A Novel Methodology for Health Assessment in Printed Circuit Boards

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ABSTRACT

The demand for Printed circuit boards (PCBs) has increased due to the rapid change in technology in recent years. Consequently, PCBs health assessment and fault detection play an important role in improving productivity. This study proposed a novel method which focused on feature engineering for health assessment in PCBs. The performance of the proposed method has been validated using data obtained from PHM Europe 2022 data challenge. In this data challenge, PCBs health assessment needs to be performed with data from the Solder Paste Inspection (SPI) and the Automated Optical Inspection (AOI) machine. The challenge has three tasks: 1) Predict the labels of the AOI machine using the SPI data. 2) Using both the SPI and AOI machine data, predict the operator's verification that the AOI machine correctly detected a defect. 3) With the SPI and AOI data, predict the classification of the defective PCBs as either repairable or unrepairable. The component level features are extracted from the original SPI and AOI data which contain the pin level features to solve these tasks. Two machine learning-based classification models, i.e., Light Gradient Boosting Machine (LightGBM) and eXtreme Gradient Boosting (XGBoost), have been used for classification purposes. Training data given by the organizer was divided into 70% training and 30% validation. Based on the validation data, the highest F1-score was observed with LightGBM in Tasks 1 and 2, whereas, in Task 3, the highest F1-score was observed with the XGBoost model. Hence, the LightGBM model has been used in Tasks 1 and 2, and the XGBoost model was developed for Task 3.

Keywords: Diagnosis, PCB, Classification, Feature Engineering

1. INTRODUCTION

A printed circuit board (PCB) goes through the printing machine, which laser prints serial numbers onto the PCB and applies solder paste according to a predefined structure. The PCB production line is equipped with automated, integrated and fully connected machines that gather data at different stages of production. The electronic components of an electric circuit board (ECB) rely on the solder joint to provide the electrical connection to the PCB (Lee et al., 2002). PCBs demand has been increased due to digitalization and the implementation of Industry 4.0. Thus, their reliability needs to be improved to increase productivity. Consequently, PCBs fault diagnosis plays an important role in technological development. Several approaches have been developed for PCBs health assessment and fault diagnosis in the past few years.

For instance, Wu et al. (2021) proposed two target detection network approaches for health assessment and fault detection of PCBs. Image datasets of PCBs with 6 kinds of defects are used for training and validation purposes. The proposed methodologies show high prediction performance in both health assessment and fault detection tasks. Nayak et al. (2017) suggests a PCB fault detection algorithm using image processing. PCB images are used to train the algorithm and detect the faults before the etching process. Al-Obaidy et al. (2017) developed a fault detection model for PCBs employing thermal image processing. Three algorithms were performed: multilayer perceptron, adaptive neuron-fuzzy and support vector machine. In Chang et al.'s work (2019), Solder Paste Inspection (SPI) data is used to enhance the solder joint's detection performance, which is a type of defect for PCB. This study indicates that the combination of SPI and Automated Inspection (AOI) can make a system with high detectability for PCB faults.

Our present work proposes a novel technique for PCB health assessment using machine learning classifiers such as LightGBM and XGBoost. The significant contribution of this study is to identify novel features for an accurate health assessment. The data from the PHM Europe (PHME) 2022 data challenge has been used to show the performance of the proposed methodology. The PHME data challenge for the year 2022 features a dataset from an actual industrial application of an ECB production system (PHM Europe Data Challenge, 2022), as shown in Figure 1. The PCB is transferred to a SPI machine, which assesses the quality of the solder by determining various characteristics of the solder's placement, such as the volume, area, size, and offset from the desired position of solder. It extracts rich metadata up to the pin level of each component in every image of a particular panel. The data is indexed according to the laser inscriptions on the PCB. The PCB now goes through the Surface Mount Device (SMD) placement machine which assembles various components on the PCB's wet solder paste at predefined locations. This assembled PCB goes through a reflow oven which reflows the solder paste to create permanent solder joints between the PCB and the assembled components. Figure 2 illustrates a PCB after solder and component placement (PHM Europe Data Challenge, 2022).

