Optimization of Solder Vision Inspection using Fiber Optic Detection and Machine Learning Application

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ABSTRACT

Product quality is the top priority in all manufacturing industries to ensure customer satisfaction. In-process inspection was a quality control method used to identify any abnormalities in the product during the manufacturing process. The most popular process inspection control was a conventional human visual inspection, where the operator conducted a 100% inspection of the product under the magnifying lamp. The developed automated optical inspection (AOI) checks and evaluates the product image condition without human intervention. However, if the target object is misaligned, the image captured by the AOI could be compromised, resulting in errors and potentially affecting the quality of the final product judgment.

In this paper, the application of fiber optic detection will be incorporated with the AOI machine to ensure the correct position of the target object (region of interest, or ROI) before the inspection process. A machine vision algorithm will process all images acquired from the AOI machine. Machine learning K- Nearest Neighbor (KNN) classifier will guarantee that the AOI machine vision judgment meets the required performance metrics, such as accuracy, precision, recall, F1 score, and ROC AUC.

Keywords: Automated Optical Inspection (AOI), K Nearest Neighbor (KNN), Machine Learning (ML), Fiber Optic, Region of Interest (ROI)

1. INTRODUCTION

In-process visual inspection is crucial for ensuring the production of high-quality products according to the company's standards. The operator randomly selected samples from identified critical processes to conduct a 100% quality visual inspection of the product to check if abnormalities occurred after machine processing. Implementing manual visual inspection, shown in Figure 1, will improve productivity and product quality [1].

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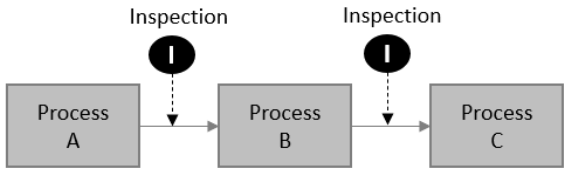

***Fig. 1**: In Process Inspection Flow.*

***Fig. 2**: Traditional Manual Visual Inspection [4].*

The traditional manual approach to visual inspection, shown in Figure 2, relies on a human operator visually inspecting every product from the production line to ensure it meets the company's quality standards. However, human inspection has a significant drawback: it is highly subjective, as the accuracy of the assessment depends on the operator's expertise and health condition [2]. Manual inspection observed a 70%-80% inspection accuracy level [3]. The prejudiced judgment may result in a product defect escapee that leads to product failure in the customer end user.

The Automated Optical Inspection (AOI) machine, shown in Figure 3, was developed to supplement manual human inspections and ensure consistent product vision inspection. AOI is a commonly adopted technology in manufacturing industries as an automated vision inspection system that captures images and measures critical parts of a product using a high-magnification optical camera.

The automated optical inspection system captures images with excellent precision and accuracy; however, product placement on the pallet is crucial. Any misalignment of the pallet can significantly impact image

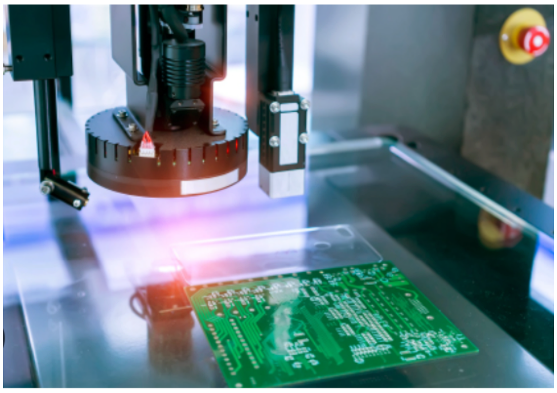

***Fig. 3**: Automated Optical Inspection (AOI) [5].*

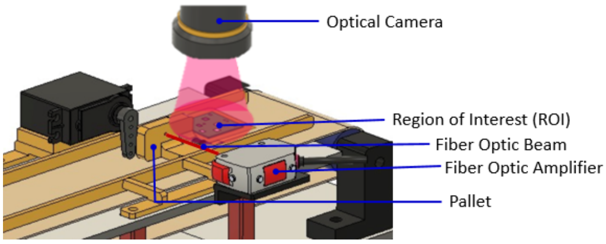

***Fig. 4**: Inspection System with Fiber Optic Detection.*

capture, particularly on the ROI (region of interest). This misalignment can affect both image quality and measurement accuracy. A fiber optics sensor, designed to detect the pallet, was integrated with the AOI machine to ensure that the product was accurately positioned on the pallet, perpendicular to the center of the optical camera's focal lens, as shown in Figure 4.

