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Developing Computational Intelligence for Smart Qualification Testing of Electronic Products

M. Ahsan[1], S. Stoyanov[2], C. Bailey[2], and A. Albarbar[1]

[1]Advanced Industrial Diagnostics, Department of Engineering, Manchester Metropolitan University, Manchester, UK
[2]School of Computing and Mathematical Sciences, University of Greenwich, London, UK

Corresponding author: M. Ahsan (e-mail: M.Ahsan@mmu.ac.uk).

ABSTRACT In electronics manufacturing, the necessary quality of electronic components and parts is ensured through qualification testing using standards and user requirements. The challenge is that product qualification testing is time-consuming and comes at a substantial cost. The work contributes to develop a novel prognostics framework for predicting qualification test outcomes of electronic components enabling the reduction of qualification test time and cost. The research focuses on the development of a new, prognostics-based approach to qualification of electronics parts that can enable "smart testing" using data-driven modelling techniques in order to ensure product robustness and reliability in operation. This work is both novel and original because at present such approach to qualification testing and the associated capability for test time reduction (respectively cost reduction) it offers are non-existent in the electronics industry. An effective way of using three different methods for development of prognostics models are identified and applied. Predictive models are constructed from historical qualification test data in the form of electrical parameter measurements using Machine Learning (ML) techniques. ML models can be imbedded within the sequential electrical tests qualification procedure and enable the forecasting of the pass/fail qualification outcome using only partial information from already completed electrical tests. Data-driven prognostics models are developed using the following machine learning techniques: (1) Support Vector Machine (SVM), (2) Neural Network (NN) and (3) K-Nearest Neighbor (KNN). The results show that with just over half of the individual tests completed, the models are capable of forecasting the final qualification outcome, pass or fail, with accuracy as high as 92.5%. The predictive power and overall performance of the researched models in predicting qualification test binary outcomes with varying ratios of Pass and Fail data in the processed datasets are analysed.

INDEX TERMS Data-driven prognostics; data analysis; machine learning; modelling; electronics manufacturing; quality; qualification testing.

I. INTRODUCTION

The global market for electronic products is anticipated to reach US$2.4 trillion per year by 2020 [1]. This growth has directed to intense competition between manufacturers to minimise the time-to-market and cost of their products while at the same time delivering high quality products to the customers. However, ensuring functional requirements and quality of electronics components, respectively products, involves the adoption of time-consuming and resource-intensive processes, which is a main tailback from an economics point of view and also for the rapid release of these products to the market. The challenges are to identify solutions for meeting the quality requirements specified for electronic products in a cost effective manner. Quality testing of the products within the shortest possible time is also one of the key priorities for many electronics manufacturers.

Qualification and reliability testing, and quality assurance processes are the most common approach to assess performance and "fit-for-purpose" characteristics of the product [2]. Qualification is a process depending on applications. Therefore, qualification specifications or requirements are not same for all applications. The process varies from one product to another product. Commonly, the manufacturers produce product according to application constraints, which meet customer requirements. Therefore,

testing is important to ensure that the anticipate products meet the specified requirements by fulfilling operational functionality and performance [3-4].

Qualification testing of electronics products is performed on several parameters which indicate functional state of each electronic component or product. The outcome of qualification test is mostly binary namely either pass or fail, true or false. It is depended on the test values as well as associated specified test limits which are required to measure for individual product. A test value within the expected test range is associated with pass status of the product under qualification and indicates that the required quality is present. Quality is important as it also predetermines, along with other attributes, the subsequent reliability. In the context of a product development process, qualification test results are regularly fed back to the design teams and to the manufacturers to enable resolving issues and realising required improvements.

Electronics industry has common practice to conduct qualification test measurements, for example, to confirm traceability information is available, and as a result companies in such instances have access to large historical sets of qualification test data for their products. In most cases, the data remains unused. However, there is a great possibility to enable the optimisation of qualification test procedures with the information in the data.

The measured parameters and logical tests in a qualification specification performed on an electronic product could vary from only a few to potentially hundreds. Therefore, it is required to minimise the overall test time by adopting an optimum qualification testing procedure. It would be a great advantage if the test times are reduced leading to a reduction in reducing production costs as well as product delivery time to the customer. One potential way of reducing qualification test time is by adopting prognostics models developed using available historical qualification test data and capable to accurately forecast the final test outcomes (pass/fail).

Data-driven prognostics approaches such as those that use machine-learning techniques can take advantage from the availability of historical data and use this data to "train" selected model structures to capture and recognise the effects of changes in measured or monitored parameters on manufacturing process or product operational trends. For example, a comparison between in-situ data and healthy baseline data helps to detect anomaly. The data is usually gathered under several modes and load conditions under which a product is projected to function. [5-6]. Machine learning is an influential approach which has capability of analysing and making decision based on pattern of historical data. The advantages of ML are not yet fully established and hence it's current use in many industrial applications domains are still limited. However, more recently the result of the increasing use of IoT, this has started to change. The use of machine learning algorithms namely Support Vector Machine (SVM), Neural Network (NN) and K-Nearest Neighbor (KNN) [7] has become more common and started to play an important role in tasks related to attaining active and ideal outcomes by intensive analytics of historical data. Machine learning techniques are currently used in electronic product manufacturing for different purposes such as product qualification, yield prediction, automatic defect detection, and defect classification.

Jaai et al. [6] have proposed a multivariate state estimation method to identify the onset of failure in ball grid arrays. A sequential probability ratio test was completed with accelerated temperature cycling (ATC) tests. Luan et al. [8] have proposed a technique for conducting qualification of IC packages. This was considered under drop impact during early design stage to qualify the package which can significantly shorten the development time and associated cost. Manufacturers also adopt predominantly standards-based qualification testing [9] to warrant quality and functional requirements of electronic products used in different applications are met. The inappropriate association between field use and test conditions stimulate to the insufficient qualification that leads to unforeseen product failure while in service and excessive economic damages.

Stoyanov et al. [10] have proposed a qualification method for determining reliability of electronic products as an alternative to physical testing for improving efficiency and robustness. Self-organising Map (SOM) is used to map a new product through similarity approach with respect to groups of previously tested parts of known qualification test results.

Park et al. [11] have suggested computational method for predicting packaging yield in semiconductor fabrication. An algorithm (random forest) has been employed to identify variables which are related in packaging yield. In addition, a nonlinear SVM is employed for yield classification. Sohan and Lee [12] have suggested canonical correlation analysis to obtain relationship between multiple process control monitoring variables and various probe bin variables of IC semiconductor to improve the yield. Kupp and Makris [13] have developed a model-view-controller (MVC) architecture to solve low yield in semiconductor manufacturing. Kim et al. [14] have proposed machine learning approach to improve packaging yield in semiconductor manufacturing. The authors have used fab measurement data, wafer test data, and package test data during analysing.

Kim et al. [15] have proposed machine learning classification models such as linear regression, KNN, decision tree, NN and support vector regression to identify wafers, which are faulty during semiconductor manufacturing. The models were developed with the use of fault detection and classification data to distinguish faulty wafers. Chou et al. [16] describes defect classification (ADC) system that performs identifying defects on semiconductor chips at various manufacturing stages. Probabilistic Neural Networks (PNN) classifiers was used to improve the defect detection accuracy and reduces operator workload.