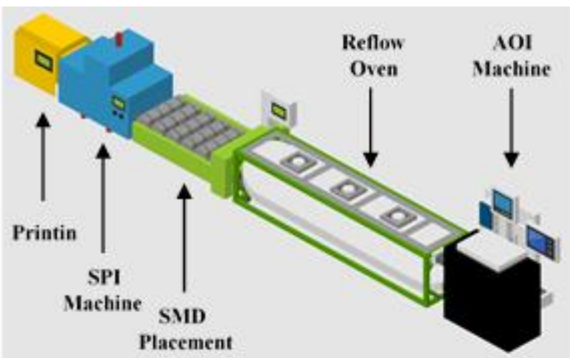

Figure 1: *ECB Manufacturing Process (PHM Europe Data Challenge 2022)*

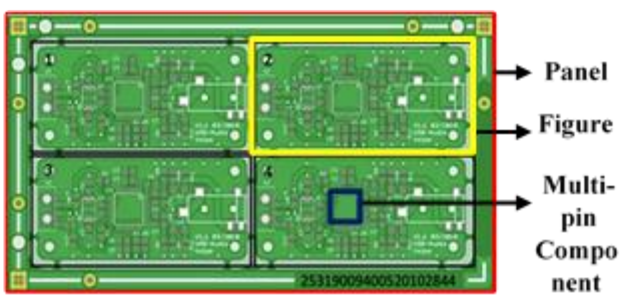

Figure 2: *Electronic Circuit Board Panel Process (PHM Europe Data Challenge 2022)*

Once the components form permanent solder joints, ECBs go through an AOI machine. The AOI machine automates the visual solder joint inspection and therefore requires the extraction of information from the solder joint surface (Kim et al., 1996). This machine uses a non-contact visual inspection method to detect and classify a solder joint's surface defects (Moganti et al., 1996). It inspects different aspects of the PCB after component placement and solder reflow, like, misalignment, size and fillets of solders, missing components or solder paste, etc.

After this stage of AOI inspection, operators (humans) are employed to verify that the AOI machine did not falsely label the PCB as defective. The operators also further classify the truly defective PCBs into different types before considering any repair work. The structure of this inspection process is outlined in Figure 3. Data is provided with labeled data from SPI and AOI machines. Using this data, three tasks have to be completed 1) Using only the SPI data, predict the labels of the AOI machine. 2) With both the SPI and AOI machine data, predict whether the operator will verify that the AOI machine correctly detected a defect or will label it as a false positive. 3) Classify, with the SPI and AOI data, the defective PCBs as either non-repairable or as PCBs that should not be scrapped.

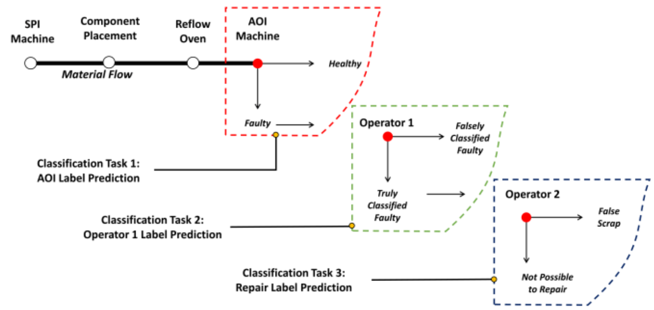

Figure 3: *Data analysis for replacing actual inspection tasks*

The dataset consists of two data types, each from a different source: the SPI machine and the AOI machine. The data from the SPI contains the attributes of the solder paste placed on the PCBs. The AOI data contains the AOI labels, operator labels, and repair labels. Every dataset contains a panel I.D., a figure I.D., and a component I.D. These three I.D.s can be used together as unique I.D.s for indexing the data. Any classification task would predict labels for the combination of these three I.D.s. This is helpful for predicting classification labels at the component level. Any unique I.D. from the SPI dataset, which can also be found in the AOI dataset, is labelled as faulty. If the unique I.D. from the SPI dataset is not found in the AOI dataset, the respective component is considered healthy.