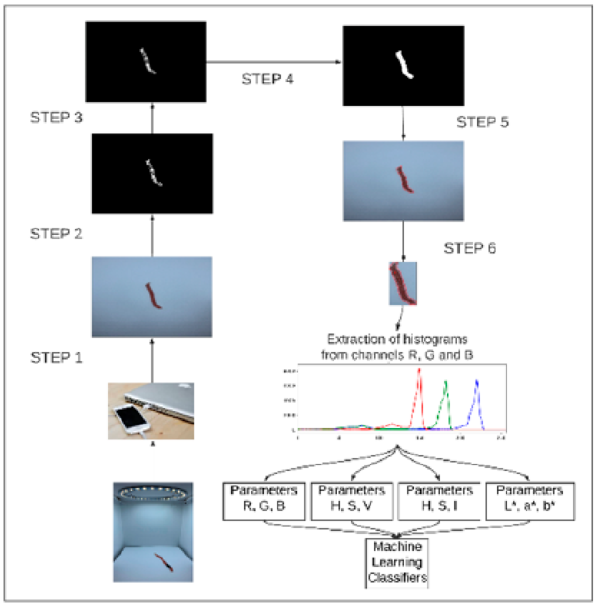

***Fig. 5**: Image Processing for Tuna.*

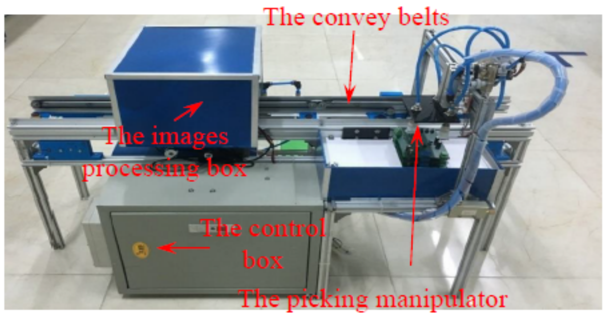

***Fig. 6**: PCB Real-Time Automated Inspection System.*

2. REVIEW OF RELATED WORKS

The authors of the study Computer Vision and Machine Learning for Tuna and Salmon Meat Classification [6], Medeiros and Almeida, created a machine vision system for evaluating the freshness of salmon and tuna. The objective of the technology is to automate the current manual visual inspection process for fish. The proposed system consists of picture-capturing hardware and software protocols, image pre-processing, and parameter extraction from RGB, HSV, HSI, and Lab* color spaces to generate datasets in the software, shown in Figure 5. The system's accuracy is measured using the K-Nearest Neighbor (KNN) machine learning technique, which achieved an accuracy rating of 86.6%.

Another related work from Nguyen and Bui, A Real-Time Defect Detection in PCB Applying Deep Learning [7], was published in 2022 and focused on using deep learning in machine learning. This study proposed a real-time automated inspection system for defect identification in printed circuit boards (PCBs), shown in Figure 6. The proposed method addresses inspection issues triggered by PCB layout complexity and component size reduction. The technique detects defective regions on the PCB surface by capturing the image characteristics and utilizing a deep learning algorithm. The accuracy of the proposed system was under two different lighting conditions: full brightness and low light intensity. One of the performance measurements displayed a high precision rate of 96.29% under full bright lighting; however, the accuracy percentage dropped from 96.29% to 83.48% using the low light intensity.

Similarly, a published paper from Zhu in 2022 regarding a Machine Vision Framework for Product Appearance Quality Inspection [8] developed and implemented an automated vision inspection machine, shown in Figure 7, using an industrial camera and other hardware equipment like a computer that serves as the central controller, an external vision light source, and an input/output (IO) communication device. Similarly to the study, they used the machine audio alarm system using a siren to notify the user if the system is abnormal.

