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ANALYSIS OF DETECTION SYSTEM FOR COVER TAPE OFFSET IN THE TAP AND REEL PROCESS USING NEURAL NET TIME SERIES METHOD

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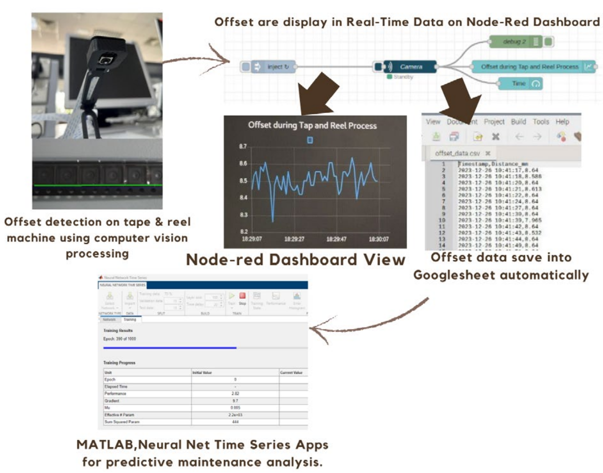
Graphical abstract



Abstract

This technical report presents a comprehensive study on the detection of cover tape offset or misalignment during the tape and reel process, which is crucial for packaging electronic components into individual pockets of carrier tape. The research aims to develop an efficient system utilizing the Raspberry Pi Camera Module for detecting and analyzing cover tape misalignment. The methodology involves integrating the Raspberry Pi Camera Module with a microcontroller to capture and process images of the carrier tape, employing image processing techniques for misalignment detection. The resulting data is displayed in a user-friendly dashboard format using Node-RED. Additionally, the data is analyzed in MATLAB Neural Net Time Series for predictive analysis. The findings of this research, including the analysis of training results, demonstrate the successful implementation of a reliable cover tape misalignment detection system. Notably, the Bayesian Regularization (BR) training algorithm outperformed the Scaled Conjugate Gradient (SCG) training algorithm for cover tape offset's predictive analysis, exhibiting lower Mean Squared Error (MSE) with 0.0015874 for BR compared to 0.0017839 for SCG, consistently lower Mean Absolute Error (MAE) values, stronger linear correlations, and superior overall performance. It emphasizes its effectiveness for accurate predictions.

Keywords: Tape and reel, computer vision, bayesian regularization, scaled conjugate gradient predictive analysis.

1.0 INTRODUCTION

Packaging electronic components is a critical process in the electronics industry, ensuring the protection and efficient handling of these delicate devices. One commonly used method is the tape and reel process, which involves packaging individual components into carrier tape pockets for easy handling and automated assembly. However, misalignment or offset of the cover tape can occur during this process, leading to various issues such as component damage, improper feeding, and increased production defects.

The current state of knowledge in this area highlights the importance of accurate and reliable detection of cover tape misalignment to ensure the quality and efficiency of the packaging process. Manual inspection methods are commonly employed but are time-consuming, labor-intensive, and prone to human error. There is a need for an automated system that can detect cover tape misalignment in real-time, providing prompt feedback for corrective actions.

Alejandro Gallegos-Hernandez and Francisco J. Ruiz-Sanchez (2002) present a 2D automated visual inspection system for the remote quality control of surface mount device (SMD) assembly [1]. The system is designed to detect defects such as missing components, component misplacement, and polarity errors, among others. In the proposed project, diffuse-reflective sensor is used to detect cover tape offset in tape and reel process, whereas in the Gallegos-Hernandez and Ruiz-Sanchez paper, a camera is used to capture images of SMD board for defect detection. Moreover, the proposed project aims to develop a low-cost monitoring system for detecting cover tape offset, while the Gallegos-Hernandez and Ruiz-Sanchez paper presents a remote quality control system for SMD assembly. Both the proposed project and the Gallegos- Hernandez and Ruiz-Sanchez paper aim to improve the quality of electronic components, which is crucial for the reliability and durability of electronic devices. Whereas, Yuqiao Cen et al. (2022) presented a defect patterns study of pick-and-place machine using automated optical inspection data assembly that discusses the use of automated optical inspection (AOI) to detect defects in the pick-and-place process of surface mount devices (SMDs) [2]. The paper highlighted that AOI systems are widely used in SMD assembly lines to improve quality control by detecting defects such as missing components, misplaced components, and soldering defects. However, AOI systems can be limited in their ability to detect defects that occur during the pick-and-place process, such as defects caused by the offset of cover tape in tape and reel packaging. Additionally, the development of a predictive maintenance system based on the situation can improve the overall efficiency of the SMD assembly process by reducing downtime and minimizing the need for manual inspection and maintenance. Hence, a machine learning approach such neural network may offer an accuracy in fault diagnosis especially in high-volume manufacturing.