2. PROPOSED METHODOLOGY

Figure 4 shows the proposed methodology for solving the three tasks in the present study. The data is first cleaned for any instances of missing values. It is then indexed according to the combination of the Panel_ID, Figure_ID, and Component_ID. All data columns are then converted to numeric formats, and the ones which cannot are discarded.

The proposed methodology focuses mostly on feature engineering and uses readily available machine learning libraries for model building. Individual task features have been engineered and ranked according to their suitability for performing the given tasks. Feature engineering combines multiple raw data features by applying various mathematical operations.

Indexing the data in the aforementioned manner enables data analysis at the component level. The original dataset, however, contains observations at the pin level. Hence, each combination of the aforementioned I.D.s will have the number of observations equaling the number of pins for a particular component. To combine the data of all pins of a single component, aggregation of each raw data variable is performed. This aggregation leads to the extraction of statistical features like mean, standard deviation, variance, etc.

Feature engineering was performed over the raw data by extracting the statistical features by aggregating the data at the component level. Finally, this dataset was then divided into a training data set with 70% of the whole data and a validation dataset with the remaining 30% while keeping the ratio of healthy to faulty classes equal to that of the original dataset. This preservation of the ratio is done by stratifying the class labels.

The proposed methodology uses two tree-based gradient boosting algorithms, LightGBM and XGBoost. After an F1-score comparison of these algorithms for different tasks, the LightGBM model was chosen and used for classification tasks1 and 2. For task 3, the XGBoost classifier model was used. Figure 4 outlines the proposed methodology for model training and evaluation.

A detailed description of the features and the reasoning for choosing different classifier models for different tasks is discussed in the next section.

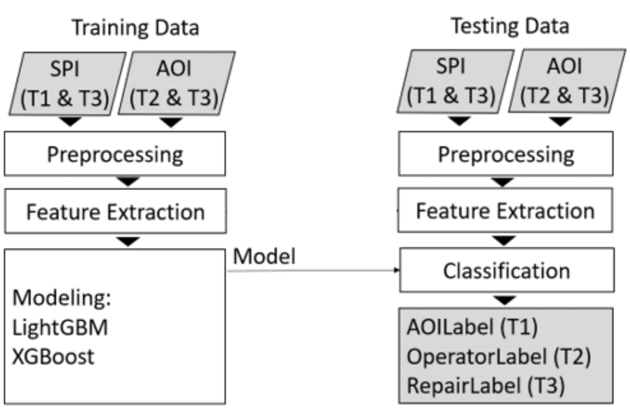

Figure 4: *Proposed Methodology*

3. Results and Discussion

3.1. Task 1: Predicting AOI Labels

The classifier model for Task 1 is expected to predict whether a data instance similar to the ones in the SPI raw dataset would be classified by the AOI machine as healthy or faulty. Special emphasis is given to position-based features since misalignment of solder paste is a leading factor in the PCB being classified as faulty (Chuang et al., 2010)

3.1.1. Data preprocessing:

The data is first cleaned by deleting all instances with null values in Panel_ID, Figure_ID and Component_ID. Data rows containing null values are also erased from the dataset. All data columns are then converted to numeric format to perform arithmetic operations.

3.1.2. Feature Extraction:

This step would include variable generation and statistical feature extraction.

Variable Generation:

Spatial and positional variables have been generated using arithmetic combinations of raw data variables. Along with 12 raw data variables and 6 additional variables, namely, the Total Height, Hypotenuse, Polar Coordinate, Circular Area, Rectangular area and Offset Area, are generated. These variables are generated at the pin level, as shown in the variable column of Table 1.

Statistical Features:

The raw data variables are aggregated with the generated variables at the component level. Several rows of observations for different pins of a single component are aggregated to extract statistical values. The statistical features extracted for this task contain: mean, standard deviation, variance, count, minimum value, maximum value and median. This process reduces the size of data while preserving the information from the raw data in terms of statistical values. Table 1 lists all the features extracted from the raw dataset along with the generated data variables.