The Developing Machine Vision System for Real-Time Automated Quality Grading of Sweet Potatoes [9], proposed by Xu and Lu, represents significant work in the paper. They developed an automated machine vision

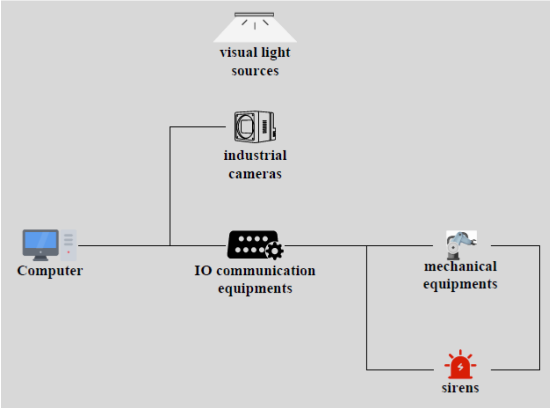

Fig. 7: Automated Vision Inspection System.

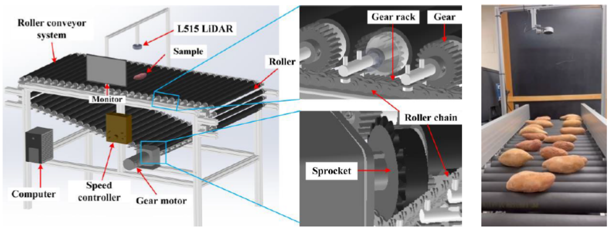

Fig. 8: Automated Machine Vision Inspection System.

system, shown in Figure 8, to improve the current human method of grading and sorting sweet potatoes. Subjective judgment, limited productivity, and high labor expenses are the drawbacks of the old approach. A camera integrated into the machine vision system captures the sweet potato's whole surface as it travels along a roller conveyor controlled by a motor. In addition to real-time tracking and defect grading, the system utilizes multi-view images to measure the length and width of individual sweet potatoes, ensuring a comprehensive inspection of their entire surface by implementing the YOLOv8 algorithm. Experimental results indicate that the overall grading accuracy achieved is 89% when assessing size and surface defects.

3. METHODOLOGY

The study used a comparative research approach to assess the difference between traditional manual and automated solder vision inspection. It compared the efficiency, quality, and effectiveness of the computerized solder vision inspection system to the conventional manual method. The methodology framework for automated solder vision inspection machines consisted of four stages, as shown in Figure 9: product loading, fiber optic detection, image processing, image (ROI) measurement, and ML classification.

A. Product Loading

The automated solder vision inspection operations start with the printed circuit board assembly (PCBA) unit loading in a pallet that fits perfectly to avoid any

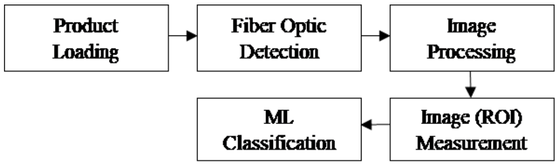

Fig. 9: Automated Solder Vision Inspection Framework.

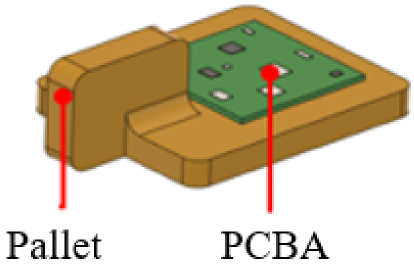

Fig. 10: PCBA Loading to Pallet.

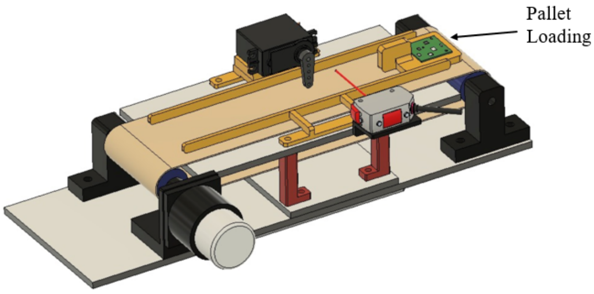

Fig. 11: Pallet Loading to Conveyor.

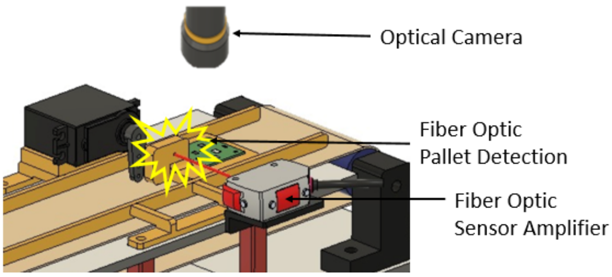

Fig. 12: Fiber Optic Pallet Detection.

movement during transport along the conveyor (shown in Figure 10).