Studies by F.Ye, et al. (2013) presented a Board-level functional fault diagnosis using Artificial neural networks, support-vector Machines, and weighted-majority voting approach in their fault detection diagnosis [3] . A a smart diagnosis method based on two ML classification models: artificial neural networks (ANNs) and support-vector machines (SVMs) were proposed to learn from repair history and accurately localize the root cause of a failure where it able to promptly and precisely locate the root failure caused on circuit board. Y. Cen, et al. (2021) conducted an investigation on defect patterns study of pick-and-place machine using automated optical inspection data [4]. The study conducted an experiment to simulate the P&P machine errors uses various machine learning methods to develop a root cause identification model based on the inspection result. Similar to [3], this study also uses SVM but with additional decision tree and also random forest. However, this study focused on analyzing the component placement based on the pre-AOI machine in order to develop a multi-class classification model which differs in our scope of research. N. Cai, et al. (2018) presented SMT solder joint inspection via a novel cascaded convolutional neural network focusing on visual- based inspection [5]. The proposed method directly implements the inspection task without low- level feature extraction with three kinds of convolutional neural network (CNN) plus the different network parameters compose the proposed cascaded CNN. First, one kind of CNN is employed to adaptively learn the regions of interest (ROIs) of SMT solder joint images. Then, both the learned ROIs and the entire solder joint images are fed into the other two kinds of CNNs, respectively. Finally, inspection results are achieved by the learned cascaded CNN. This proposed method can be applied to any inspection filed as well. Therefore, this research project aims to develop a robust and automated system for detecting cover tape misalignment during the tape and reel process with an analysis using machine learning classification method: neural network. In addition, Node-RED, a visual programming will be developed as a real-time dashboard for offset monitoring purposes.

2.0 METHODOLOGY

Detecting cover tape offset or misalignment from the carrier tape during the tape and reel process is critical for ensuring product quality. This section addresses this challenge using computer vision and neural network techniques. Hence in this section, the sequential actions and techniques implemented are presented to achieve the study's objectives.

2.1 Measurement from Industry

The cover tape can also be in the offset position with more than 20 mm towards the sprocket hole, as shown in Figure 1. Understanding the industry standards for cover tape offset measurement in the project context is important to designing a system that meets these requirements. The cover tape should be precisely at the very bottom area of the sprocket hole. The Raspberry Pi Camera Module 3 used in the project should be capable of providing accurate measurements of the cover tape position within the industry-standard tolerance levels. The testing was conducted on the conveyor belt of the FMS 200, as shown in Figure 1, which has some misalignments that can be evaluated and analysed.

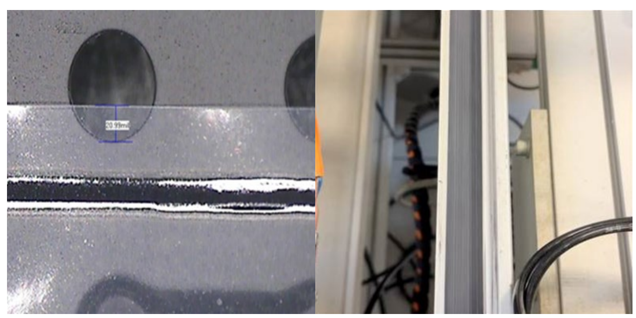


Figure 1: Example visualisation of offsets in the industry and conveyor belt on FMS 200.

2.2 Initialize Raspberry Pi Camera Module

In this initial phase, the Raspberry Pi Camera Module is set up to capture real-time data during the tape and reel process. Figure 2 shows the setup for the camera with the support of a camera case and adjustable arm to protect the camera and to easily make the camera mounted in the industry. Figure 2 shows the connection from the camera to the Raspberry Pi via the CSI port.