Table 1*: List of Features for Task -1*

Pin Level Features		Operation Required	Component Level Features	
Sr. No.	Variable Name		Feature No.	Feature Name
[1]	Volume(%)	NA	01 - 07	{mean, std, var, count, min, max, median}
[2]	Height(um)	NA	08 - 14	{mean, std, var, count, min, max, median}
[3]	Area(%)	NA	15 - 21	{mean, std, var, count, min, max, median}
[4]	OffsetX(%)	NA	22 - 28	{mean, std, var, count, min, max, median}
[5]	OffsetY(%)	NA	29 - 35	{mean, std, var, count, min, max, median}
[6]	SizeX	NA	36 - 42	{mean, std, var, count, min, max, median}
[7]	SizeY	NA	43 - 49	{mean, std, var, count, min, max, median}
[8]	Volume(um3)	NA	50 - 56	{mean, std, var, count, min, max, median}
[9]	Area(um2)	NA	57 - 63	{mean, std, var, count, min, max, median}
[10]	Shape(um)	NA	64 - 70	{mean, std, var, count, min, max, median}
[11]	PosX(mm)	NA	71 - 77	{mean, std, var, count, min, max, median}
[12]	PosY(mm)	NA	78 - 84	{mean, std, var, count, min, max, median}
[13]	Hypotenuse	= sqrt({6}^2 + {7}^2)	86 - 91	{mean, std, var, count, min, max, median}
[14]	Rectangular_Area	= {6} * {7}	92 - 98	{mean, std, var, count, min, max, median}
[15]	Total_Height	= {2} + {10}	99 - 105	{mean, std, var, count, min, max, median}
[16]	Circular_Area	= π *({13}^2)	106 - 112	{mean, std, var, count, min, max, median}
[17]	Offset_Area	= π *({13}^2 + {5}^2)	113 - 119	{mean, std, var, count, min, max, median}
[18]	Polar_Coordinate	= sqrt({11}^2 + {12}^2)	120 - 126	{mean, std, var, count, min, max, median}

3.1.3. Modelling:

After statistical feature extraction, the resulting feature pool consists of 126 distinct data features.

The dataset used for training the task 1 classifier is the highly imbalanced SPI data (98.7% Healthy Class, 1.3% Faulty Class). Due to the highly imbalanced nature of SPI data, the simplest classifier would yield high accuracy but low recall models. Hence, a better metric to assess the performance of the classifier would be the F1 score for the minority class (faulty PCBs). The performance of the LightGBM model in terms of F1-score was compared and found to be better than the XGBoost model for task 1, as shown in Table 1.

***Table 2:** F1-score comparison for Task 1*

Type of Classifier	F1-Score	
	Training Data set	Validation Data set
XG-Boost	0.32	0.31
Light-GBM	0.43	0.42

The Light-GBM model for Task 1 considers the values of the hyperparameters as follows: learning rate of 0.1 and boosted trees of 100. Figure 5 represents the top ten features obtained from the LightGBM classifier model while training.

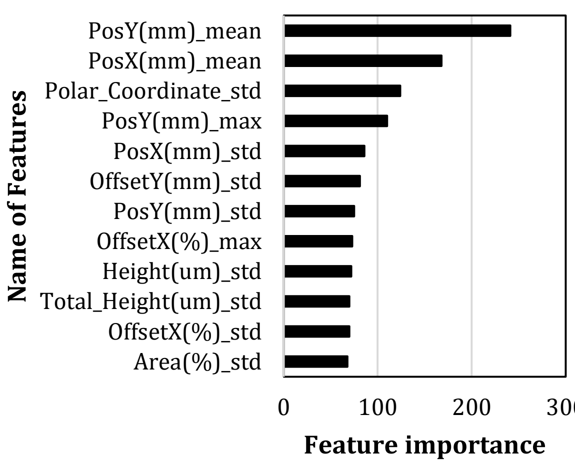

***Figure 5:** Feature Importance for Task 1*

Predictions:
Based on the best trained LightGBM model, an F1-score of 0.44 was observed on the unseen test data set.