After securely loading the PCBA inside the pallet, the operator places the pallet on a conveyor that transports it to the vision inspection system in Figure 11.

B. Fiber Optic Detection

The pallet moves towards the inspection camera until the fiber optic sensor detects the pallet, as shown in Figure 12, causing the conveyor motor to stop. The PCBA has already reached the center of the camera inspection position.

When the fiber optic sensor detects a pallet, it triggers the conveyor belt to stop, ensuring it is positioned

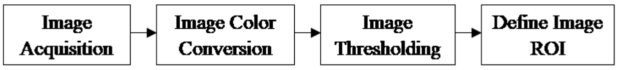

***Fig. 13**: MATLAB Image Processing Framework.*

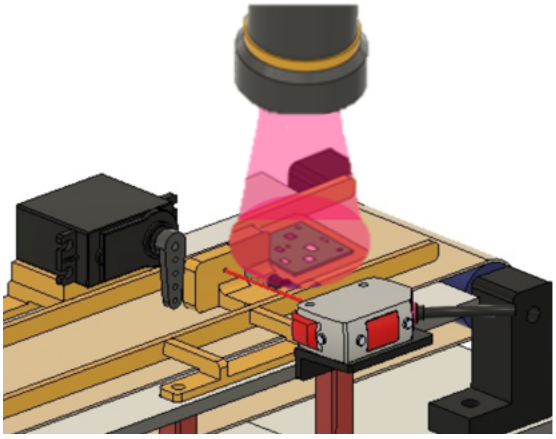

***Fig. 14**: PCBA Image Acquisition.*

precisely in the center, directly aligned with the optical camera. This exact positioning guarantees the pallet is correctly aligned for vision image capturing. By halting the conveyor belt at this specific point, the optical camera can capture a clear and accurate image of the PCBA within the defined region of interest (ROI).

C. Image Processing

Machine vision was developed in the context of technological advancements and innovative thinking, allowing for quick and precise inspections that increase the efficiency of production processes [10]. It utilizes the MATLAB image processing algorithm to acquire the PCBA image base from the region of interest (ROI). Figure 13 presents the MATLAB image processing flowchart, beginning with image acquisition and progressing to defining the region of interest.

The optical camera captures the image of the PCBA from the pallet using the MATLAB image acquisition programming script, shown in Figure 14.

The PCBA images acquired will undergo image transformation from original color to grayscale. This process removes the hue and saturation from the original images, resulting in grayscale images. The MATLAB script "rgb2gray" was used to convert all acquired images from color to grayscale, as shown in Figure 15.

After being converted to grayscale and transformed back into a black-and-white format. This operation of image thresholding produced a binary image mask, where black elements represent the binary number 1 and white areas represent the binary number 0, as shown in Figure 16.

The binary image 0 (white color) in the PCBA solder area will be considered the region of interest. The "Red Square Box" encloses the solder area or region of interest (ROI) to measure the solder area, as shown in Figure 17.