Figure 2: Camera's design setup and the connection from the camera to the Raspberry Pi.

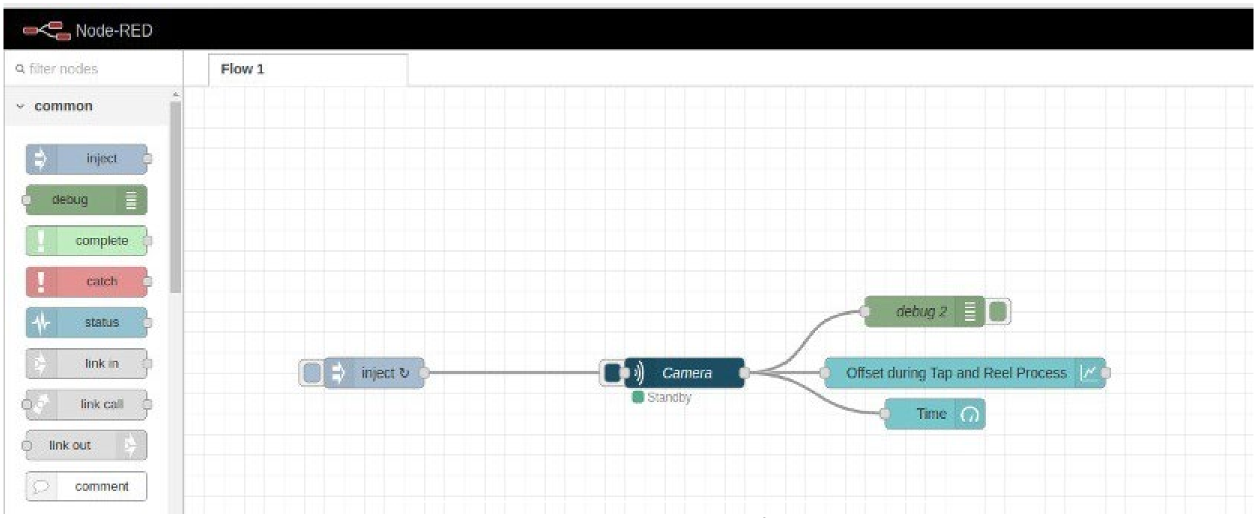


Figure 3: Node-RED workflow

2.3 Computer Vision Processing

Utilizing the OpenCV library, a powerful computer vision library offers the Canny edge detection method as a robust technique for identifying edges within images [6]. Moreover, it provides the Hough Line Transform method, which plays a pivotal role in identifying the lines that represent the boundaries of the tape [7]. Within the broader context of computer vision processing, Canny Edge Detection is specifically employed to identify edges within the images. It enhances the delineation of objects in the images, providing a foundation for subsequent steps in the analysis [8].

Building on the results of Canny Edge Detection, the Hough Line Transform is applied to detect lines within the images. This step is crucial for identifying features such as the alignment and orientation of the cover tape during the tape and reel process [9]. Figure 4 shows the detection of straight lines on the selected region of interest. The most prominent feature in this image is the green line, which represents the straight line detected by the Hough line detection algorithm.

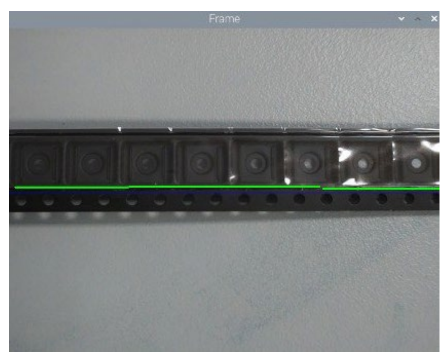


Figure 4: Hough Line detection on the selected

2.4 Display Real-Time Data on Node-Red Dashboard

To facilitate real-time monitoring, the captured and processed data is seamlessly integrated into Node-Red. Figure 3 shows the Node-RED workflow. The "Camera" node captures images or data from the Raspberry Pi Camera Module 3. This data is then passed to the next node in the flow. Then, the "debug 2" node displays messages during the development or testing phases. It might show real-time data or log information about the cover tape alignment process. Finally, the extracted features from the Hough line detection algorithm are translated into large set of sample size (21393 of sample sizes) which are presented in the Node-Red Dashboard and saved Into the CSV files. Then, the CSV data was imported into MATLAB to implement Neural Net Time Series Apps.

