Integrating Support Vector Machine Models into the Engineering Lifecycle Design Roadmap Process for Innovative Practices using Project Based Learning

Willie L. Brown, Jr.
Department of Engineering and Aviation Sciences
University of Maryland Eastern Shore
Princess Anne, Maryland, USA
wlbrown@umes.edu

Ibibia Dabipi
Department of Engineering and Aviation Sciences
University of Maryland Eastern Shore
Princess Anne, Maryland, USA
ikdabipi@umes.edu

Dinesh Sharma
Department of Business, Management and Accounting
University of Maryland Eastern Shore
Princess Anne, Maryland, USA
dksharma@umes.edu

Lei Zhang
Department of Engineering and Aviation Sciences
University of Maryland Eastern Shore
Princess Anne, Maryland, USA
lzhang@umes.edu

Weiwei Zhu-Stone
Department of Computer Science and Engineering Technology
University of Maryland Eastern Shore
Princess Anne, Maryland, USA
wzhu@umes.edu

Lanju Mei
Department of Engineering and Aviation Sciences
University of Maryland Eastern Shore
Princess Anne, Maryland, USA
lmei@umes.edu

Alvernon Walker
Department of Engineering and Aviation Sciences
University of Maryland Eastern Shore
Princess Anne, Maryland, USA
awalker1@umes.edu

Tiara T. Cornelius
Department of Mathematics
University of Maryland Eastern Shore
Princess Anne, Maryland, USA
tdturner@umes.edu

Jason Cornelius
Department of Mathematics
University of Maryland Eastern Shore
Princess Anne, Maryland, USA
jmcornelius@umes.edu

Urban Wiggins
Department of Computer Science and Engineering Technology
University of Maryland Eastern Shore
Princess Anne, Maryland, USA
utwiggins@umes.edu

Etahe Johnson
Department of Computer Science and Engineering Technology
University of Maryland Eastern Shore
Princess Anne, Maryland, USA
ejohnson2@gmail.com

Lakeisha Harris
School of Graduate Studies and Research
University of Maryland Eastern Shore
Princess Anne, Maryland, USA
llharris@umes.edu

John P. Murray
Department of Aviation
Hampton University
Hampton, Virginia, USA
john.murray@hamptonu.edu

Enrique Jackson
George C. Marshall Space Flight Center
Nationa Aeronautics and Space Administration
Huntsville, Alabama, USA
enrique.m.jackson@nasa.gov

Terence H. Fontaine
Department of Transportation Studies
Texas Southern University
Houston, Texas, USA
terence.fontaine@tsu.edu

Linda B. Hayden
Center of Excellence in Remote Sensing Education and Research
Elizabeth City State University
Elizabeth City, North Carolina, USA
haydenl@mindspring.com

***Abstract*—The full paper using innovative practices category as an analysis of the engineering education in the to advance lifecycle design includes an understanding of the user experience through teaching and engagement. In creating an environmental approach according to data set guidelines through these strategies, the engineering practices provides education objectives by using teaching and engagement as a roadmap in the design process for innovation. To explore this concept using a data-driven focus tool solution (e.g., SAS Enterprise Miner), the initial results were considered using the training output results with variable information as an approach to determine the study's modeling abilities. Hereby, this study had examined the findings to define teaching and engagement strategies using predictive modeling analysis through support vector machine (SVM) as the proposed method. The study's results identified SVM nodes as a point of observation to examine how a variable-solution approach can be defined according to the output determinants. As such, the variable-solution approach had created an investigative framework of the learners' role in the engineering lifecycle design process. This includes how the lifecycle design roadmap (e.g., input and target results) can be measured with associated levels (binary, interval, and nominal) and frequency count of the requirements as a data set. The examination of a data set indicates the target variables with the relationships of roles associated to the specific measurement levels can be integrated as frequency counts regarding the innovative practices. Since SVM has a decomposition using a decision-making system based on the features proposed in data modeling, the demand to forecast an engineering lifecycle design process can be applied to optimize parameters and methods for supportive analysis. This proposed approach as defined by the output variables creates a roadmap to a desired target, which allows for the results of each learner (user) experiences to be verified as binary according to the engineering lifecycle design process.**

Keywords*—*Engineering Design Roadmap, Engineering Lifecycle, Predictive Analysis, Support Vector Machine (SVM), Roadmap for Lifecycle Design, Innovative Practices, Project Based Learning, Engineering Education

I. Introduction

The introduction of analytics into an engineering course setting using project-based learning has its unforeseen challenges and difficulties due to the ability to change (or improve the decision-making towards future practices) as fundamental differences are influenced by conditions. The conditions are defined due to the emergence of new approaches and data driven strategies relative to the roles within the engineering lifecycle design process. Thus, these difficulties are comprehended as fundamental differences to address education objectives requiring a viewpoint of comparisons for project-based learning in engineering education. This concept was revealed and mentioned from a recent study of about 804 scholarly publications related to a systematic approach in analytics that a scientific framework of interdisciplinary practices can create a better understanding of how the developments of a data driven strategy can improve the lifecycle design process through comparative analysis [1]. The data-driven path to determine a value from an engineering design lifecycle can be best defined as the relationships to specific environments using resources-based views that include five (5) areas: a) understanding of data types in the project design; b) integration of analytical techniques in engineering education; c) identifying the design capabilities and roadmap to deployment; d) determining the values and challenges according to the engineering and society practices; and e) defining the future aspects with improvements in the lifecycle design process [1][2]. This study can be beneficial to the different expectations with the need to examine the historical data approach in engineering designs as a comparative approach versus using predictive modeling of the engineering design process. In using a comparative approach, the transformation of data from an engineering design process provides how these specific capabilities allows for future evaluation of applications by addressing the path to value regarding the engineering education objectives [1].