Boubezoul et al. [17] have proposed a classification approach to detect defective wafer. Machine learning algorithms such as Generalized Relevance Learning Vector, SVM, KNN and Parzen were employed to improve detection rate of defective wafers. Lee et al [29] have presented a data-driven method capable of reducing qualification time of Lithium-ion (Li-ion) batteries before its end-of-life (EOL). The method fast detects anomaly in unhealthy batteries using curvature value of a capacity fade curve. Particle filter was employed to reduce test time by 1.8 months from 3-6 months. However, the system did not provide any relationship between time-to-anomaly detection and EOL.

While most of the research and applications of machine learning and computational intelligence techniques relate to the process monitoring and control of electronics and diagnostics/prognostics under failure test or in-field operational loads, the use of such technologies to improve or optimise qualification testing of electronics parts is yet to be realised and demonstrated.

In the authors' previous work, an Off-line data analytics and imbedded in-line model-enabled prognostics approach has been proposed for smart qualification test of an electronic product using SVM [18]. The aim of this study is to develop a machine learning based novel computational approach for predicting qualification test outcomes of an electronic module using historical test data. This approach would help to reduce test time and huge cost associated with the qualification testing. The proposed approach has explored the competency of machine learning algorithms such as NN, SVM, and KNN in predicting qualification test outcomes. Prediction accuracies from each algorithm are assessed and a performance comparison of the algorithms is presented in this paper.

II. FRAMEWORK FOR PREDICTING QUALIFICATION TEST OUTCOME

The type of qualification testing considered in this research work is the most common electrical parameter testing where the qualification involves undertaking a sequence of discrete tests associated parameter measurements of the electronic part/product. For each of the individual tests, the measured parameter value must fall under the specification range if it is to be considered as PASS

An electronic part is qualified when all discrete tests constituting the qualification specification are passed. The testing of a part is stopped if the part is failed under a test in the sequence. Huge number of electrical, logical and other functional parameter measurements are involved for most of the qualification procedures of the complex electronic product and therefore, the total test time could be a lengthy process. Given the sequential nature of executing the individual qualification tests, a prospective way to shorten the qualification time is taking benefit of the fact that as the testing progresses, more and more data of already completed individual tests becomes available, and thus it becomes possible to minimise the available measurement's and aim to infer if remaining tests are likely to be passed or if one or more of them may fail. In essence, developing machine-learning models could provide huge opportunities for predicting qualification test outcome of an electronic part of interest with the use of past historical data. The models could forecast the qualification outcome using known individual test results up to a given point in the sequence of tests.

The proposed prognostics framework for predicting the qualification test outcomes (Pass/Fail) of the electronic product is shown in Fig 1. The framework is capable of assisting smarter testing by employing knowledge gained through test data analytics. Data-driven prognostics models were developed using test data for forecasting anticipated qualification tests outcome. Offline smart tests was accomplished through failure statistics and similarity tests and details of the tests data analytics are presented in [18]. This paper presents an offline analytics to develop prognostic models for forecasting the overall test outcome by evaluating model performances following five individual steps.

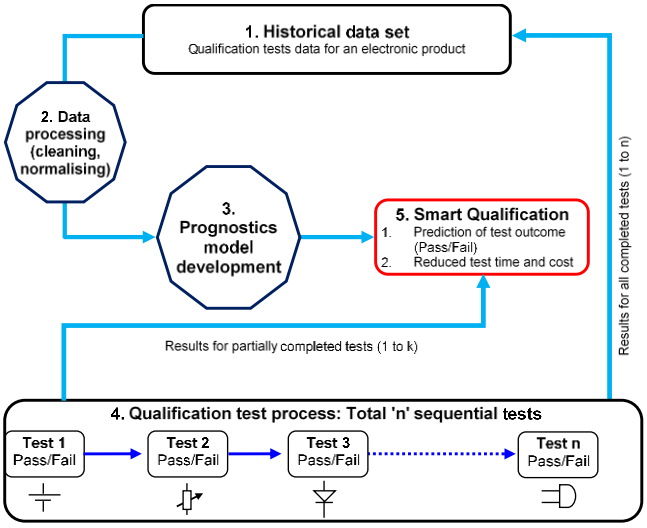


FIGURE 1. Conceptual schematic of the proposed prognostics approach.

Step 1: Qualification testing is required for the electronics industry to obtain electrical/functional test measurements. At the beginning, a qualification test data set of an electronic part with a mix of known pass and fail data was obtained from an electronic manufacturer.

Step 2: The data related to pass and fail electronic parts are separated at the data pre-processing stage. Detection and elimination of data outliers in the data set is typically a required step that can be automated and be executed by adopting a number of techniques and criteria. The measured values in the individual tests are normalised, for example in the range 0 to 1 to facilitate prognostics model development. The strategy of considering upper and lower limit as the maximum and minimum values from the cleaned data has

been implemented. The main advantage of this technique is that one rule can be applied across the whole range of tests. Further details of normalization can be found in [18].

Step 3: A master data set is organised to develop several training data sets using different combinations of data related to pass and fail with their corresponding (known) qualification outcomes. The training data sets are employed to develop models with different machine learning algorithms (SVM, KNN and NN).

Step 4: During the qualification test process ML is developed with first k tests in the test sequence as training datasets. The model can predict outcome of all future n sequential tests using the partially completed tests (1 to k).

Step 5: A validation data set is also generated from the master data set to test the prediction accuracy of the developed models and to validate them. The performance of each model structure is evaluated by calculating a prediction error. The models are then used to predict the likely outcome of the overall qualification – PASS or FAIL for a new device.

Fig. 2 outlines schematically the approach for optimisation of the qualification process using machine learning predictive models. If the total number of qualification tests in the sequential testing is n, and the number of completed tests is k (i.e. k is the current test being completed, and tests k+1, k+2, ..., n not yet undertaken), a machine learning model built with past historical data and taking the tests parameter values as inputs for tests 1, 2, ..., k can be executed to forecast what the expected final outcome of the qualification is. The model infers, on the basis of completed test results, if a failure under the remaining, not yet undertaken tests, is likely (prediction FAIL outcome) or not (prediction for PASS outcome). If the evaluated expected model accuracy is acceptable for the application where the electronic part is used, a decision might be accepted to terminate the testing at test k and not to run the remaining tests. This will reduce the qualification test time as part of the quality assessment procedure and respectively provide cost savings.

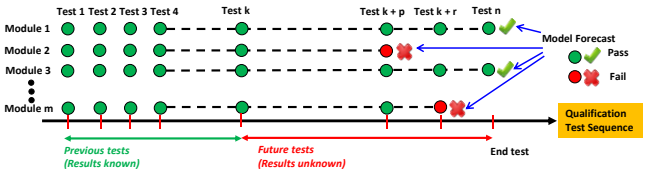


FIGURE 2. Prediction scenario for qualification test outcome.