2.5 Neural Net Time Series Apps for Predictive Analysis

Additionally, all the processed data from Node-RED is logged into a CSV file. This file is a structured repository of the captured information, enabling further analysis and providing a basis for data transfer to external platforms, such as MATLAB, for this machine learning analysis. Then, the CSV data was imported into MATLAB to implement Neural Net Time Series Apps. A key focus is placed on comparing two distinct training algorithms, Bayesian Regularization (BR) and Scaled Conjugate Gradient (SCG).

This neural network with a single hidden layer is created to approximate the underlying model. This network structure includes an input layer, a hidden layer processing information, and an output layer producing the result. The hidden layer's size can be adjusted based on problem complexity. The network's initial parameters are random, which can lead to slight variations in outcomes. To ensure consistency, a random seed can be used but is optional. The available data is divided into training, validation, and testing sets. The network learns from the training data, its performance is monitored using the validation set, and its final accuracy is assessed with the test set. Training continues until improvement on the validation set stops, indicating optimal network performance.

In order to compare these two-training algorithm's (BR and SCG) performances, Mean Squared Error (MSE) and Mean Absolute Error (MAE) will be used. Both MSE and MAE provide valuable insights into the performance of this machine learning model during training. MSE represents the average squared difference between predictions and actual values, but it is highly sensitive to outliers. While MAE represents the average of the absolute differences between predictions and actual values, it is more robust to outliers and less sensitive.

3.0 RESULTS AND DISCUSSION

This analysis compares two training techniques, BR and SCG, to determine their impact on the prediction model's performance. BR is well-known for reducing overfitting using a probabilistic approach to weight regularization [10]. SCG, a quasi-Newton optimization approach, is well-known for its ability to quickly reach minima on the error surface [11]. Both techniques are implemented in the Neural Network Time Series applications in MATLAB, and their impacts on training dynamics and overall forecast accuracy are examined.

3.1 Node-RED

The graph on the Node-RED dashboard, as shown in Figure 5, displays fluctuations in offset values over a specific period, allowing for monitoring and analysis of variations during this process.

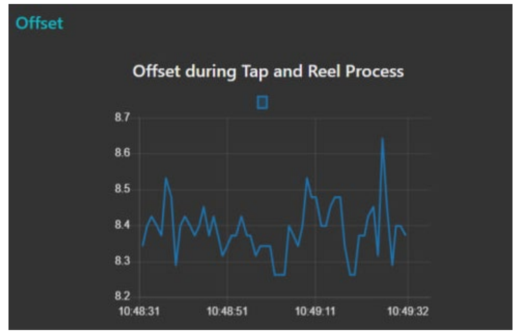


Figure 5: Offset graph in Node-RED dashboard.

The offset values fluctuate between 8.2 mm and 8.7 mm. This range could indicate the variability in the alignment of the cover tape during the tape and reel process. This also suggests that the alignment of the cover tape is not constant and varies throughout the process. Apart from that, there is a noticeable spike in the offset value. The fluctuations and the noticeable spike in the offset values could be due to wear and tear on the conveyor belt on the FMS 200 machine. As the conveyor belt wears out, it can cause misalignments or variations in the alignment. By detecting changes in the offset, predictions can be made for potential issues with the conveyor belt, and corrective action can be taken before failure occurs [12]. Simultaneously with real-time data display, the processed data is logged into a CSV file which serves as a structured repository of the captured information, enabling further analysis using Neural Net Time Series Apps for predictive maintenance analysis in MATLAB.

3.2 Comparison between BR and SCG

In this section involves integrating the data from Node-RED which was save into a CSV data and implemented it in the MATLAB's Neural Net Time Series Apps for predictive maintenance. A key focus is placed on the comparison analysis between two distinct training algorithms, Bayesian Regularization (BR) and Scaled Conjugate Gradient (SCG)A scatter plot was generated to represent the results of BR training and a SCG neural network for the combined data (4 days).