The ability to change and improve the decision-making process in analytics remains complex to implement guidance for users regarding a lifecycle roadmap. As described in this study, the potential methods and various roles for evaluation can introduced a potential negative effect from the lack of understanding. In the recent advancement of engineering roles and tasks, the education practices have recognized that a source of bias to perform critical techniques using a data-driven approach is still complexed due to associated activities (i.e., the challenges of analytic decision-making practices, despite of new insight and guidance in the design process) [2]. This study introduces how innovation can be discovered from the proposed dilemma as described regarding the engineering lifecycle design. The engineering lifecycle design is part of the problem that a roadmap has not been determined for project-based learning according to education objectives. This concept is being understood as a path to strategically communicate learning objectives with the need to identify an appropriate lifecycle design for engineering environments in education. Our team created a data-driven environment to understand the dichotomy between knowledge and nonknowledge, which can be misleading amongst users, learners, and stakeholders [3]. This parallel practice in engineering education may present challenges associated with related areas; however, the working methods and knowledge had allowed for further investigation with project-based learning using predictive modeling techniques [3]. According to authors [4], the predictive modeling techniques of support vector machine (SVM) models can be adaptive using a paradigm to sample features by allowing weighted confidence. This demonstration of sample features to allow weighted confidence creates an investigative approach to explore innovation in the lifecycle design and how experimental results are influenced based on corresponding methods and observations.

II. Scope

The scope of this study is to provide an analysis that will defined the engineering practices and strategies of a multi-team environment related to the lifecycle design in project-based learning. Our engineering students had investigated the design process to develop a system environment for model-based engineering. Due to the engineering student limited understanding about the engineering design processes and the supportive lifecycle roadmap, the study was considered to examine how education strategies can be performed to improve the design process according to the requirements of stakeholders in a team environment. The study adopted previous examples of project-based learning environments and the implications gained from the data findings. These findings were previously explored using SAS Enterprise Miner as a tool for evaluation and will be considered for this study. From the initial approach, our learners had considered the training output solutions by understanding the variable information. This is determined through our abilities to model previous requirements and the findings of the engineering education environments associated with project-based learning. This future study presents a predictive modeling analysis using SVM as a proposed method. As such, the predictive modeling approach can potentially create an understanding about attributes to examine project outcomes associated with the conditions (variables), roles, measurement levels, and functions. These conditions according to the data set description includes features such as inputs and output results (e.g., this is defined as a result-based solution for a data according to outcomes). Hence, the result-based solutions are used as nodes with a point of view for discovery and to advance a pathway through observations.

III. Background and Theoretical Framework

The background approach using software integration of SAS Enterprise Miner as a product to evaluate the engineering lifecycle has been mentioned as a data mining tool to introduce new features and capabilities for assessment with modeling analysis abilities. The engineering education community has been considered the need of integration to advance modeling approaches and strategies. This serves as a solution to the learners and stakeholders by using model-based systems engineering of projects via predictive analytics [5]. The approach is introduced as project-based learning with concepts expanding beyond engineering education. This is promoted by business practices as advanced solutions can be addressed in the higher education community with research abilities of the engineering lifecycle design. Whereas in the traditional engineering lifecycle design model, a roadmap to assess the developments and advancements for integration must be considered due to the need of integration. This adaptation approach using SAS Enterprise Miner as a tool has allowed for engineering education practices to build an optimal and a predictive model environment within the classroom setting. This design solution also addresses the data set challenges to determine the model's best fit using appropriate evaluation features and techniques in data mining and data science [6].

As a theoretical framework, the authors had highlighted specific features and techniques to develop new insight about how a hypothesis can be used to analyze the data according to the variables and conditions (e.g., missing or inaccurate data values and outliers). This framework in the engineering lifecycle can serve as a roadmap to determine how misclassification rates, average square errors, and receiver operating characteristics (ROC) can improve engineering outcomes through the lifecycle design process [6].

A. Data Cleansing and Preparation to Advance Engineering Lifecycle Designs as Roadmap to Manage Projects

Experts in the field had once described data cleansing and preparation as an approach to improve data quality of results about specific features and the facilitation in data validation and transformation [7]. It was also perceived from this study and observed using a survey finding that out of 187 data mining projects about 64% of the participants had indicated that more than 60% of the time was spent on data preparation and cleaning [7]. Despite the efforts mentioned and frequently covered in the data science community, the data cleansing and preparation are often overlooked in projects and the lifecycle process [7]. This section will consider adopting and implementing a design method to deploy data cleansing and preparation strategies using SAS Enterprise Miner. The ability to deploy data cleansing and preparation techniques with the use of software allows for constantly in practice according to the efforts by analyzing reports for better understanding (e.g., data handling).