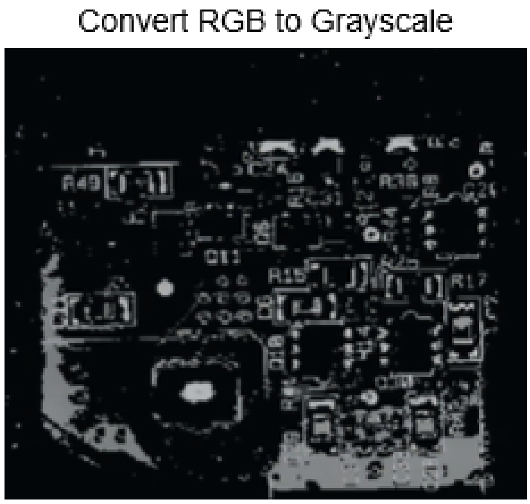

***Fig. 15**: Image Conversion to Grayscale.*

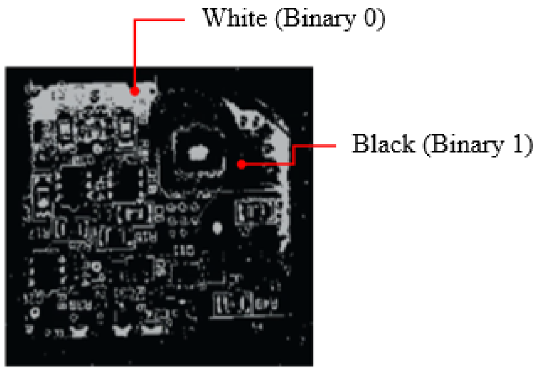

***Fig. 16**: Image Thresholding (Binary Image).*

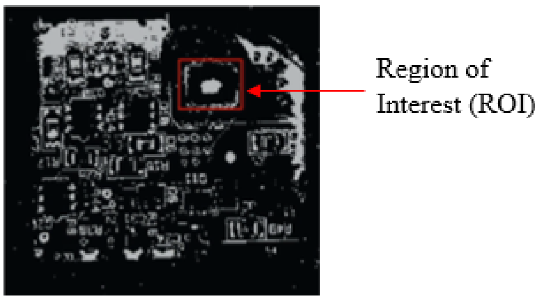

***Fig. 17**: Defined Region of Interest (ROI).*

D. Region of Interest (ROI) Measurement

The white pixels inside the bounds of the region of interest (ROI) are collected to calculate the solder area and determine whether the solder image in Figure 18 meets the specifications. The solder area was measured in the region of interest (ROI) and compared to solder area specifications to determine whether the measurement data passed or failed the judgment.

E. Machine Learning (ML) Classification

The classification process makes data identification

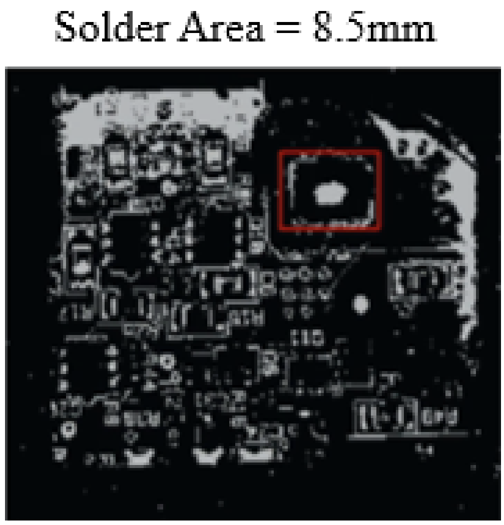

Fig. 18: *Solder Area Measurement.*

```
Command Window
Descriptive Statistic:
Number of samples: 1000
Mean: 7.64
Median: 7.67
Standard Deviation: 1.50
Variance: 2.24
Minimum: 2.31
Maximum: 11.91
Range: 9.60
---------------------------------
Category Counts:
Category      Count      Percent
    {'Fail'}     {[500]}     {[50]}
    {'Pass'}     {[500]}     {[50]}
```

Fig. 19: *Descriptive Statistic (MATLAB R2024a).*

and accessibility easier. It is essential to data security, regulatory compliance, and risk management. Data classification improves the searchability and traceability of information. Each data mining model provides a different level of information [11].

The model's accuracy was analyzed using machine learning classification techniques. All randomly selected PCBA samples were allocated for training and testing the model. Figure 19 shows the calculated average (mean) and standard deviation (sigma).

The dataset was partitioned into an 80:20 ratio, as shown in Figure 20. 80% of the data was used for training the model, while the remaining 20% was allocated for testing. This division enabled the model to learn patterns and relationships from 80% of the data during training. Subsequently, the performance and generalization capability of the model were assessed using 20% of the data. This approach ensures that the model's accuracy can be measured on unseen data, indicating how well it would perform in real-world scenarios.

```
Command Window
Number of training samples: 801
Number of testing samples: 199
```

Fig. 20: *Data Splitting (MATLAB R2024a).*

Table 1: *Machine Learning Hyperparameter Setting.*

Machine Learning Classifier	**Hyperparameter Setting**
K Nearest Neighbor (KNN)	Preset: Cosine KNN No. of Neighbor: 10 Distance Metric: Cosine Distance Weight: Equal
Support Vector Machine (SVM)	Preset: Linear SVM Kernel Function: Linear Scale (Automatic) Box Constrain Level: 1 Multiclass Coding: Ove-vs-One Standardize Data: Yes
Logistic Regression (LR)	Preset: Linear Efficient Logistic Regression Kernel Function: Logistic Regression Box Constrain Level: 1 Multiclass Coding: Ove-vs-One

The model was evaluated with different sets of hyperparameter values (shown in Table 1) utilizing K Nearest Neighbor (KNN), Support Vector Machine (SVM), and Logistic Regression (LR) classifiers. The automated solder vision inspection system measures the solder area within an identified region of interest. The measurements are scaled to fit within the specified range and are used as feature data or independent variables, as shown in Figure 21. When features are on the same scale, most machine learning and optimization methods tend to perform significantly better [12]. Additionally, scaling features to the same range improves convergence rates, accuracy, and overall performance by ensuring that every feature contributes equally to the model's learning process. Standardization and normalization techniques are commonly employed to achieve this consistency in scale.

