, the role of instructors in determining the learning strategies in maritime domain remain unscathed.

Considering the utility of ML in providing automated insights into the future performance of seafarers, maritime employers could use these tools to identify candidates with high potential for success in real workplaces. Our proposed model utilizing AutoML could assist industry stakeholders during on-campus recruitment or early selection of candidates for internships and employment opportunities. A deeper analysis may be performed using ML if data related to external factors such as age of students, their socio-economic status, past school grades etc. is available depending on the goal and scope of the investigation.

CONCLUSION

This study highlights the potential benefits of ML in detecting group of maritime students who may struggle with their coursework early in the studies which might lead to a lower GPA in their final exam. The importance of critical reflection and human intervention are stressed along with other automated decision-support system in determining educational strategies.

Future studies could explore the potential of utilizing ML in assessing seafarers in differing MET contexts, e.g., in simulator training to predict their future performance in real workplaces. Additionally, exploring external factors that might be associated with seafarers' education as well as their professional success holds potential value.

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