This approach provides insight about engineering lifecycle design projects using software integration for exploration of data according to relationships, trends, types, defining targets, measurement levels, roles, and frequently counts. The StatExplore functions (feature) in SAS Enterprise Miner logged the class variable summary statistics beyond the role, variable names, levels, and labels. The data handling methods for missing data, mode percentage variables, mean, standard deviation, non-missing, minimum, median, maximum, skewness and kurtosis were evaluated based upon the appropriate methods for data cleansing and preparation strategies offered by the function (feature). The data presented by the StatExplore feature logged had also defined how statistical exploration methods for data cleansing and preparation can determine attributes of the design process (evidence provided in the figure below).

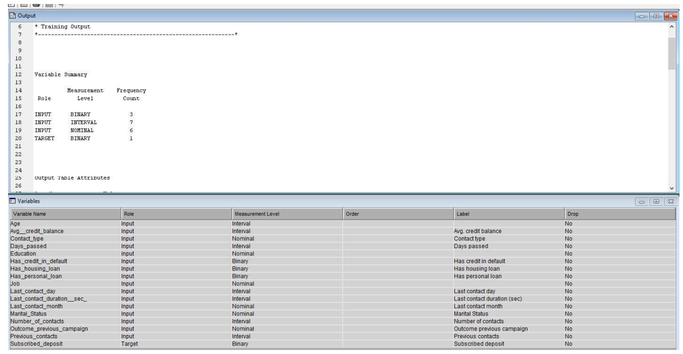

Fig. 1. Exploring the data set to determine the variable summary and table attributes using SAS Enterprise Miner.

B. Defining the Engineering Implementation Strategies for Data Exploration with Project Based Learning

SAS Enterprise Miner enables the solution to address the challenges for timely data cleansing and preparation to efficiently managed the integration with scaling. The concern of scaling includes the lifecycles design performance factors related to data volumes, inconsistently, information correctness, completeness, and availability [8]. The impute functions in SAS Enterprise Miner proposed methods to define the complexity and difficulty of data analysis for optimization pertaining to incomplete and missing data. The authors findings [9] had documented their difficulties using data analysis due to the existence of missing values in real-world datasets. The impute function (optimization of missing values) promotes a classification structure implied in an incomplete database by validating the effectiveness of the proposed method for imputation [9]. This imputation methods can be defined in recent studies to evaluate the performance of missing data conditions and dealing with associated decision-making process. Since SVM has a decomposition to a decision-making system based on the features and the demand to forecast data predication for modeling purposes using parameters and features (see figure below for supportive analysis).

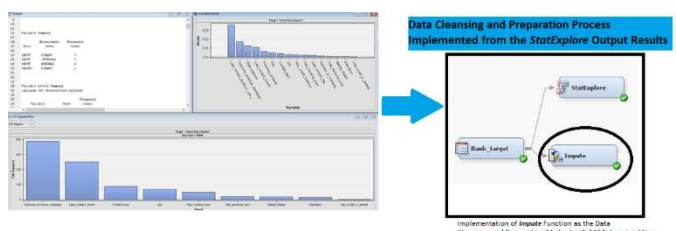

Fig. 2. *StatExplore* feature with *Impute* function as a method using SAS Enterprise Miner for data cleansing and preparation.

IV. METHODOLOGY AND THE STRATEGY FOR ENGINEERING EDUCATION ASSESSMENT

The ability to develop predictive models using SVM provides benefits to the project campaign for evaluation purposes. In predictive modeling analysis, the method for SVM allows for classification by examining the parameters proposed to the desirable effects respectively to the applied features. Currently, there are studies using SVMs from a statistical learning theory, which this study had build upon with specific modeling practices regarding the dataset [10]. The learners included enrolled students in the department who were participants in response to the course offerings. There was a total of fourteen (14) learners with two groups and the recruitment selection was only applied to a classroom setting according to the lab environments. This methodology in the engineering lifecycle design adopts the approach to consider a traditional concept, which includes the following phases- a) requirement phase, b) design phase, c) development phase, d) test phase, e) implementation phase, and f) deployment phase. This was used to capture the students' experiences and to learn about the innovative practices proposed according to the lifecycle design process for effectiveness in project innovation (see figure below).

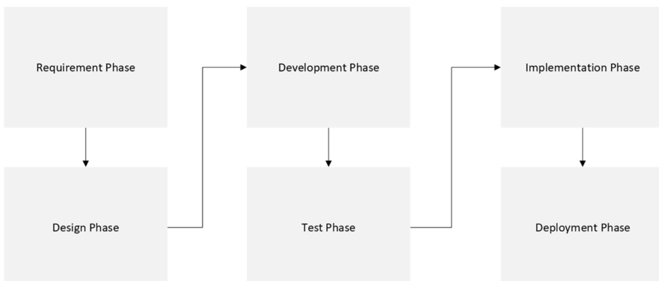

Fig. 3. Adopted traditional concept for assessment within the methodology approach regarding the engineering education design lifecycle process for predictive analysis.

Many industrial standards and engineering education communities have adopted aspects of the traditional concept as a theoretical framework for development. This study will integrate the traditional concept as a theoretical framework using SAS Enterprise Miner tool to enhance data mining strategies. The statistical models from the study described the limited ability to understand scoring practices relative to the sparseness of the data [10]. The classification methods in SVM with such pattern information about boundary and the critical patterns leads to the researcher ability to improve generalization analysis (e.g., comparison of models) [10]. As such, the study outlines the predictive modeling techniques with the development of different SVM models (i.e., understanding the parameters of the model according to the previous findings). To provide insight about the importance of SVM from an analytical study, the methodology using SAS Enterprise Miner allows for specific techniques in training and testing of decisions to be performed and examined. The investigation of predictive modeling to advance engineering education design methods of each node created an approach to evaluate the various identities (Li, Wang, & He) (see table about the node details and each identity findings).