One of the simplest and most widely used techniques for classification tasks is the k-nearest neighbors (KNN) algorithm, which is widely known for its highly flexible and simple-to-understand architecture [13]. K-nearest neighbors (KNN) is a supervised machine learning algorithm for solving classification and regression problems. It measured the similarity between features to determine the distance between a query point and each instance in the dataset. The algorithm selects the closest data points

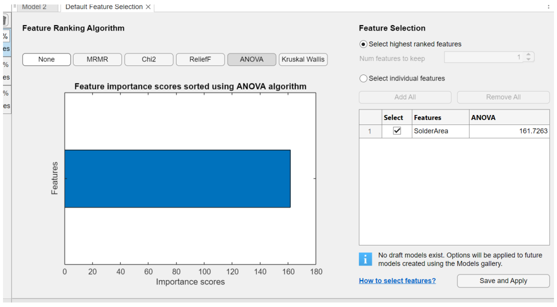

Fig. 21: Feature Scaling using ANOVA Algorithm.

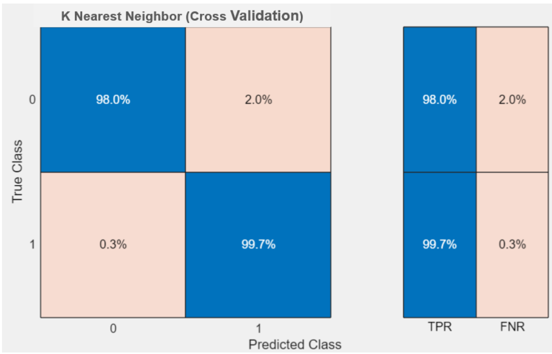

Fig. 22: Confusion matrix (Cross Validation).

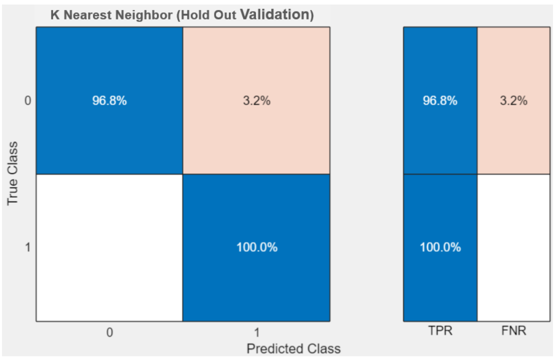

Fig. 23: Confusion matrix (Hold-Out Validation).

based on their highest frequency for classification or the average frequency for regression relative to the query and each data sample [14].

Applying the K Nearest Neighbor machine learning classification shows that the confusion matrix for cross-validation indicates a prediction accuracy of 99.7% for true positives and 98.0% for true negatives, as shown in Figure 22. The confusion matrix demonstrates that the model effectively identifies solder area measurement results for both pass and fail conditions.

Similarly, the K Nearest Neighbor confusion matrix for hold-out validation shows a 100% accuracy prediction score for true positives and 96.8% for true negatives, as shown in Figure 23.

E. Inspection Cycle Time Comparison

The machine inspection cycle time (shown in Figure 24) was evaluated using the proposed automated solder

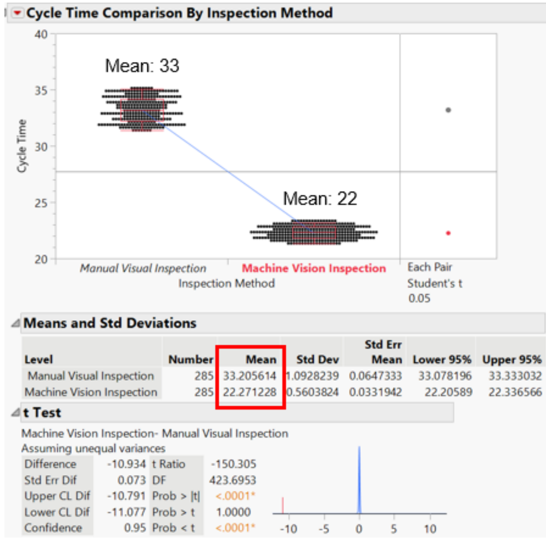

Fig. 24: Cycle Time Comparison Result.