III. MACHINE LEARNING ALGORITHMS: DATA CLASSIFICATION

Machine learning techniques are extensively used to solve classification problems particularly where large amount of data are used [19]. Supervised and unsupervised are the two core branches of machine learning techniques. Supervised machine learning is built with input data and associated output data whereas unsupervised learning have only input data without having any corresponding output data [20-22]. Supervised machine learning can be divided as classification and regression. Classification is used as supervised learning method. The model is built and learned functions from a training data set (input and output data). In a classification problem, output data represent different categories such as pass or fail and good or bad. Classification has data mining capability that can discover the knowledge embedded in databases using artificial intelligence, statistical and mathematical methods for extracting and classifying useful information.

A. NEURAL NETWORK (NN)

NN is a network model structure that can be seen as being arbitrary function approximation of highly nonlinear data. Fig. 3 shows a generic NN model structure. The definition of the model structure has high degree of flexibility which enables the NN to etablish effectively the relationship within the modelled data, and thus to be used for predicting the performance of the observed system. To formulate different data sets it is required to avoid over-fitting of data for training with the network. Different training and validation data sets are required to execute and validate the model.

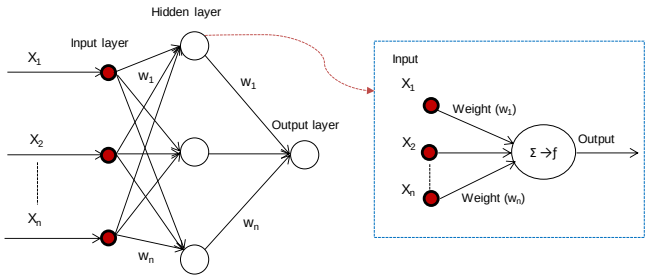


FIGURE 3. A Generic NN Model Structure.

Input, output and validation are three main data sets for building a NN model. First, a NN model is created after training with the input data and the known output data. Then the validation data set is used to measure the prediction performance of the model [22].

Feed forward NN and Levenberg Marquardt (LM) learning algorithm are used to construct a complete NN model. Feed forward NN is selected for predicting the test outcomes of the qualification data. Levenberg Marquardt (LM) learning algorithm is used to train the NN [22]. Gradient descent method and the Gauss-Newton method are combined in this network. The algorithm has the capability to solve nonlinear problems using its standard technique. Training performance is evaluated using mean squared error to simplify the construction of a network by minimising the sum of the squared errors. The sum of squares is estimated by Hessian matrix as $H = J^T J$, where J is Jacobian matrix, gradient $g = J^T e$ where e is considered as network error and Levenberg-Marquardt training algorithm is presented by Eq. 1.

$$X_{k+1} = X_k - [J^T J + \mu I]^{-1} J^T e \quad (1)$$

Where X_k denotes connection weight at iteration k, μ represents scalar combination coefficient that performs a transformation to gradient descent or Gauss-Newton algorithm and I represents as Identity matrix. The descent gradient method is a common learning rule used for realising the NN training process. The error function is used to compute the error between the outcome of training and the desired output. This is completed by determining the sum of the squared errors of the total number of input and desired output patterns of the training set. The error function is given by Eq. 2.

$$\varepsilon = \sum t_p - f_{p,} \quad (2)$$

Where t_p is the desired output and f_p is the actual output. The target of this learning rule is to find the appropriate values of weights that can minimise the error.

B. SUPPORT VECTOR MACHINE (SVM)

SVM is a linear or non-linear classifier that contains mathematical function to differentiate two different kinds of objects. Input and output data sets are required to train and create an SVM model.

A validation data set (unknown output) is used to validate the performance of the model. However, the SVM model is also capable of holding data from the training set for automatic model validation. SVM is a supervised machine learning algorithm mainly used for binary classification problems that can minimise generalisation errors. The algorithm is also used for multiclass problem. The fundamental concept of this algorithm is to separate classes of objects in the data space with the use of kernel function and functional margin. Kernel functions solve nonlinear problems with higher dimension as feature space. Then the functional margin minimises the generalisation errors of classifier by finding optimal hyperplane. This hyperplane creates the finest split-up boundary between two classes. To separate training data linearly, SVM technique can help to prepare the training data for classification into a higher-dimensional space [23-24].

Assume $\{x_i, y_i\}$ where $i = 1, 2,...,N$, is a set of training data where each sample $x_i \in R^n$, n is size of the input space which belongs to a class. The samples are assumed have two classes namely positive and negative, which can be expressed as $y_i \in \{-1,+1\}$. In the case of linearly separable data set, a decision boundary or separating hyperplane can be expressed by Eq. 3 to separate the given data.

$$\omega x + b = 0 \quad (3)$$

Where, ω, a hyperplane normal vector and b, a scalar offset are parameters of the model and x is the set of attributes of the model. Fig. 4 shows an example of the optimal hyperplane of two data sets and support vectors which are on the margin. The optimal hyperplane decision function can be formulated by Eq. 4 [23].

$$f(x) = \mathrm{sgn}(w_0 x + b_0) = \mathrm{sgn}\left(\sum_{i=1}^{N} \alpha_i^* y_i (x_i x) + b_0\right) \quad (4)$$

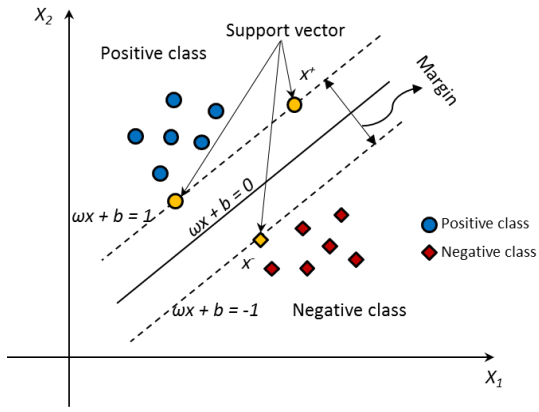


FIGURE 4. Optimal hyperplane used in SVM for separating data.

C. K-NEAREST NEIGHBOR (KNN)

KNN algorithm is a classification procedure that is capable of classifying objects of available closest training instances in the problem domain using supervised learning technique. KNN algorithm works according to the following steps: (1) parameter determination, (2) distance calculation between query-instance and all the training samples, (3) sorting of distances samples (training) and determination of nearest neighbor on the basis of Kth minimum distance, (4) categorisation of the training samples for the arranged value which exist under K and (5) measurement of the prediction value using majority of nearest neighbors [25].

KNN accomplishes classification of objects from the nearest learning data of the objects. K is considered as a positive integer and the neighbors are selected from the classified object. A learning set represents the data characteristics while the data are situated in many dimensional spaces. K value can decrease the influence of noise and creates boundaries on each classification. Euclidean distance is commonly used to calculate distance within new data set and training data. Euclidean distance between two points p and q can be expressed by Eq. 5

$$R^{d1} = \sqrt{(p_x - q_x)^2 + (p_y - q_y)^2}$$
$$R^{d2} = \sqrt{(p_x - q_x)^2 + (p_y - q_y)^2 + (p_z - q_z)^2} \quad (5)$$

Where space dimension considered as, d = 2 and d = 3. Assume that set S contains n points, query point is defined as P_i ($P_i \in S$) and subset C comprises k points then $C \in S$, $k < n$, for $P_1 \in C$, $P_2 \in S\text{-}C$, that can be met by Eq. 6 [26].

$$\mathrm{dist}(P_i, P_1) \leq \mathrm{dist}(P_i, P_2) \quad (6)$$

Fig. 5 shows an example of KNN decision rule in two dimensions for K= 2 and K= 7 for a set of samples divided into two classes.