TABLE I. NODE REPRESENTATION TO PROMOTE EVALUATION OF IDENTITIES IN THE ENGINEERING PROJECT DESIGN

Methodology for Node Representation with Evaluation regarding the Engineering Project Design and Education Outcomes	
Node ID	**Node Label with Identities**
HPSVM	*HP SVM (RBF 2)*
HPSVM2	*HP SVM (linear)*
HPSVM3	*HP SVM (polynomial 2)*
HPSVM4	*HP SVM (RBF)*
HPSVM5	*HP SVM (Sigmoid 1)*
HPSVM6	*HP SVM (Sigmoid 2)*
HPSVM7	*HP SVM (polynomial 3)*

From the training and testing of decisions, the data train using the *data partition* function in SAS Enterprise Miner had considered the following properties and values as defined: a) output type (data) with partitioning method at default and the random seed (12345); b) data set allocations values for training (70%), validation (30%), and test (0%); and c) report of the data partition to include both interval targets and class targets for evaluation purposes (see figure as evidence for development).

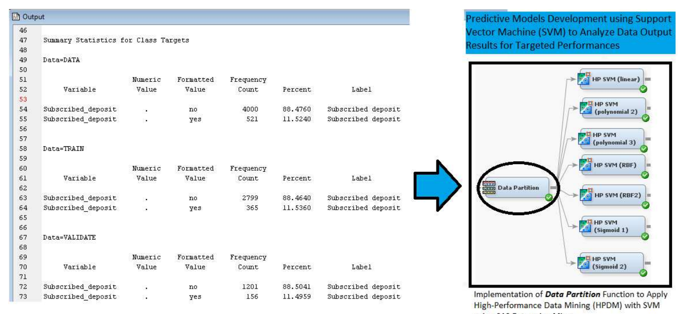

Fig. 4. Examining the data set of class targets to develop predictive models for analysis and development..

The objective was to define the engineering lifecycle design from the dataset of project-based learning requirements using the output determinants as a predictive analytic solution. From the methodoloy proposed, this examination of data set indicates that the target variables and the relationship of roles associated with the specific measurement levels and frequency counts can increase knowledge to understand a roadmap of the engineering lifecycle design process. As considered, the variable summary had revealed that only one target role being established as a binary type can be made possible in an engineering design process. The variable identity was used as a target role in order to create a measurable binary type. This output variable allowed for a desired target as the results verified that the decision-making process for a roadmap can addressed the engineering lifecycle as a roadmap (i.e., with decision of yes or no).

V. CASE STUDY RESULTS USING THE INTERGATIVE LIFECYCLE DESIGN PROCESS IN ENGINEERING EDUCATION

From the results, the variables were defined, and the details of the project findings mentioned highlights an engineering lifecycle design approach integrated with SVM methods. For example, the project had discovered that the high-performance data mining (HPDM) node had reference seven (7) SVM models according to the properties and values revealed in the training and testing of decisions. Each node ID of the high-performance (HP) SVM was trained to address maximum iteration of 25 with a tolerance and penalty parameters. Thus, the train properties did not address values that considered missing. Therefore, the predicted decisions with variables were scored according to the targets and the optimization methods of both interior points and active sets with kernel values (interior points – linear and polynomial; active set – polynomial, radial basis function (RBF), and sigmoid). The kernel conditions and types were addressed in the interior point based upon the polynomial degree specific to the SVM uses. The same approach had applied to the active set with additional properties to apply according to the parameters (e.g., RBF and sigmoid) (see table below to understand the lifecycle process for evaluation of engineering projects with optimization methods and features presented during development of the roadmap).

TABLE II. CASE STUDY RESULTS: NODES OF KERNEL HIGH PERFOMANCE (HP) USING SUPPORT VECTOR MACHINE MODELING FOR AN INTEGRATIVE DESIGN LIFECYCLE AS A ROADMAP

Node ID	**Defining the Kernel of High-Performance (HP)**	**Optimization of Methods**	**Case Study Assessment of Features and the Roadmap to Manage the Design Process**
HP SVM (linear)	Kernel is Linear with the Polynomial Degree value set at 2	Interior Point	Cutoff feature applied to address the imbalanced target at .085 cutoff rate
HP SVM (polynomial 2)	Kernel is Polynomial with the Polynomial Degree value set at 2	Active Set	RBF Parameter is value at 1.0, Sigmoid Parameter 1 is value at 1.0, Sigmoid Parameter 2 is value at -1.0
HP SVM (polynomial 3)	Kernel is Polynomial with the Polynomial Degree value set at 3	Interior Point	No features were presented as a parameter
HP SVM (RBF)	Kernel is Radial Basis Function with the Polynomial Degree value set at 2	Active Set	RBF Parameter is value at 1.0, Sigmoid Parameter 1 is value at 1.0, Sigmoid Parameter 2 is value at -1.0
HP SVM (RBF 2)	Kernel is Radial Basis Function with the Polynomial Degree value set at 2	Active Set	RBF Parameter is value at 2.0, Sigmoid Parameter 1 is value at 1.0, Sigmoid Parameter 2 is value at -1.0
HP SVM (Sigmoid 1)	Kernel is Sigmoid with the Polynomial Degree value set at 2	Active Set	RBF Parameter is value at 1.0, Sigmoid Parameter 1 is value at 1.0, Sigmoid Parameter 2 is value at -1.0
HP SVM (Sigmoid 2)	Kernel is Sigmoid with the Polynomial Degree value set at 2	Active Set	RBF Parameter is value at 1.0, Sigmoid Parameter 1 is value at 2.0, Sigmoid Parameter 2 is value at -1.0