3.2. Task 2: Predicting Operator Labels

For task 2, predicting the operator label based on SPI and AOI data is the objective. The presented approach includes steps such as data preprocessing, feature extraction, and modeling.

3.2.1. Data preprocessing:

All samples that have null values in the Panel_ID, Figure_ID or component I.D. are erased. Furthermore, all continuous values that are in a string format are converted into a numeric format.

3.2.2. Feature Extraction:

The feature extraction step considers two datasets: AOI and SPI data. A data pivoting technique (Kim et al., 2019) is applied to the AOI data. Eleven features corresponding to the eleven AOI fault modes (AOILabel) in the training data are generated by this technique. The value of the new features is the count of each failure mode per component. In Figure 6, an example of data pivoting for two fault modes is shown.

PanelID	FigureID	ComponentID	AOILabel
13	1	C5	Coplanarity
14	2	C4	Coplanarity
15	3	C8	LeanSoldering
16	4	C2	Coplanarity
17	5	C7	LeanSoldering
17	5	C7	LeanSoldering

PanelID	FigureID	ComponentID	Number of Coplanarity	Number of LeanSoldering
13	1	C5	1	0
14	2	C4	1	0
15	3	C8	0	1
16	4	C2	1	0
17	5	C7	0	2

***Figure 6** Data conversion to pivot table*

Moreover, the total number of AOI fault modes and the number of unique AOI fault modes per component are also considered features. Additionally, the component type and number are extracted from the component I.D. variable. This feature can be extracted either from the SPI or AOI data. The list of extracted features is described in Table 3.

***Table 3** Features list for AOI Data*

Feature Number	Feature Name
1	Number of Soldered
2	Number of UnSoldered
3	Number of Coplanarity
4	Number of LeanSoldering
5	Number of Translated
6	Number of Size
7	Number of Misaligned
8	Number of Missing
9	Number of Broken
10	Number of Jumper
11	Number of Polarity
12	Total number of AOI labels
13	Total number of unique AOI labels
14	Component type (ex. C, R)
15	Component number (ex. 5)

Due to the low frequency in the training data of the AOI fault modes "Missing", "Broken", "Jumper", and "Polarity", they are considered as "others" and grouped together. This grouping approach reduces the number of features generated from AOI from fifteen to twelve.

For SPI data, statistical features are extracted from the pin level to the component level. Using SPI data, features such as minimum, maximum, and mean values of Volume(%), Height(um), Area(%), OffsetX(%), OffsetY(%), SizeX, SizeY, and Shape(um) are extracted.

Table 4 *Features list for SPI Data*

Feature Number	Feature Name
1-3	Volume(%) (max, min, mean)
4-6	Height(um) (max, min, mean)
7-9	Area(%) (max, min, mean)
10-12	OffsetX(%) (max, min, mean)
13-15	OffsetY(%) (max, min, mean)
16-18	SizeX (max, min, mean)
19-21	SizeY (max, min, mean)
22-24	Shape(um) (max, min, mean)

3.2.3. Modeling

Similar to task 1, two algorithms are used and compared for modelling: LightGBM and XGBoost. Each algorithm is trained using cross-validation ensemble to enhance robustness.

Furthermore, three combinations of features were performed: only AOI features, only SPI features, and both AOI and SPI features. As shown in Table 5, models that use only the AOI features perform better than the other attempted approaches.

The model leads to overfitting using AOI-SPI features and only using SPI features. Thus, only the AOI features are used, and LightGBM is selected due to its higher F1 performance than XGBoost.