vision inspection system and compared to the conventional manual vision inspection process performed by an operator

4. RESULTS AND DISCUSSION

The proposed automated solder inspection system presents an innovative approach by integrating fiber optics detection technology with machine learning-based vision applications, improving upon the traditional manual visual inspection performed by operators. The fiber optic sensor is employed to ensure proper positioning of the PCBA before capturing images with the camera. Various machine learning techniques are also explored to ensure product quality after machine vision inspection, providing highly accurate inspection results.

The machine learning model underwent training and testing using K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Logistic Regression (LR) classifiers. The dataset was partitioned into an 80:20 ratio, with 80% allocated to the training set and the remaining 20% to the testing set. The test validation results indicate that the K-Nearest Neighbor (KNN) classifier algorithm achieved the highest accuracy performance metrics score of 98.90% for hold-out validation and 98.99% for cross-validation, as shown in Figure 25.

The Support Vector Machine (SVM) is a kernel-based machine learning model for classification and regression tasks [15]. Its primary objective is to find the optimal decision boundary or hyperplane that separates the data into distinct sections, allowing for the accurate classification of new data points. However, one major drawback of SVM is its inefficiency in handling large datasets, as it demands considerable training time. Additionally, working with imbalanced datasets might compromise the model's accuracy.

The model was trained and tested using the support vector machine (SVM) machine learning classifier. The

```
Command Window
Performance Metrics: Mean - Hold Out Validation
--------------------------------------------
Accuracy: 0.9899
Precision: 1.0000
Recall: 0.9808
F1 Score: 0.9903
ROC-AUC: 0.9850

Performance Metrics: Mean - Cross Validation
--------------------------------------------
Accuracy: 0.9890
Precision: 0.9980
Recall: 0.9800
F1 Score: 0.9889
ROC-AUC: 0.9890

Performance Metrics: STD - Cross Validation
--------------------------------------------
Accuracy: 0.0042
Precision: 0.0045
Recall: 0.0100
F1 Score: 0.0043
ROC-AUC: 0.0042
```

Fig. 25*: KNN Performance Metrics Results.*

```
SUPPORT VECTOR MACHINE
Performance Metrics: Mean - Hold Out Validation
--------------------------------------------
Accuracy: 0.9648
Precision: 0.9400
Recall: 0.9895
F1 Score: 0.9641
ROC-AUC: 0.9659

Performance Metrics: Mean - Cross Validation
--------------------------------------------
Accuracy: 0.9730
Precision: 0.9648
Recall: 0.9820
F1 Score: 0.9733
ROC-AUC: 0.9730

Performance Metrics: STD - Cross Validation
--------------------------------------------
Accuracy: 0.0097
Precision: 0.0171
Recall: 0.0045
F1 Score: 0.0094
ROC-AUC: 0.0097
```

Fig. 26*: SVM Performance Metrics Results.*

```
LOGISTIC REGRESSION
Performance Metrics: Mean - Hold Out Validation
--------------------------------------------
Accuracy: 0.9548
Precision: 0.9273
Recall: 0.9903
F1 Score: 0.9577
ROC-AUC: 0.9535

Performance Metrics: Mean - Cross Validation
--------------------------------------------
Accuracy: 0.9490
Precision: 0.9212
Recall: 0.9820
F1 Score: 0.9505
ROC-AUC: 0.9491

Performance Metrics: STD - Cross Validation
--------------------------------------------
Accuracy: 0.0074
Precision: 0.0095
Recall: 0.0148
F1 Score: 0.0075
ROC-AUC: 0.0074
```

Fig. 27*: LR Performance Metrics Results.*

Table 2*: Performance Metrics Summary Result.*

Performance Metrics	**Cross Validation**		**Hold Out**
K-Nearest Neighbor	**Mean**	**STD**	**Mean**
Accuracy	0.9890	0.0042	0.9849
Precision	0.9980	0.0045	1.0000
Recall	0.9800	0.0101	0.9808
F1	0.9889	0.0043	0.9903
ROC-AUC	0.9890	0.0042	0.9850
Support Vector Machine	**Mean**	**STD**	**Mean**
Accuracy	0.9730	0.0097	0.9648
Precision	0.9648	0.0171	0.9400
Recall	0.9820	0.0045	0.9895
F1	0.9733	0.0094	0.9641
ROC-AUC	0.9730	0.0097	0.9659
Logistic Regression	**Mean**	**STD**	**Mean**
Accuracy	0.9490	0.0074	0.9548
Precision	0.9212	0.0095	0.9273
Recall	0.9820	0.0148	0.9903
F1	0.9505	0.0075	0.9577
ROC-AUC	0.9491	0.0074	0.9535

hold-out validation performance metric score is 96.48%, and the cross-validation score is 97.30%, as shown in Figure 26.