The table results indicated that each node id was defined using optimization of methods to feature a selective design process as a roadmap. The HP SVM functions (includes - linear, polynomial 2, polynomial 3, RBF, RBF2, sigmoid 1, and sigmoid 2) were assessed based upon feature and the integrative design approach in the lifecycle practice of students. According to the parameters, the learners had discovery the need of imbalanced targets to address the lifecycle design examples to manage the various features. Hereby, the results of each parameters revealed that the various requirements can be mapped to the performance conditions and project design. This roadmap presented in table two (2) was used to manage the integrated design process related to the properties associated with requirements and nodes values with performance.

The results of the HP SVM demonstrated conditions to address and account for the changing of the cutoff criterion. An important discovery of this study includes the dataset size, which was addressed at the cutoff point to applied according to the modified lifecycle design process. This practice improved the visibility with the number of observations providing a more optimistic performance in datasets of the case study. The ability to provide a *Cutoff* function was beneficial to the need of linear modeling and to determine the implementation strategy in the engineering design. The learners had considered data shared beyond the imbalanced point within the lifecycle design process as a roadmap for development. According to findings, the statistical analysis of the SVM environments using project-based learning had directly generated target probabilities to determine the optimal lifecycle design and to transition in the lifecycle phases (this is due to our ability to perform classification of the dataset to group requirements). The engineering students had focused on how to handle imbalanced data problems with the interaction of a linear SVM modeling. As a result, the engineering students had recognized that this strategy could also cause biases to prediction of results in the lifecycle design process. Therefore, engineering students had adopted a solution to compare the varies models as an integrative approach for implementation. This strategy is presented below in the figure as the proposed method can be used to determine oversampling and under sampling methods to reduce the bias rate in the evaluated imbalanced data (i.e., this project case study discovery of cutoff rates was proposed at .085).

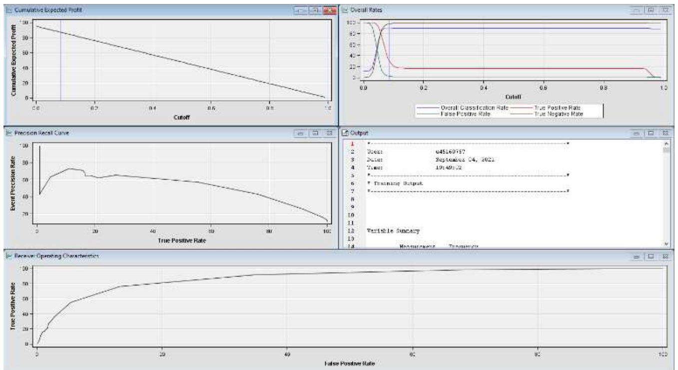

Fig. 5. Investigation of HP SVM (linear) cutoff results for implemnetation.

VI. CASE STUDY FINDINGS AND FUTURE IMPLICATIONS

The findings of the SVM models allowed for the various conditions mentioned according to the kernel, optimization methods, and assigned features for assessment to be evaluated and analyzed using the project-based learning activity in education. This proposed comparison of application in predictive modeling created a correlation for cross-validation of training data according to the differences (modeling output)s [11]. A comprehensive comparison of techniques with a common dataset had demonstrated behaviors that were achieved through the lifecycle design [12] (see table below as evidence).

TABLE III. NODE BEHAVIORS USING THE SVM MODEL COMPARISON OF TRAIN DATA FOR EVALUATION OF THE LIFECYCLE PHASES

Node ID	**Node Label**	**Train: Misclassification Rate**	**Train: Number of Wrong Classifications**	**Train: Total Profit**
HPSVM 4	*HP SVM (RBF)*	0.077433628	245	2919
HPSVM	*HP SVM (RBF 2)*	0.10619469	336	2828
HPSVM 2	*HP SVM (linear)*	0.106510746	337	2827
HPSVM 3	*HP SVM (polynomial 2)*	0.043931732	139	3025
HPSVM 7	*HP SVM (polynomial 3)*	0.006321113	20	3144
HPSVM 6	*HP SVM (Sigmoid 2)*	0.172566372	546	2618
HPSVM 5	*HP SVM (Sigmoid 1)*	0.172882427	547	2617

This allows for the SVM model created to be assessed regarding the prediction accuracies (70.0% for the training set and 30.0% for the test with overall significance values). Authors [11] [12] have defined classification to achieve these significance values as an identifiable targeted feasible to a purposed solution in development.