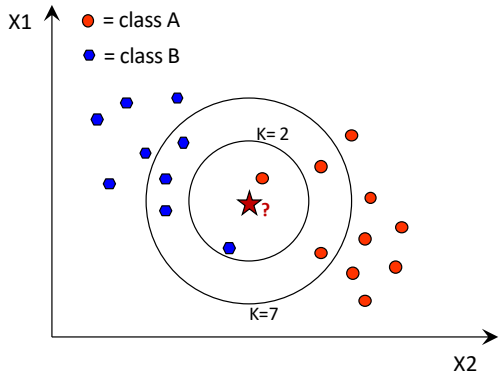


FIGURE 5. Two dimensional KNN.

An unknown sample (star symbol) is classified by using two closest known samples when k = 2. However for k = 7, seven known closest values are used to classify the unknown sample. In the last case, four samples belong to the same class whereas three belongs to the other class.

IV. STUDY CASE

A. QUALIFICATION TEST DATA

Qualification test of an electronic module is used to demonstrate the proposed approach for test time reduction. The data is derived based on qualification specification for the product that includes different types of electrical parameter tests total of 95 individual tests, performed sequentially, are conducted on each module to determine whether it passes or fails the qualification requirements. Fig. 6 shows a sample of normalised raw data from the qualification test of the electrical module collected from a manufacturer. The column wise measured parametric values indicate each sequential test whereas the test results for each module are presented in rows.

Test number	1	2	3	4		10		60		95	Known outcome
Upper limit	1	1	1	1		1		1		1	
Lower limit	0	0	0	0		0		0		0	
Module 1	0.11897	0.88349	0.48914	0.53865		0.18535		0.02012		0.22222	PASS
Module 2	0.08448	0.99432	0.55154	0.56794		0.17126		0.02273		0.88889	PASS
Module 3	0.08046	0.91191	0.51449	0.53167		0.14965		0.01976		0.33333	PASS
Module 4	0.03448	0.90622	0.41700	0.43496		0.16493		0.02335		0.22222	PASS
Module 5	0.13594	0.88349	0.18204	0.22847		4.11831					*FAIL*
Module 6	0.08851	0.99432	0.55154	0.57819		0.18305		0.02172		0.66667	PASS
Module 7	0.08621	0.91191	0.49792	0.50350		0.18197		0.01984		0.22222	PASS
Module 8	0.08793	0.99147	0.52619	-0.92373							*FAIL*
Module 9	0.09195	0.99147	0.45112	0.51727		0.12586		0.02080		0.66667	PASS
Module 18	0.12644	0.88349	0.44430	0.52459		0.19251		0.02379		0.33333	PASS
Module 19	0.07759	0.88633	0.51254	-0.99374							*FAIL*
Module 20	0.09310	0.99147	0.49889	0.52723		0.17413		0.02128		0.77778	PASS
Module 21	0.08908	0.91191	0.47939	0.49403		0.15793		0.02003		0.44444	PASS
Module 22	0.12471	0.88349	0.37313	0.48915		0.20590		0.02207		0.33333	PASS
Module 10000	0.06264	0.90338	0.24541	0.22934		0.26134		0.02012		0.33333	PASS

FIGURE 6. Sample of raw qualification test data in a normalised form.

Once a module is failed then the test is stopped and it is not required to carry out further tests. Then a value with an asterisk (*) is showed for the module. Hence no test data will be available for the module from that failure point. First four rows indicate parametric tests no, parameters, upper limit and lower limit of the individual test.

B. DATASETS FOR MACHINE LEARNING

The development of prognostics models in this study follows a machine learning based data-driven approach. The models are developed and validated using historical datasets of measured parameters (i.e. this is the data on the qualification test measurements of electrical parameters) and associated data of the observed outcome (in this study this is the qualification status outcome, pass or fail).

The study demonstrates the proposed prognostics approach for the case when the prognostics models are to be used on a tested electronic module after completion of the first 60 individual qualification tests in the overall sequential procedure. In this instance, there are another 35 remaining tests yet to be undertaken. Thus, this particular investigation is looking at the potential to use developed models with the measured test data of the tested module for tests 1 to 60 (model inputs) to evaluate the final qualification outcome. If the model accuracy is acceptable, in practice and in this instance it may be possible to accept status of qualification without undertaking the remaining 35 tests, and hence reduce qualification time. The first 60 individual sequential tests have been used to develop ML models. Then the remaining new 35 sequential tests are used to predict the tests outcome with the developed models. The last 35 tests are not related to first 60 tests. This will reduce the test number through prediction.

A dataset, in this study, contains qualification test data records (data points) for electronic modules, either pass or fail; each of which is represented mathematically as a vector holding the measurement test results of the first 60 sequential tests in the qualification. These vector components will act as model inputs [27]. Because this is historical data, the qualification outcomes for each tested module are known. Hence, each data point can be associated with a known status for qualification, pass (1) or fail (0), thus forming a pair of known data in the form of (input, output).

1) TRAINING DATASETS OF QUALIFICATION TEST DATA

The quality of the developed models is highly dependent on the data used. To obtain diverse and deep insight knowledge of the effects of the datasets, five training data sets are arranged from the master data set, each containing and combining in a certain way pass and fail data from tested electronic modules. The respective sizes of the five qualification test training datasets are 1164, 2000, 4000, 5000 and 10000 respectively. The total number of the data records, both pass and fail, in the master dataset is 50,000+ but the fail data records are only 622. Building predictive models from data to forecast pass or fail qualification status for the electronic modules requires both pass and fail data to enable the learning algorithms establishing the potential correlations between qualification tests measurements

(model inputs). Therefore, the definition of the datasets for model training purposes aimed to maximise the size, selected to be 582 data points, of the data associated with qualification failure. The remaining 40 failed module data records are used as part of the validation datasets. Therefore, in each data five datasets, with set, to the number of the data points for the failed electronic modules is constant and fixed to 582.

Three sub-training sets are formulated from each training set by varying the ratio between the numbers of data points associated with fail and pass modules. The ratio of number of fail and pass modules is expressed as R by Eq. 7.

$$\text{Ratio, } R = \frac{\text{No. of FAIL modules in training data sets}}{\text{No. of PASS modules in training data sets}} \quad (7)$$

The three data sub-sets to each of the five datasets are defined on the basis of using three sub-sets of failed data records with sizes 582 (i.e. all failed data in the training set), 400 and 200. As the total size of the data in the five training sets (TS1 to TS5) increases from 1164 to 10,000, the 15 sub-sets of data obtained have varying ratio in the range 0.02 to 1.0. Table I provides summary of the definition of the training sets and their respective subsets along the size of data of pass and fail modules. The last column of the table provides the ration R of fail to pass data in the data subsets.