For this section, scatter plot was generated to represent the results of a Bayesian Regularization (BR) training neural network from data. The scatter plot is a graphical representation of the relationship between the target values and the output values. The scatter plot provides a visual representation of the model's performance. The closer the points are to the diagonal line (y=x), the better the model's predictions are to the actual values [13]. The identity line (Y = T) represents perfect predictions. If all data points were on this line, it would mean that the model's predictions were exactly equal to the actual values. Figure 6 reveals a strong positive linear correlation (R = 0.9546) between the Target and Output variables. Basically, target value is the desired or correct answer, the goal of our model wants to achieve and aimed for. Output is the value produced by the model as a prediction or result. It's the model's best guess based on the given input. This implies a consistent upward trend in the Output as the Target value ascends. The data points exhibit close proximity to the regression line, suggesting a robust model fit that accurately captures the underlying relationship between the two variables.

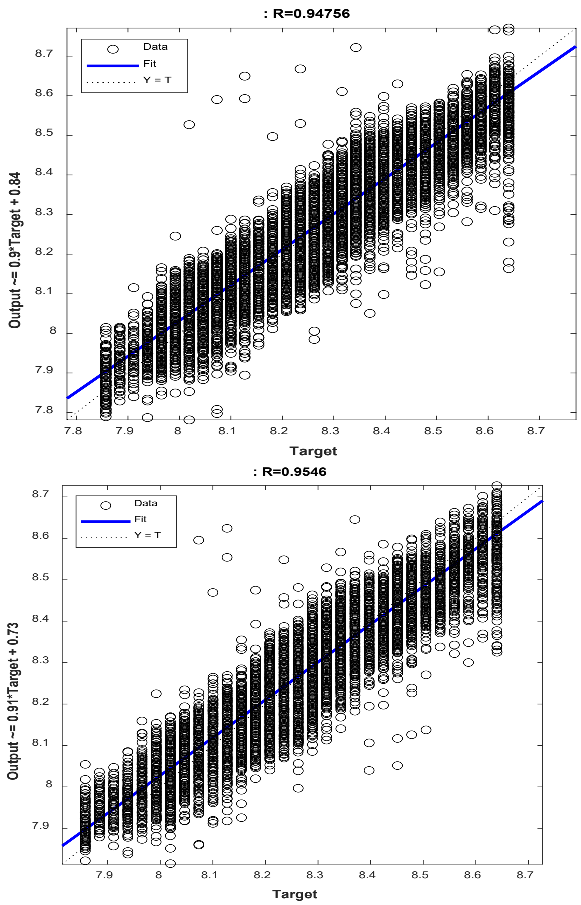


Figure 6: Scatter plot for BR (Bottom) and SCG (Top).

The correlation coefficient (R) of 0.94756 signifies a robust positive linear association between the Target and Output variables. While this correlation is substantial, it is marginally lower than the R value of 0.9546 obtained with the BR method, implying a potentially stronger linear relationship in the latter case. Meanwhile, the data points are closely aligned with the fit line, similar to the results with BR. This suggests that both methods effectively capture the relationship between these two variables. Table 1 compares BR and SCG in terms of correlation coefficient.

Table 1: Correlation coefficient comparison between BR and SCG.