TABLE IV. SVM MODEL COMPARISON OF TRAIN DATA IN THE ENGINEERING EDUCATION PROJECT DESIGN PROCESS TO PROMOTE LIFECYCLE DEVLOPMENT STRATEGIES

Node Label	**Train: Roc Index**	**Train: Gini Coefficient**	**Train: Kolmogorov-Smirnov Statistic**	**Train: Kolmogorov-Smirnov Probability Cutoff**
HP SVM (RBF)	0.981	0.962	0.934	0.146
HP SVM (RBF 2)	0.958	0.916	0.862	0.147
HP SVM (linear)	0.894	0.788	0.648	0.054
HP SVM (polynomial 2)	0.967	0.933	0.875	0.445
HP SVM (polynomial 3)	0.995	0.99	0.972	0.47
HP SVM (Sigmoid 2)	0.577	0.154	0.151	0.395
HP SVM (Sigmoid 1)	0.602	0.205	0.168	0.452

Henceforth, the emerging techniques using SVMs can also present a weakness to the SVMs due to the lack of rule generation especially in analyzing results as mentioned [13]. This investigation to develop a hybrid model to integrate the SVM techniques with decisions of the lifecycle design (e.g., decision in generating rules and predicting the outcomes) was presented in the authors study as a benefit [13]. As exhibited, the differences to explore the various benchmarks of SVM's prediction against application is still emerging in the environments of the engineering lifecycle design [14]. However, the evaluation to understand both the strengths and weaknesses from the existing framework offers an adoptative standard by introducing complexity of relationships between predictors and target variables [14]. The table below introduces the node of the SVM model as a comparison, which created a learner environment to validate the data findings using ROC index, Gini coefficient, Kolmogorov-Smirnov statistic and Kolomogrov-Smirnov probability cutoff.

TABLE V. SVM MODEL COMPARISON OF VALID DATA IN THE ENGINEERING EDUCATION PROJECT DESIGN PROCESS TO PROMOTE LIFECYCLE DEVLOPMENT STRATEGIES

Node Label	Valid: Roc Index	Valid: Gini Coefficient	Valid: Kolmogorov-Smirnov Statistic	Valid: Kolmogorov-Smirnov Probability Cutoff
HP SVM (RBF)	0.81	0.62	0.532	0.151
HP SVM (RBF 2)	0.88	0.761	0.625	0.134
HP SVM (linear)	0.905	0.81	0.656	0.055
HP SVM (polynomial 2)	0.858	0.715	0.602	0.419
HP SVM (polynomial 3)	0.781	0.561	0.417	0.445
HP SVM (Sigmoid 2)	0.562	0.124	0.134	0.402
HP SVM (Sigmoid 1)	0.586	0.172	0.153	0.431

In the comparison of the SVM models, the findings had demonstrate the potential of further use of techniques by mapping the findings to the proposed practice with includes development understanding of team and personal environments in engineering education. According to the findings, the compared details to the train and valid data mapped to each specific node can promote a project-based learning environment. This was defined by the lifecycle phases of each condition for future developments. The engineering students design process had demonstrated that the various lifecycle phases could be compared with the ability to train and valid data according to lift and cumulative lift values (see evidence in the table as an example below).

TABLE VI. SVM MODEL COMPARISON OF TRAIN AND VALID DATA IN THE ENGINEERING EDUCATION PROJECT DESIGN PROCESS TO PROMOTE LIFECYCLE DEVLOPMENT STRATEGIES

Node ID	Node Label	Train: Lift	Train: Cumulative Lift	Valid: Lift	Valid: Cumulative Lift
HPSVM4	*HP SVM (RBF)*	7.296896134	7.875476428	2.686368779	3.198058
HPSVM	*HP SVM (RBF 2)*	7.296896134	7.027768896	3.453902715	4.541242
HPSVM2	*HP SVM (linear)*	4.608565979	5.140936002	4.605203621	5.052932
HPSVM3	*HP SVM (polynomial 2)*	6.693393446	7.465295364	3.709747361	4.221437
HPSVM7	*HP SVM (polynomial 3)*	8.668493152	8.668493152	3.325980393	3.709747
HPSVM6	*HP SVM (Sigmoid 2)*	1.810508063	1.750105873	2.046757165	1.599029
HPSVM5	*HP SVM (Sigmoid 1)*	2.084827467	2.132941533	1.535067874	1.854874

The mapping of the target values (for example of subscribed values for future engineering design developments) can be visualized using SAS Enterprise Miner as provided in the example with regard to receiver operating characteristic (ROC) chart, fit statistics, score rankings overlay and overall output (see the figure below).

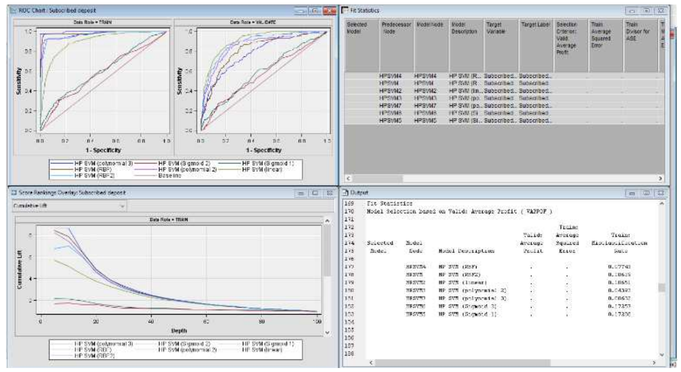

Fig. 6. *Model Comparison* Feature using SAS Enterprise Miner of SVM Results..

These results and findings can be validated using SAS Enterprise Miner to generate predictive models of SVM for future implications as an overview (see figure of the diagram overview accoridng engineering education findings for intepretation).