TABLE I
DATA ARRANGEMENT FOR TRAINING AND VALIDATION IN SVM, NN AND KNN FOR DIFFERENT TRAINING DATA SETS

Number of data in training sets	Reference for data sub-sets	Training data arrangement	Fail to Pass ratio, R
Training Dataset 1 (TS1) Size of data: 1164	S1A	582 pass & 582 fail	1.00
	S1B	764 pass & 400 fail	0.52
	S1C	964 pass & 200 fail	0.21
Training Dataset 2 (TS2) Size of data: 2000	S2A	1418 pass & 582 fail	0.41
	S2B	1600 pass & 400 fail	0.25
	S2C	1800 pass & 200 fail	0.11
Training Dataset 3 (TS3) Size of data: 4000	S3A	3418 pass & 582 fail	0.17
	S3B	3600 pass & 400 fail	0.11
	S3C	3800 pass & 200 fail	0.05
Training Dataset 4 (TS4) Size of data: 5000	S4A	4418 pass & 582 fail	0.13
	S4B	4600 pass & 400 fail	0.09
	S4C	4800 pass & 200 fail	0.04
Training Dataset 5 (TS5) Size of data: 10000	S5A	9418 pass & 582 fail	0.06
	S5B	9600 pass & 400 fail	0.04
	S5C	9800 pass & 200 fail	0.02

2) MODEL VALIDATION DATASETS OF QUALIFICATION TEST DATA

As detailed in Table I, 15 sub-sets of training data are defined and used to develop the prognostics models. As part of the model development strategy, validation of the accuracy of the constructed models is performed. The validation uses qualification test data not used as part of the model training computations. In this study, three validation datasets are defined as follows:

1. Validation set VS1: Size of the data sets is 40 and all data is associated with electronic modules that passed the qualification specification. There is no data in this data set from modules which failed the qualification
2. Validation set VS2: Size of the data sets is 40 and all data is associated with electronic modules that failed the qualification specification. There is no data in this data set from modules which passed the qualification.
3. Validation set VS3. A combined data set of VS1 and VS2, with size of 80.

The rationale to use three different validation datasets as defined above is to enable better assessment and evaluation of the performance of the constructed models in predicting the two possible qualification outcomes in the context of the different data ratios used in the training datasets test.

3) PROGNOSTICS MODELS DEVELOPMENT USING MACHINE LEARNING

Machine learning models are developed for each of the 15 training subsets listed in Table I. NN, SVM and KNN algorithms were employed and their performance in the context of the specification of the training datasets was investigated. NN, SVM and KNN models predict the pass-fail outcome using different model structures suitable for classification of data. The model input the test measurements available for the first 60 tests in the qualification. Results from these models are in the form of the so-called confusion matrix, which details the results as percentage of correct/incorrect classification of the predicted outcomes. An example of predictive accuracy for the SVM model when developed with the training dataset S1C are illustrated in Fig. 7.

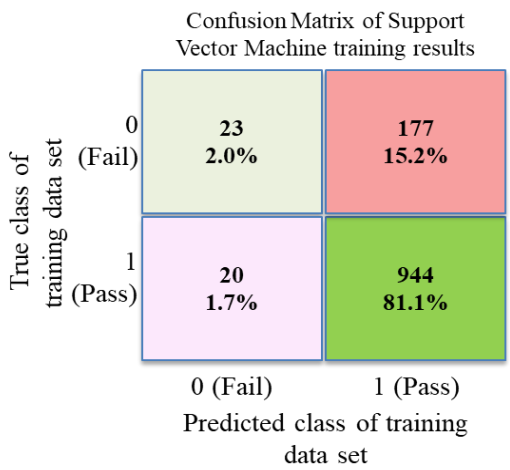
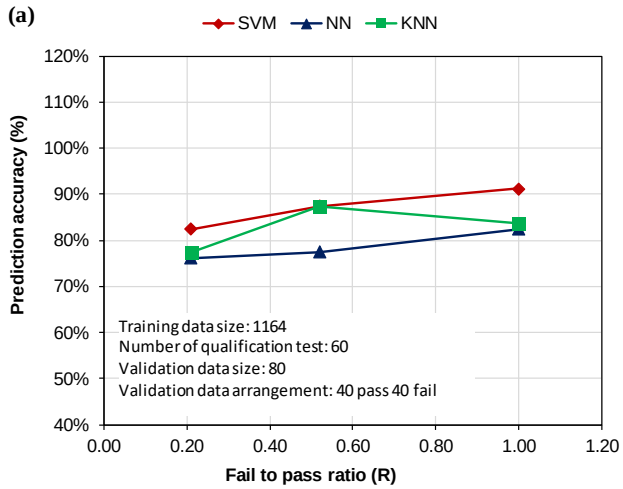


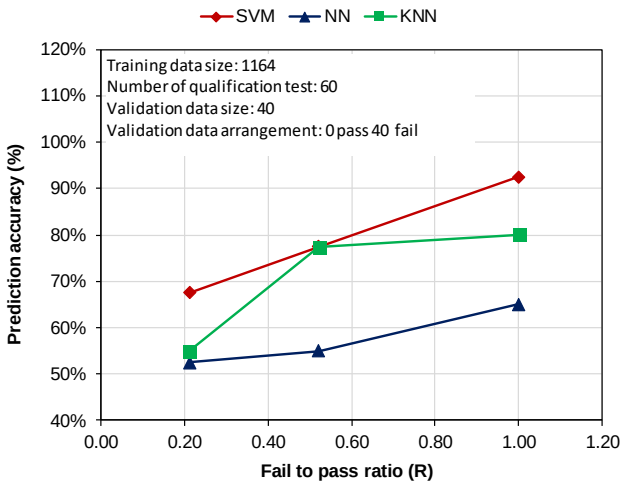
FIGURE 7. Examples of training models developed by SVM algorithm using the S1C training dataset.

C. VALIDATION RESULTS

Fig. 8 presents prediction accuracies of the qualification test outcomes by SVM, NN and KNN algorithms using the training sets containing 1164 data points (TS1) and three different validation data sets. When the models were validated with pass and fail data the results in Fig. 8(a) showed that for SVM and NN the accuracies increased with the fail to pass ratio and reached to the maximum values when the ratio is highest (R=1.0; implying same number of pass and fail data points in the training set). This indicates that accuracy is sensitive to the sizes of fail and pass data, and accuracy overall increases as good balance of both is present. Based on the validation result using the sub-set of fail data, it is also observed that there is a strong dependency of accuracy, across all model structures, on the amount of failed data in the training data set. Similarly, the models from predominantly pass training data when R=0.2 showed best performance in the case of the pass only validation dataset. The results also showed that for all ratios SVM performed better than the other two algorithms. Similar behavior was also observed in the prediction accuracy results validated with the fail data only (Fig. 8(b)). However, the rate of increase of prediction accuracies with the ratio is higher for all three algorithms though the accuracies decreased significantly at the lower ratios (0.21 and 0.52). In this case, SVM performance is again far better than the other two.

Different behavior was observed in the prediction accuracies when validated with the pass data only (Fig. 8 (c)). All models show higher prediction accuracies compared to the other two validation cases.