Training Algorithm	Correlation Coefficient (R)
BR	0.95460
SCG	0.94756

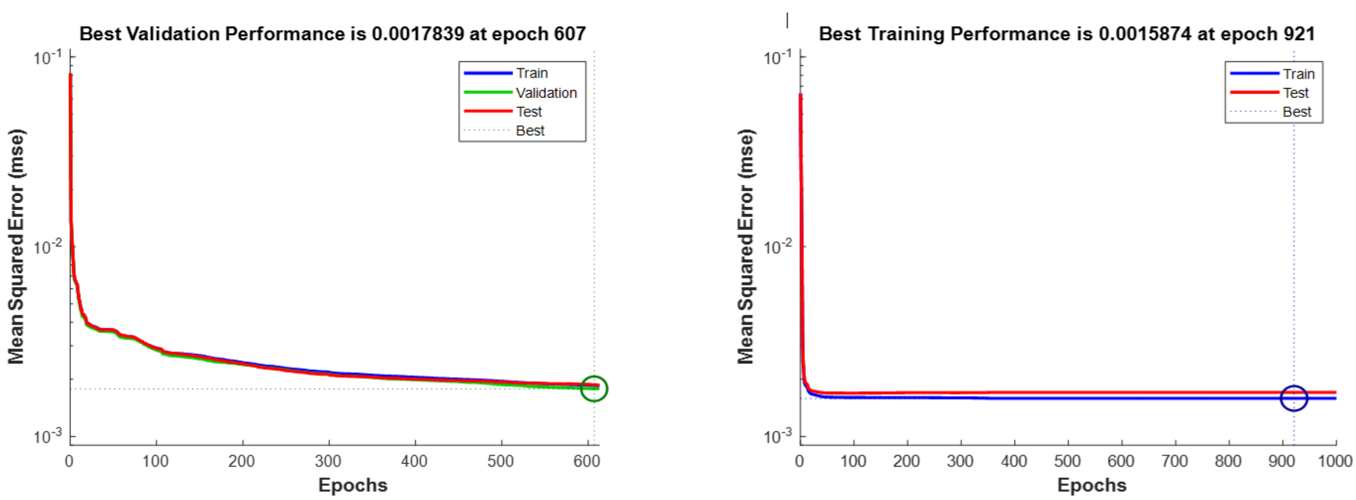


Figure 7: Best Training Performance for BR (left) and SCG (right).

A graph representing the Mean Squared Error (MSE) was generated to represent the results of the BR and SCG training neural network for the combined data (4 days). The graph in Figure 7 represents the MSE during the training of a neural network using the BR and SCG methods. The best training performance is achieved at epoch 921 with an MSE of 0.0015874. This suggests that the model minimized the error significantly during the training process. The plot also shows both training and test errors. The best validation performance is achieved at epoch 607 with an MSE of 0.0017839. This is slightly higher than the 0.0015874 achieved with BR, suggesting that BR might have resulted in a slightly better fit to the training data. However, the model took 607 epochs to achieve the best performance. This is fewer than the 921 epochs it took with BR, suggesting that SCG may have converged faster.

Table 2 compares BR and SCG in terms of performance and convergence time.

Table 2: Best Training Performance for Combined Data.

Training Algorithm	Epoch	Best Training Performance (MSE)
BR	921	0.0015874
SCG	607	0.0017839

A graph representing the actual value was compared with the predicted value. This graph represents the results of BR and SCG training neural network for the combined data (4 days). Figures 8 and 9 presented the overview comparison between actual and predicted offset for BR and SCG training algorithms.

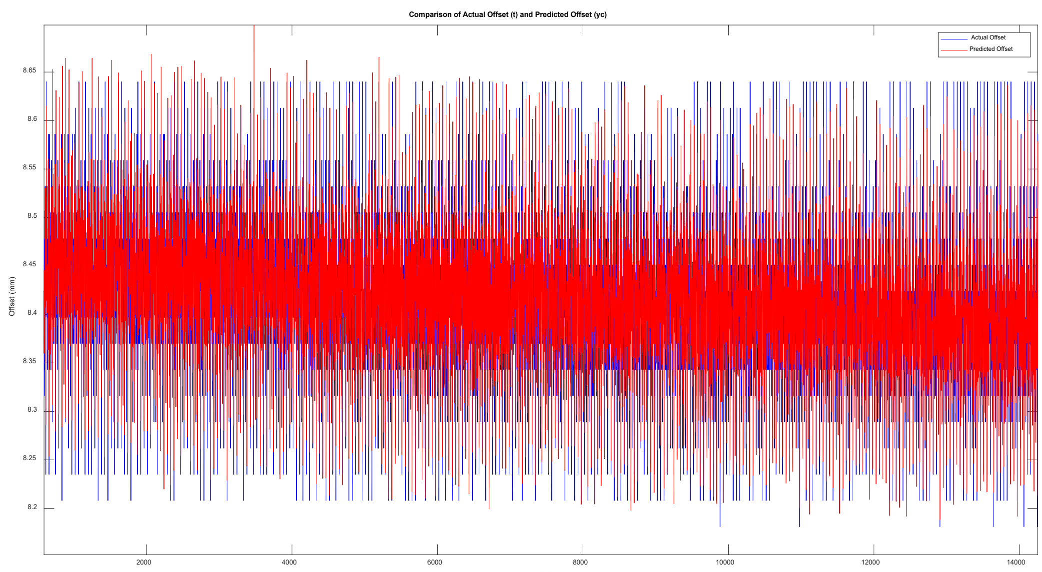


Figure 8: Comparison between actual and predicted values using BR training.