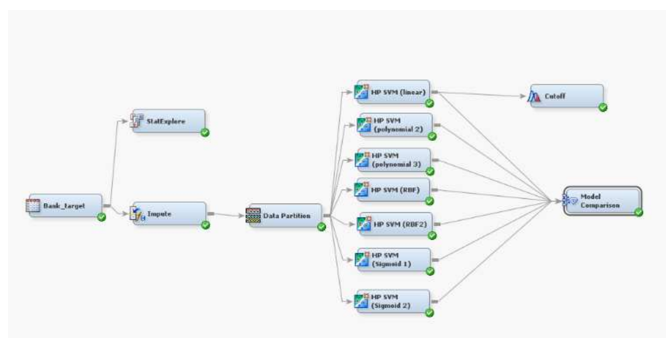

Fig. 7. Lifecycle design with roadmap features from the engineering education environment to demonstrate SAS Enterprise Miner specific to SVM modeling in project-based learning

Furthermore, many studies have also discussed the design of SAS Enterprise Miner as a software platform as adoptable to open-source solutions and project goals. The ability to demonstrate how the information gained and performed from a selected data set can potentially support target areas offers further incentives to environments both as practical and strategic reasoning [16]. SAS Enterprise Miner has been used to navigate and perform business-centric data analytics in these environements for innovation. The journey of innovation in engineering education can be understood to develop skills around the emerging of details and opportunities presented. This approach can reveal how requirements can be capture according to the decision approach knowledge to gain insight of performed data practices [16] [17].

The survey questions were Institutional Review Board (IRB) approved by the university for innovative practices to advance the following categories of pre-survey assessment test and post-survey assessment test: a) Confidence in the Engineering Design Lifecycle Progress; b) Integration of Methods Provides Evidence to Make Better Engineering Decisions; c) Integration of a Data Collection Process to Aid in the Development of an Engineering Design Approach; d) Learners Integration of Data Analytics Techniques into the Design Process for Engineers; and e) Learners Confidence about the Team Project to Plan and Carry out an Engineer Design Lifecycle. The distributed findings are graph according to pre-survey assessment test (N=11) findings and post-survey assessment test (N=14) findings. The survey participation was voluntary to the learners as consent forms were considered for educational purposes (e.g., the pre-survey and post-survey administered to determine overall effectiveness of the findings).

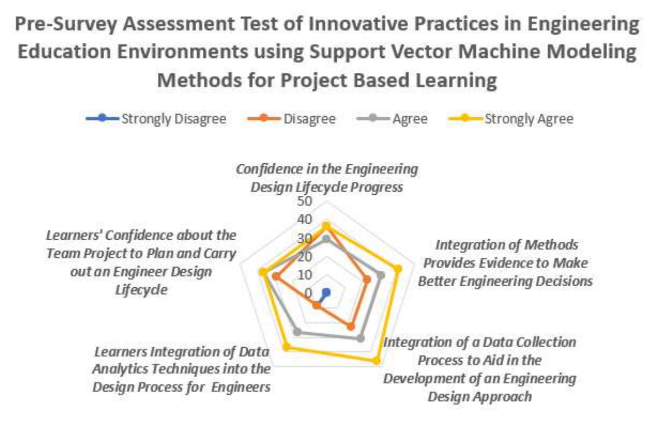

Fig. 8. Findings from the post-survey assessment tests from a project-based learning environments (N=11).

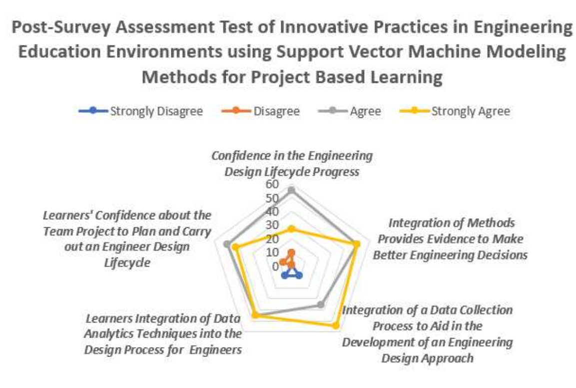

Fig. 9. Findings from the post-survey assessment tests from a project-based learning environments (N=14).

VII. CONCLUSION

In conclusion, the predictive analytics models had demonstrated the ability to build on outcome-solutions through the decision-making process as data become ready accessible. The ability to analyze learning strategies with regard to industry, education, government, and community developments allow for business problems to be studied and analyzed in the traditional classroom environment. The advancement to build an optimal predictive model can determine the need to further investigate techniques to best fit developed models and methods [8]. Overall, SVM provides the ability to trained data and forecast the best model to explore a more robust prediction [18]. In research development, the emergence of a big data era reveals potential benefits for techniques of forecast accuracy and reliability [18]. The engineering education design strategies are more representative of a preference rather than modeling concerns for advancement [19] This study presents how the model concerns can be used to promote strategies using SVM as an investigative approach for assessment [19].