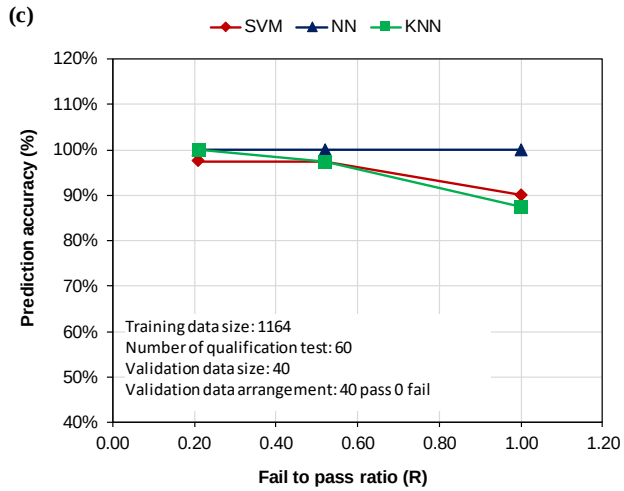


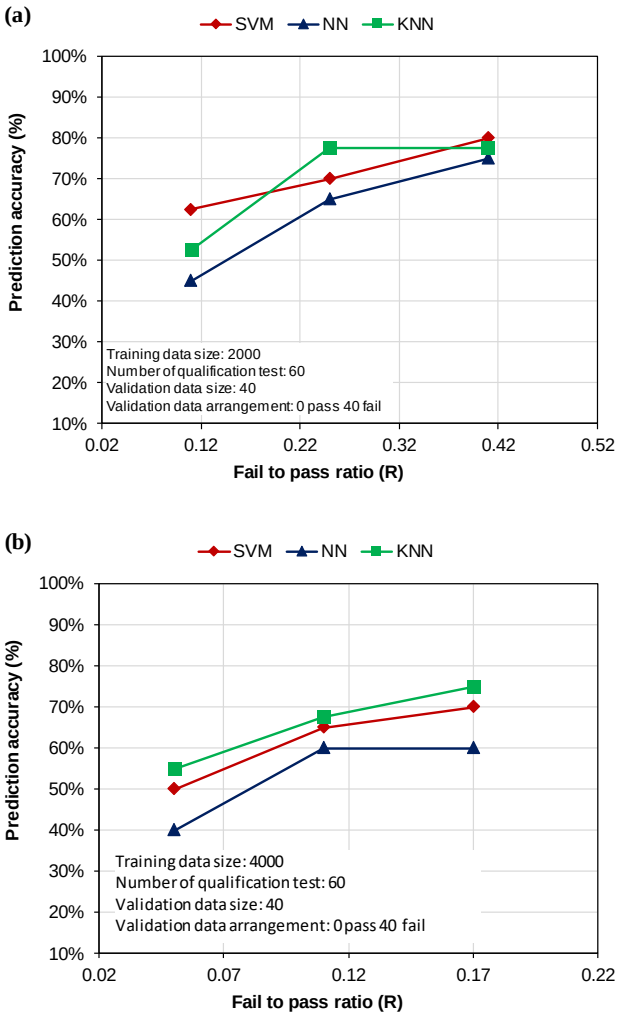
FIGURE 8. Comparison of qualification test outcome prediction accuracies by SVM, NN and KNN using a training set TS1 when validated with (a) pass and fail data (b) only fail data and (c) only pass data.

The prediction accuracies achieved by the NN models remain constant to 100% for all the ratios. On the other hand, the prediction accuracies by the SVM and KNN models slightly decreased with an increase of the ratio in contrast to the results obtained using the other two validation sets. The absence of fail data in the validation set could contribute to this behavior. However, even the lowest accuracy values at the ratio 1 in this case are somewhat closer to the highest accuracy values at the same ratio for the other two validation scenarios. In summary, for all algorithms the best prediction accuracies for all algorithms were achieved when the ratio is 1. NN models show highest prediction accuracies when validated with the pass data only. However, SVM performs best when validations were conducted with only the fail data or pass and fail data. Therefore, the number and arrangement of fail data both in the training and validation sets have influenced the prediction accuracies.

As it was observed previously that among all three validation sets, the worst results are obtained for the

validation set with only the fail data. Therefore, in the following sections, results are presented for the validation data set with only the fail data to demonstrate the performance of the models in the worst-case scenario.

Fig. 9 shows further results for the training data set TS2 to TS5 (see Table I). The general rising trend of prediction accuracies was observed with the increase of fail to pass ratios in all the training data sets. It should be noted that the fail to pass data ratios plotted in the horizontal axes in the graphs does not remain same but decreases with the size of the training sets, as the number of fail data in all training sets remain constant to 582. It is apparent that the best prediction accuracies for every training set were obtained with the largest fail to pass ratios. When the ratio is 0.42 for the Training set 2 (2000), the best prediction accuracy (80%) was obtained by SVM. However, for other training sets (3, 4 and 5), the best prediction accuracies (75%, 72.5%, and 70%) were obtained by KNN with the largest ratios respectively (0.17, 0.13 and 0.06).



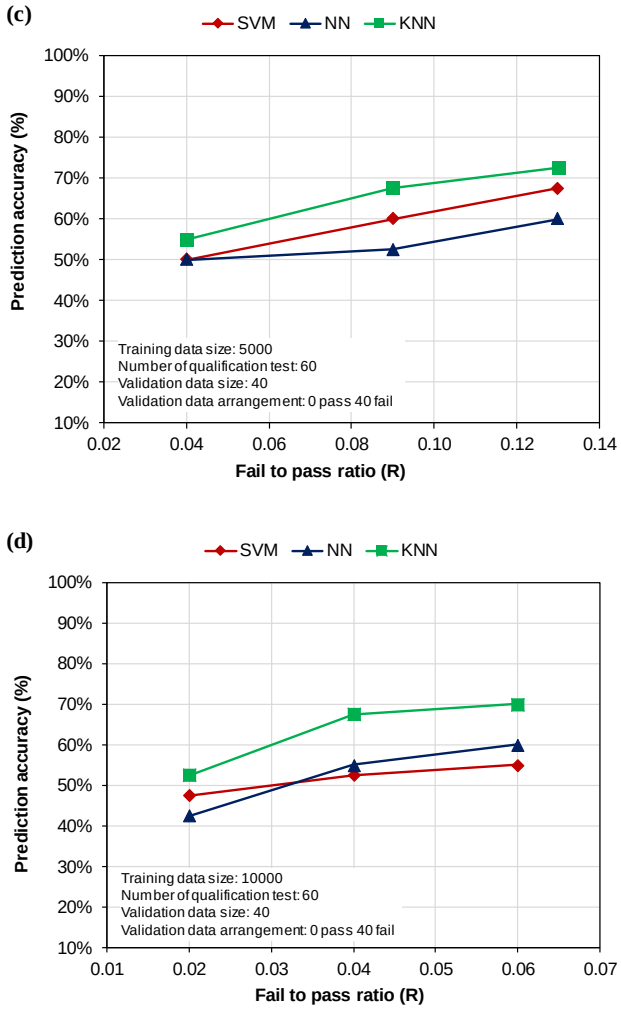


FIGURE 9. Comparison of prediction accuracies of qualification test outcomes obtained by SVM, NN and KNN for (a) Training set TS2 (b) Training set TS3 (c) Training set TS4 and (d) Training set TS5, as formulated in Table I.