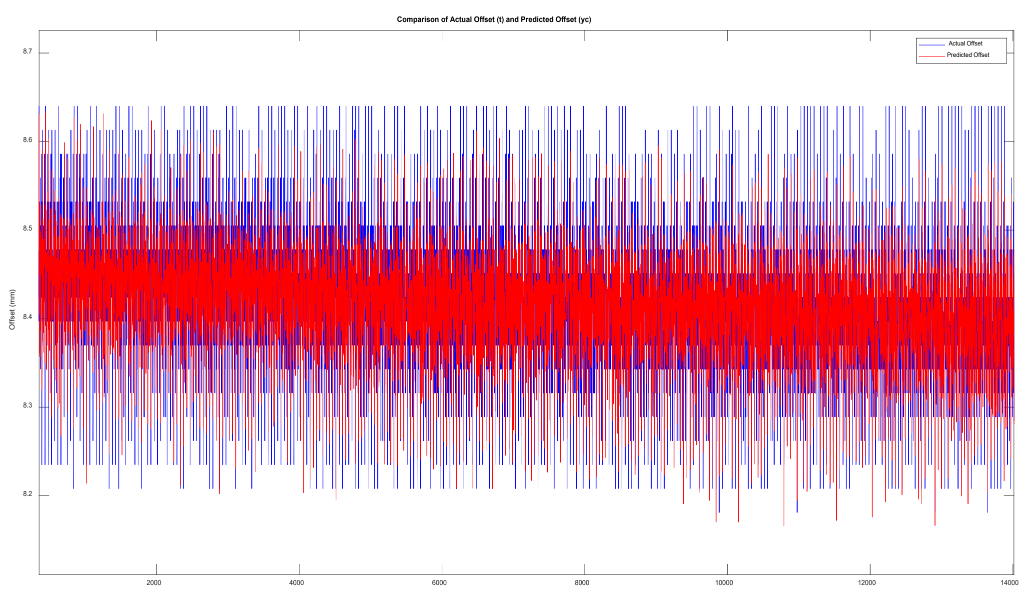


Figure 9: Comparison between actual and predicted values using SCG training.

The red line represents the predicted offset, and the blue line represents the actual offset, as shown in Figures 8 and 9. If the two lines are closely aligned, the predictions are accurate. In this case, the red and blue lines do not align closely, suggesting that the predictions may be inaccurate [14]

However, without quantitative measures such as Mean Absolute Error (MAE), it is difficult to definitively say which method is performing better [15].

Figure 10 shows the MAE graph to compare the performance of BR and SCG training neural networks in prediction. Most MAE values are concentrated below 0.2, indicating that the predictions are generally close to the actual values. However, noticeable peaks are reaching up to approximately 0.5, suggesting moments of significant error between predicted and actual offsets.

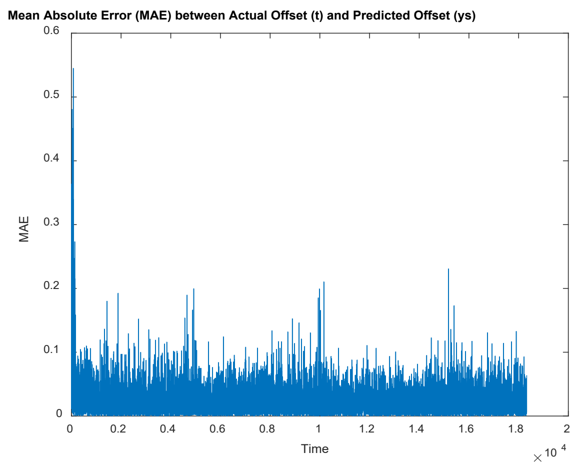


Figure 10: MAE between actual and predicted values for BR (left) and SCG (right).

The numerous spikes in MAE throughout the graph could suggest that the model struggles with certain patterns in the data. These could be due to outliers, noise, or complex patterns in the data that the model fails to capture [16][17]. This differs from [18], who use the F-score method to measure the accuracy of the detection method.

Figure 11 shows the comparison plot between the MAE for BR (blue) and SCG (orange). The MAE for the SCG method is consistently higher than the MAE for the BR method. This suggests that the BR method has lower average prediction errors and thus performs better than the SCG method. Lower MAE values indicate better model performance as they represent smaller average errors between the predicted and actual values. Therefore, the BR method, which has lower MAE values, will likely provide more accurate predictions.