Table 5 *F1-score calculation using different classifiers*

Type of Classifier	AOI data		SPI data		AOI-SPI data	
	Train	Val	Train	Val	Train	Val
XGBoost F1-Score	0.66	0.68	0.65	0.34	0.78	0.62
LightGBM F1-Score	0.69	0.69	0.66	0.33	0.71	0.61

The LightGBM model for Task 2 considers the hyperparameters such as a learning rate of 0.2 and a count of boosted trees of 5000. The feature importance ranking given by the LightGBM classification model is shown in Figure 7.

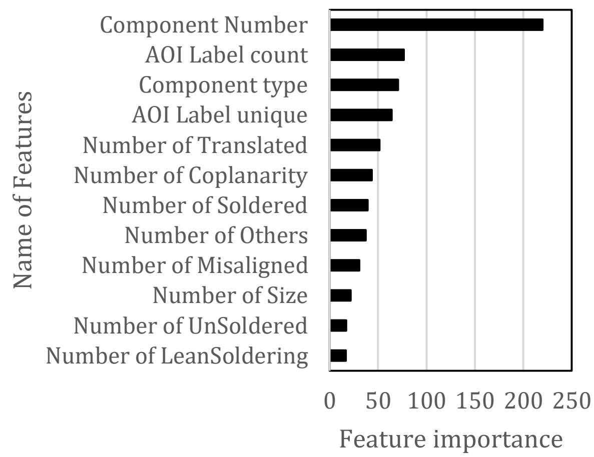

Figure 7 *Feature importance ranking*

Predictions:
The classification model gives probabilities as its output. Then, the probabilities are used to calculate the optimal threshold to maximize the F1-score of the validation data. The thresholds are obtained using the package 'metric' from the Sklearn library. The optimal threshold is obtained by iterating all possible thresholds and selecting the one that provides the maximum F1-score for the validation data. The approach for task 2 gives an F1-score of 0.48 in the unseen test data.

3.3. Task 3: Predicting Repair Labels

The objective of Task 3 is to predict the Repair Labels based on SPI and AOI data. Similar to other tasks, the approach includes steps such as data preprocessing, feature extraction, and modeling.

3.3.1. Data preprocessing:

Similar to task 2, null values in the Panel_ID, Figure_ID or Component_ID are erased from SPI data. Also, all continuous values have been converted into the float type.

3.3.2. Feature extraction

The solution for task 3 first uses the component level features instead of the pin level features like the solutions for the other tasks. In this task, 17 variables are already available from SPI and AOI data, and additional 11 variables shown as serial numbers 18 to 28 in Table 6 are formed using the existing 17 variables. From these 28 pin level variables, component level features have been created from pin level features which have the same Panel_ID, Figure_ID, and Component_ID. These features are calculated based on statistical metrics such as mean, sum, standard deviation, maximum, minimum, peak-to-peak, median, and count. A total of 153 component-level features have been extracted, as shown in Table 6.