Logistic regression is a widely used classification technique in machine learning. It employs the logistic (sigmoid) function to model the relationship between the independent and dependent variables [16]. The model is trained using the training dataset and evaluated using machine learning performance metrics like accuracy, precision, recall, F1 score, and ROC-AUC [17].

The logistic regression hold-out validation performance metric score is 95.48%, and the cross-validation score is 94.49%, as shown in Figure 27. .

In summary, the K-Nearest Neighbor (KNN) classifier has demonstrated superior performance relative to the Support Vector Machine (SVM) and Logistic Regression classifiers, based on the overall performance metrics scores of 0.989, as presented in Table 2.

Achieving excellent machine learning performance metrics ensures the delivery of a high-quality product from the automated solder vision inspection machine.

***Table 3**: Inspection Accuracy Comparison Result.*

Type	Method	Inspection Accuracy (Under Environment Light)		
		High (15W Bulb)	Medium (10W Bulb)	Low (5W Bulb)
Manual	Visual	80%	80%	80%
Auto	Machine Learning (KNN)	99%	98%	97%
Auto	Machine Learning (SVM)	97%	96%	95%
Auto	Machine Learning (LR)	95%	95%	94%

Furthermore, Table 3 demonstrates the impact of environmental lighting on the accuracy of machine inspections. Increasing the intensity to compensate for brighter environmental lighting results in a higher inspection accuracy of up to 99%. Conversely, reducing the ambient lighting intensity lowers the inspection accuracy to 97% using KNN as the best machine learning algorithm.

Additionally, the cycle time study shows that the average inspection cycle duration of manual visual inspection, 33 seconds, was reduced to 22 seconds using the automated inspection machine, as shown in Figure 24. These improvements in inspection time have significant effects on production output. The reduced inspection duration will help speed up the entire manufacturing process, resulting in higher production volume.

5. CONCLUSION AND RECOMMENDATION

This research successfully developed a prototype machine that optimized the solder inspection system by integrating fiber optics detection and machine learning applications. With a fiber optic detection system, the pallets are aligned perpendicular to an optical inspection camera, which can capture a clear image of the region of interest on the PCBA. The machine vision application algorithm captures, processes, and evaluates the solder image condition of PCBA without human intervention. Additionally, the hardware setup incorporated a conveyor system to automatically transport the product from the inspection station to the subsequent processing station. The K-Nearest Neighbor (KNN) classifier has shown the best performance among machine learning models, with exceptional metric scores. It achieves an accuracy of 98.90% for hold-out validation and 98.99% for cross-validation. Other performance metrics, including precision, recall, F1 score, and ROC-AUC, also reach around 98%. This level of performance ensures that the quality of the products inspected by the automated solder vision inspection machine is within the defined specifications. Finally, the proposed automated PCBA solder inspection machine complements traditional manual visual inspection by removing the subjectivity associated with human assessment. The automated PCBA solder inspection system ensures that products meet quality standards. Moreover, evidence demonstrated that the system achieves higher inspection accuracy in well-lit environments. Its advanced design enables the capture of high-resolution images through a high-magnification optical camera, providing superior image clarity compared to manual visual inspection with a magnifying lamp. Furthermore, the system reduced the overall inspection cycle time from 33 seconds to 22 seconds, significantly improving manufacturing productivity through faster automated inspection compared to the manual visual inspection performed by an operator.

While the prototype automated solder vision inspection machine offers numerous advantages over traditional manual visual inspection of PCBA solder, there is potential for further performance enhancement in future research. The automated transfer of printed circuit board assemblies (PCBAs) to pallets reduces the machine's overall cycle time. Explore other color spaces that are insensitive to lighting conditions. Implementing this change will eliminate the need for an external light source, reducing energy consumption and carbon emissions.

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