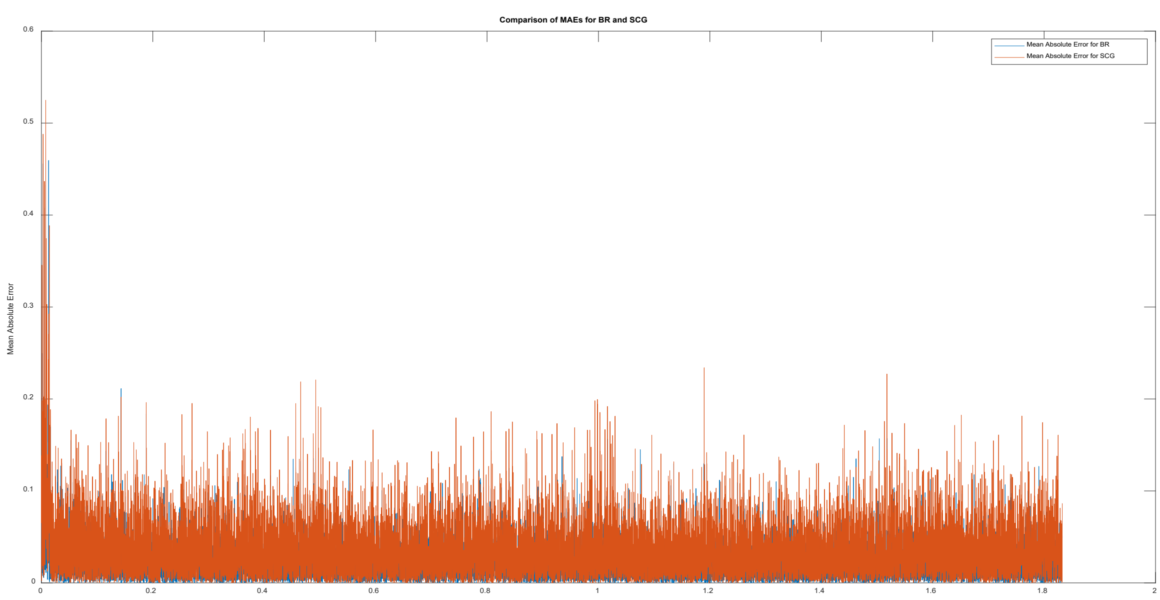


Figure 11: Comparison plot between MAE for BR and SCG.

The MAE analysis provided a significant assessment of prediction accuracy. It not only revealed the general proximity of predictions to actual values but also pinpointed specific instances of substantial errors. Comparative visualizations consistently demonstrated lower MAE values for the BR model, signifying its superior performance in terms of average prediction error.

4.0 CONCLUSION

This research proposes an automated system for cover tape misalignment detection during the tape and reel process. The system has utilized a neural network, a machine learning classification method, for real-time analysis. A user-friendly dashboard for offset monitoring was built using Node-RED, a visual programming tool. Captured data were analyzed further in MATLAB using Neural Network Time Series Apps. Two training algorithms, Bayesian Regularization (BR) and Scaled Conjugate Gradient (SCG), will be compared to determine the most effective approach.

Furthermore, the project explored predictive maintenance by employing BR and SCG training algorithms in MATLAB with Neural Network Time Series Apps. Both algorithms converged successfully, with BR demonstrating a slight edge in fitting the training data. Analysis of MSE graphs revealed efficient error minimization for both methods. The MAE analysis provided detailed insights into prediction accuracy. While occasional spikes indicated model challenges with specific patterns, BR consistently exhibited lower average errors compared to SCG, signifying its superior performance.

As for future advancements for the cover tape offset detection system, the primary focus lies on incorporating real-time feedback mechanisms, including operator alerts via email, text messages, or on-screen notifications. Additionally, the Node-Red dashboard will be enhanced with visual indicators to facilitate operator interaction. Furthermore, data logging capabilities will be strengthened through the implementation of a robust database system, enabling in-depth analysis of historical trends and predictive maintenance strategies. Finally, the system is envisioned to evolve towards autonomous model training via machine learning integration within the Python codebase, bolstering its predictive capabilities and aligning with contemporary research advancements.

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Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper

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