Fig. 10 provides the effects of varying the training data sizes on the prediction accuracy and varying the number of fail data in the training sets.

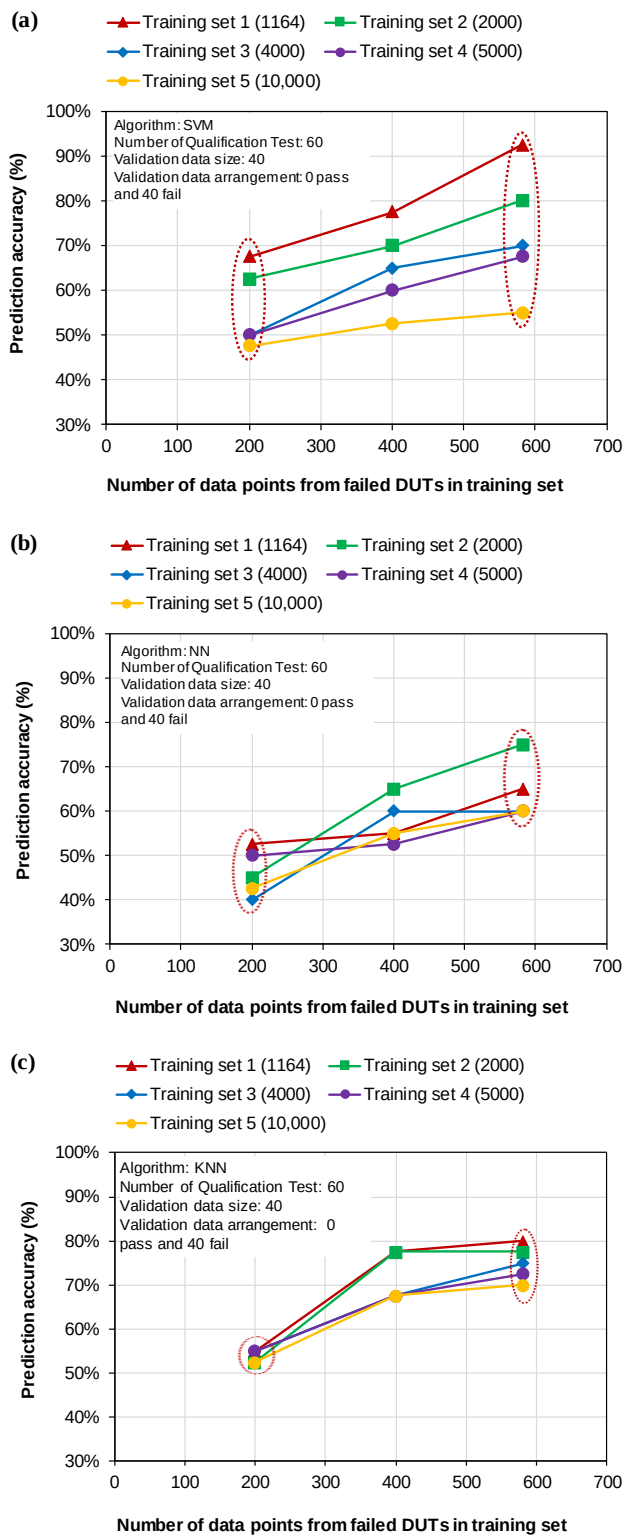


FIGURE 10. Effects of size of training dat sets on the prediction accuracies obtained by (a) SVM (b) NN and (c) KNN algorithms.

It should be noted that in all training sets, the maximum number of fail data is limited to 582, while only an increase in number of pass data makes the changes in the size of the training sets.

A general trend is very clear from the Fig. 10 that if the ratio of the pass and fail data in the dataset becomes closer to one, the prediction accuracy gradually increases for all sizes of training sets and for algorithms employed in this study. Therefore, the best accuracy is obtained for any particular training set and algorithm when the number of the fail data included in the training set is at its maximum of 582 records.

For SVM algorithm, if the size of the training set increases, the prediction accuracy gradually decreases. A study by Raikwal and Saxena et al. [28] on predicting future disease found that the prediction accuracy measured by SVM algorithm increased with the size of the training data set. However, the results found in this investigation does not agree with the results found in the literature. This could be due to the fact that in this case although the training data set size increases but the number of fail data in all sizes of the training sets remain constant; only the pass data number increases. As it is the primary interest to predict the fail outcome, the increase in pass data number in the training sets makes the prediction accuracy worse. For KNN, a similar trend of decreasing prediction accuracies with the training set sizes was observed. On the other hand, for NN, no clear trend in the prediction accuracies was observed when the size of the training data sets increased.

It is interesting to note that for all algorithms, when the number of fail data in the training sets is 200, the dispersions of the prediction accuracies is much narrower compared to that when the number of fail data in the training sets is 582. The exact reason for this is not quite clear. However, for any number of fail data in the training sets, minimum and maximum dispersions were found in the results obtained by KNN and SVM algorithms respectively. This means that the effect of size of training data sets on the prediction accuracy in KNN is smaller than in SVM.

D. COMPARATIVE ANALYSIS AND DISCUSSIONS

When all the results are plotted for each training set and algorithms (Fig. 11), it is very clear that overall, SVM provides the best prediction accuracy (92.50%) and KNN provides the second best prediction accuracy (80%) for the smallest size (1164) of the training set where the ratio of fail to pass data is 1.0. However, NN provides the best prediction accuracy (77.50%) for the Training set 2 (2000).

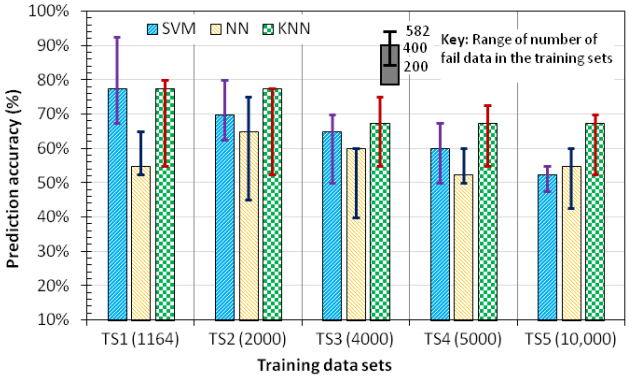


FIGURE 11. Range of prediction accuracies obtained by SVM, NN and KNN models built with different training datasets.

For the largest training set size (10,000), KNN provides the best accuracy (70%) than that by NN (60%) and SVM (55%). Therefore, SVM should be used for the smaller size data set but for the larger size data set with the same number of fail data (582), KNN is recommended to achieve the best performance. In addition, a clear trend of continuous decrease in prediction accuracies with the increase of training set size was observed for SVM and KNN, although the trend is unpredictable for NN. However, in general, an increase in training data size should improve the prediction accuracy. This could be due to a decrease in fail to pass ratio with an increase in the training data size. This can be explained by an increasing trend of prediction accuracies with an increase of the fail to pass ratios as shown in Fig. 12. It is interesting to note that for the same ratio 0.04 (S4C: 200/4800 and S5B: 400/9600 in Table I), higher number of fail data in the training set has increased the prediction accuracies for all three algorithms. Similar trend was also noticed for ratio 0.11 (S24C: 200/1800 and S3B: 400/3600 in Table I). Therefore, the increase of fail to pass ratio in training data sets positively using historical datasets of measured parameters (i.e. this is the data on the qualification test measurements of electrical parameters) and associated data of the observed outcome (in this study this is the qualification influence the prediction accuracy of the qualification tests outcome with the ratio being 1 producing the best prediction result.