Table 6 Features extracted for Task 3

Pin Level Features				Operation Required	Component Level Features	
Sr. No.	Variable Name	SPI	AOI		Feature No.	Feature Name
[1]	Volume(%)	X			01-06	{mean, std, var, count, min, max, median}
[2]	Height(um)	X			07-12	{mean, std, var, count, min, max, median}
[3]	Area(%)	X			13-18	{mean, std, var, count, min, max, median}
[4]	OffsetX(%)	X			19-24	{mean, std, var, count, min, max, median}
[5]	OffsetY(%)	X			25-30	{mean, std, var, count, min, max, median}
[6]	SizeX	X			31-36	{mean, std, var, count, min, max, median}
[7]	SizeY	X			37-42	{mean, std, var, count, min, max, median}
[8]	Volume(um3)	X			43-48	{mean, std, var, count, min, max, median}
[9]	Area(um2)	X			49-54	{mean, std, var, count, min, max, median}
[10]	Shape(um)	X			55-60	{mean, std, var, count, min, max, median}
[11]	PosX(mm)	X			61-66	{mean, std, var, count, min, max, median}
[12]	PosY(mm)	X			67-72	{mean, std, var, count, min, max, median}
[13]	PinNumber		X		73-74	{median, count}
[14]	PadType_*		X		75-76	{count} (* = 0, 10)
[15]	PinNumber_*		X		77-80	{count} (* = 0,1,2,3)
[16]	AOILabel_*		X		81-86	{count} (* = 1,2,3,4,5,6)
[17]	AOILabel		X		87	{count}
[18]	OffsetX and Y	X		= sqrt([4]^2 + [5]^2)	88-93	{mean, std, var, count, min, max, median}
[19]	SizeX and Y	X		= sqrt([6]^2 + [7]^2)	94-99	{mean, std, var, count, min, max, median}
[20]	Volume / area	X		= [8] / [9]	100-105	{mean, std, var, count, min, max, median}
[21]	Volume / Volume	X		= [9] / [1]	106-111	{mean, std, var, count, min, max, median}
[22]	PosX and Y	X		= sqrt([11]^2 + [12]^2)	112-117	{mean, std, var, count, min, max, median}
[23]	OffsetX/OffsetY	X		= [4]/[5]	118-123	{mean, std, var, count, min, max, median}
[24]	OffsetX/SizeX	X		= [4]/[6]	124-129	{mean, std, var, count, min, max, median}
[25]	OffsetY/SizeY	X		= [5]/[7]	130-135	{mean, std, var, count, min, max, median}
[26]	Volume/OffsetX	X		= [1]/[4]	136-141	{mean, std, var, count, min, max, median}
[27]	SizeY/PosY	X		= [7]/[12]	142-147	{mean, std, var, count, min, max, median}
[28]	PosX/PosY	X		= [11]/[12]	148-153	{mean, std, var, count, min, max, median}

3.3.3. Modeling

Two classification algorithms were tested, XGBoost and LightGBM, and the best performing model was selected. Based on these 153 features, Table 7 shows the F1-score obtained using each model. Based on the F1-score, XGBoost was found to perform better and hence has been used for model development.

Table 7 F1-score calculation using different classifiers

Type of Classifier	F1-Score	
	Training	Validation
XGBoost	0.99	0.90
LightGBM	0.87	0.89

The XGBoost model for Task 3 considers the hyperparameters such as a learning rate of 0.1 and a maximum of boosted trees of 100. The feature importance ranking given by XGBoost for this task is shown in Figure 8.

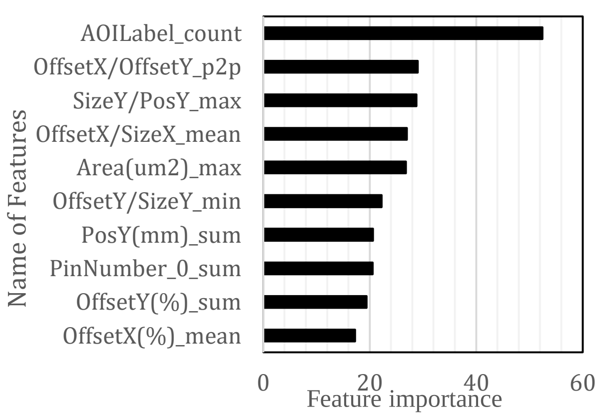

***Figure 8** Feature importance ranking*

Predictions:
The approach for task 3 gives an F1-score of 0.78 in the unseen test data.

4. CONCLUSIONS

This work has developed methodologies to detect printed circuit board manufacturing defects based on SPI and AOI data released by the PHM Society (2022). The component level features are extracted from original SPI and AOI data which contain the pin level features. The PCB health assessment problem has been divided into three tasks, and based on the extracted features, two machine learning algorithms, LightGBM and XGBoost, have been applied. It was determined that the models using LightGBM for tasks 1 and 2 had a better F1-score on the validation data set than the XGBoost models. Hence, LightGBM classification models were selected for first two tasks. The XGBoost model has been used in task 3, due to its higher F1-score compared to the LightGBM model's results. The F1-score obtained from Task 1, Task 2 and Task 3 are 0.44, 0.48 and 0.78 respectively.

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BIOGRAPHIES

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