This study has guided and demonstrated a lifecycle design adapted to engineering education through the combination of analytic discourse and direct empirical comparison. The roadmap outlines the major areas of SVM, which differs from conventional models for innovation in engineering education [14]. The challenge is to careful and not to examine the various perspectives as an investigative framework. This investigative drawback is due to the data-driven environment and need lack of understanding for mapping other functions in the lifecycle design process. In exploring the degrees of predictability and capabilities, the level of accuracy is vital to the practical implementation. These practical implementations of the SVM model were compared in order to classify techniques using a nonlinear decision boundary [20]. Whereas this can be a strength, the weakness creates the need to assess requirements due to sensitivity. Without being too sensitive to noisy observations/outliers, the approach to create a roadmap for lifecycle design process was performed in this study [20]. Our findings have also drawn attention regarding the conclusion of the strengths and weaknesses using SVMs. As this choice of method examined the featured targets, which allows for the performance to be subjective relative to statistical testing and overall significance of these findings [21]. The study gives an investigative approach to how predictive modeling can be used to advance engineering education by creating a structure to assess the learning environment conditions of students using project-based learning.

REFERENCES

[1] P. Galetsi, K. Katsaliaki, and S. Kumar, “Values, challenges and future directions of big data analytics in healthcare: A systematic review,” Social Science & Medicine, vol 241, 2019.

[2] C. Collins, N. Andrienko, T. Schreck, J. Yang, J. Choo, U. Engelke, A. Jena, and T. Dwyer, “Guidance in the human–machine analytics process,” Visual Informatics, vol 2, issue 3, 2018, pp. 166–180.

[3] D. Schneider and U. Seelmeyer, “Challenges in using big data to develop decision support systems for social work in Germany,” Journal of Technology in Human Services, vol 37, issue 2/3, 2019, pp. 113–128.

[4] W. Zhang, L. Yu, T. Yoshida, and Q. Wang, “Feature weighted confidence to incorporate prior knowledge into support vector machines for classification,” Knowledge & Information Systems, vol 58, issue 2, 2019, pp. 371–397

[5] D. Haughton, J. Deichmann, A. Eshghi, S. Sayek, N. Teebagy, and H. Topi, “A review of software packages for data mining,” The American Statistician, vol 57, issue 4, 2003, pp. 290–309.

[6] R. McCarthy, W. Ceccucci, M. McCarthy, and L. Halawi, “Alpha Insurance: A predictive analytics case to analyze automobile insurance fraud using SAS Enterprise Miner,” Information Systems Education Journal, vol 17, issue 2, 2019, pp. 20–24

[7] K. B. Yue, “A realistic data cleansing and preparation project,” Journal of Information Systems Education, vol 23, issue 2, 2012, pp. 205–216.

[8] S. Bolohan, and S. Ciobanu, “SAS Enterprise Data integration server - a complete solution designed to meet the full spectrum of enterprise data integration needs. Database Systems,” Journal, vol 3, issue 1, 2012, pp. 41–48.

[9] X. Lai, X. Wu, and L. Zhang, “Autoencoder-based multi-task learning for imputation and classification of incomplete data,” Applied Soft Computing, 2021, pp. 98.

[10] K. B. Schebesch, and R. Stecking, “Support vector machines for classifying and describing credit applicants: Detecting typical and critical regions,” The Journal of the Operational Research Society, vol 56, issue 9, 2005, pp. 1082–1088.

[11] P. D. H. Wall, and J. D. Fontenot, “Application and comparison of machine learning models for predicting quality assurance outcomes in radiation therapy treatment planning,” Informatics in Medicine Unlocked, vol 18, 2020.

[12] N. Gourmelon, S. Bayer, M. Mayle, G. Bach, C. Bebber, C. Munck, C. Sosna, & A. Maier, “Implications of experiment set-ups for residential water end-use classification,” Water, vol 1, issue 2, 2021, pp. 236.

[13] P.F. Pai, L. H. ChangLiao, and K. P. Lin, “Analyzing basketball games by a support vector machines with decision tree model,” Neural Computing & Applications, vol 28, issue 12, 2017, pp. 4159–4167.

[14] D. Cui, and D. Curry, “Prediction in Marketing Using the Support Vector Machine,” Marketing Science, vol 24, issue 4, 2005, pp. 595–615.

[15] R. Subramanian, and D. Cote, “Using SAS Software to enhance pedagogy for text mining and sentiment analysis using social media Twitter data,” Journal of International Technology & Information Management, vol 27, issue 2, 2018, pp. 73–98.

[16] A. H. Zadeh, S. Schiller, K. Duffy, and J. Williams, Big data and the commoditization of analytics: Engaging first-year business students with analytics,” E-Journal of Business Education & Scholarship of Teaching, vol 12, issue 1, 2018, pp. 120–137.

[17] B. De Ville, “SAS Enterprise Miner-first looks,” Marketing Research, vol 10, issue 1, 1998, pp. 37–40.

[18] M. A. Villegas, D. J. Pedregal, and J. R. Trapero, “A support vector machine for model selection in demand forecasting applications,” Computers & Industrial Engineering, 121, 2018, pp.1–7.

[19] S. Maldonado, R. Montoya, and R. Weber, “Advanced conjoint analysis using feature selection via support vector machines,” European Journal of Operational Research, vol 241, issue 2, 2015, pp. 564–574.

[20] J. Rohmer, and N. Brisset, “Short-term forecasting of saltwater occurrence at La Comté River (French Guiana) using a kernel-based support vector machine,” Environmental Earth Sciences, vol 76, issue 6, 2017, pp. 1–16.

[21] C. Hor, C. Yang, C. Chang, C. Tseng, and H. Chen, “A tool preference choice method for RNA secondary structure prediction by SVM with statistical tests,” Evolutionary Bioinformatics, vol 9, 2013, pp. 163–184.