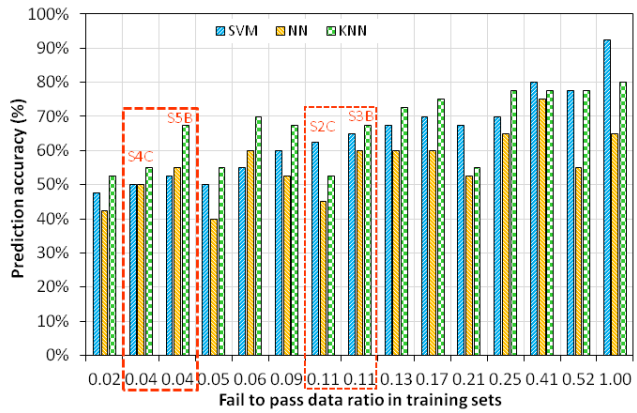


FIGURE 12. Range of prediction accuracies obtained by SVM, NN and KNN models built with different training datasets

Further work can focus on different ways of designing the training and validation data sets, for example by uncovering certain data attributes dependencies and using data records from selected devices in a more intelligent way. Further prognostics models can be developed by using different deep learning algorithms to compare their performances with the algorithms employed in the present study.

VII. CONCLUSION

This study has intended to the formulation and the development of a computational approach, which can be applied to optimise qualification test procedures of electronic products by reducing test times through imbedded in-line model-based prognostics. It is established from this investigation that data-driven predictive models in the domain of machine learning such as SVM, NN and KNN are capable of predicting the pass/fail qualification test outcomes of sequentially performed measurements on electrical parameters with accuracy, which might be acceptable for many applications in electronics manufacturing. Out of total 95 numerical tests in the full qualification specification, the researched models, developed assuming data availability form 60 tests, are shown to be able to predict the testing outcome (pass or fail) for the remaining tests with an acceptable accuracy. Such in-line prognostics in the instance of the problem will enable an approximate 37% reduction in the numerical tests saving significant cost and qualification test time for the electronic product manufacturers. .

The developed approach and the associated models investigated and tested in this work which were developed and tested with rigour using comprehensive datasets from historical qualification data on an electronic module. For all models and training sets, the prediction accuracies were found to improve when the ratio of the number of fail to pass data points used in the training sets increase to 1. Therefore, it is important to maintain balance between pass and fail data in the training sets and to make their respective sizes as equal as possible and as large as possible. The results from this investigation have shown that machine-learning models built from such balanced datasets show better prediction accuracy of the qualification test outcomes. This improvement is consistent when the validations are conducted with the data sets containing either a combination of pass and fail data or only fail data. Overall SVM models showed better prediction accuracies (92.50%) over the KNN (80%) and NN (77.50%).

The proposed approach to optimise qualification times through use of ML techniques and imbedded model-based prognosis of qualification test outcomes has the potential to transform current practices of undertaking comprehensive, time consuming and expensive tests on electronic parts and in general electronic products. This can have huge impact as it can cut cost of qualification testing in applications that can tolerate the accuracy of the model forecast.

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Mominul Ahsan is a Postdoctoral Researcher in the Department of Engineering, Manchester Met University. He completed his PhD degree in 2019 from the School of Computing and Mathematical Sciences at University of Greenwich, London, UK. Mr. Ahsan has obtained his MEng by Research degree form the Faculty of Engineering and Computing at Dublin City University, Dublin, Ireland in 2014 and Bachelor Degree in Computer Science and Engineering from Dhaka, Bangladesh in 2008. Mominul's research interests include prognostics, data analytics, machine learning, reliability, power electronics, and wireless communication. He is currently a member of Institution of Engineering and Technology (IET), associate member of Bangladesh Computer Society (BCS), a recipient of PhD scholarship at University of Greenwich in 2014, and Excellent Poster Award in the International Spring Seminar on Electronic Technology in 2017.

Stoyan Stoyanov (M'08–SM'16) received the BSc degree in mathematics from Sofia University, Bulgaria in 1994 and the MSc degree in applied mathematics from the same institution in 1996. He has obtained his PhD degree in computational engineering at University of Greenwich, London, United Kingdom, in 2004. Since 2004, he is a member of the Computational Mechanics and Reliability Group (CMRG) at the School of Computing and Mathematical Sciences at University of Greenwich, London, UK.

In 2009 he was promoted from the position of Senior Research Fellow to Reader in Computational Engineering and Optimization. His research interests include the development and application of modelling and simulation tools for numerical analysis of the performance and reliability of electronics products and microsystems, physics-of-failure modelling, computational intelligence for data-driven and prognostics modelling, additive manufacturing and design optimization. He has published over 90 peer-reviewed papers.

Dr. Stoyanov is a member of the IEEE Electronics Packaging Society and a member of the Steering Committee of the IEEE International Spring Seminar on Electronics Technology. Dr. Stoyanov holds Fellowship of the UK's Higher Education Academy. In 2009 his team received the UK's Times Higher Education Award for Outstanding Engineering Research Team of the Year.

Chris Bailey (M'03-SM'05) received his PhD in Computational Modelling from Thames Polytechnic, UK, in 1988, and an MBA in Technology Management from the Open University, UK, in 1996. He then joined Carnegie Mellon University as a Research Fellow within the Department of Materials Science from 1988-1991. Returning to the UK, he joined the University of Greenwich in London as Senior Research Fellow and in 2001 he obtained a Professorship in Computational Mechanics and Reliability.

Professor Bailey is Director of the Computational Mechanics and Reliability Group at the University of Greenwich, London, United Kingdom. His research interests include Prognostics and Health Management, Engineering Reliability, Embedded and Smart Systems, Optimization, Computational Mechanics, Multi-physics modelling, Maritime Engineering, Structural Analysis, Micro and Nano Systems and Additive Manufacturing. He has published over 250 papers in the field of modeling and reliability of micro-technology based processes and products and consults with a number of companies worldwide.

Professor Bailey is VP (Conferences) on the board of governors of IEEE-EPS, member of the Heterogeneous Integration Roadmap team, Chair of the UK&RI IEEE EPS/Reliability chapter, and an associate editor of the IEEE CPMT Transactions. He is also a member of several IEEE conference committees including EuroSime, ESTC and EPTC. He is also an executive member of the EPSRC funded Centre for Power Electronics in UK.

Alhussein Albarbar is a Reader at the Department of Engineering, Manchester Met University. He has well over 27 years of industrial working experience and as an academic active researcher. Alhussein led and participated in over $7M of major projects and supervised over 21 research degrees including 15 doctoral studies. He has published 3 books, 5-book chapters, over 100 technical papers in refereed journals and international conference proceedings. His current research activities include Industry 4.0 applications, renewable power systems, smart sensing, intelligent control and monitoring algorithms used for electromechanical power plants.