Failure Prediction Using Multimodal Classification of PCB Images

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Abstract: In the era of Industry 4.0, where digital technologies revolutionize manufacturing, a wealth of data drive optimization efforts. Despite the opportunities, managing these vast datasets poses significant challenges. Printed Circuit Boards (PCBs) are pivotal in modern industry, yet their complex manufacturing process demands robust fault detection mechanisms to ensure quality and safety. Traditional classification models have limitations, exacerbated by imbalanced datasets and the sheer volume of data. Addressing these challenges, our research pioneers a multimodal classification approach, integrating PCB images and structured data to enhance fault prediction. Leveraging diverse data modalities, our methodology promises superior accuracy with reduced data requirements. Crucially, this work is conducted in collaboration with Bosch Car Multimedia, ensuring its relevance to industry needs. Our goals encompass crafting sophisticated models, curbing production costs, and establishing efficient data pipelines for real-time processing. This research marks a pivotal step towards efficient fault prediction in PCB manufacturing within the Industry 4.0 framework.

1 INTRODUCTION

In the era of Industry 4.0, integrating digital technologies into manufacturing processes generates vast data volumes, optimizing production (Kullu & Cinar, 2022). This shift offers unprecedented opportunities but also poses challenges in managing and extracting insights from extensive datasets. The manufacturing industry leverages data-driven approaches to enhance efficiency, quality, and operational performance.

Printed Circuit Boards are vital in the modern industrial landscape. The complex manufacturing process of PCBs requires swift fault detection to avoid significant economic and safety consequences, particularly in the automotive sector. Robust fault detection mechanisms are essential to safeguard financial interests and end-user safety.

Traditional fault detection in PCB production relied on conventional classification models, which have shown limitations and lack widespread implementation due to their immaturity. This gap highlights the need for efficient, reliable, and scalable fault prediction solutions.

Imbalanced datasets in PCB production, where specific fault classes are underrepresented, are addressed with techniques like oversampling and undersampling. Despite these efforts, results have not met desired satisfaction levels.

Another challenge is the enormous volume of data generated by manufacturing machines in Industry 4.0, posing logistical and computational processing difficulties.

This research proposes a multimodal classification approach that leverages both PCB images and structured data to address existing gaps. This methodology combines rich visual information from PCB images with structured data, providing a comprehensive understanding of the manufacturing process. Conducted in collaboration with Bosch Car Multimedia as part of their "Quality for Manufacturing" projects, this study ensures relevance to contemporary challenges in electronic component manufacturing.

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2 GOALS

This paper aims to develop and implement a sophisticated multimodal classification model for integration into Bosch Car Multimedia's production lines. The model aims to reduce production costs by preventing the use of faulty Printed Circuit Boards (PCBs), thereby avoiding resource wastage. Using innovative multimodal image analysis, we seek to enhance fault detection precision and effectiveness, mitigating financial losses from defective component assembly. Our research includes a comprehensive comparative analysis between our multimodal models, which combine structured data and images, and traditional classification models using only tabular data. By examining these approaches, we aim to validate the multimodal model's effectiveness and improve fault prediction accuracy.

Additionally, our approach aims to address the challenge of data imbalance, striving to achieve enhanced efficacy with reduced data volume. This involves employing specialized preprocessing techniques and statistical modeling to rectify data imbalances, all with the aim of enhancing the overall predictive capabilities of our models. This dual emphasis on mitigating data imbalances and achieving superior outcomes with reduced data volumes underscores our commitment to efficiency and efficacy in this research endeavor.

Furthermore, a critical aspect of our research initiative involves establishing a robust and efficient data pipeline that seamlessly integrates both PCB images and structured data. Our objective is to develop a real-time data processing framework capable of supporting the multimodal classification model during deployment. This pipeline plays a pivotal role in ensuring the sustained adaptability and relevance of our model amidst the dynamic industrial environment.

3 RELATED WORK

In the rapidly evolving landscape of Industry 4.0, ensuring PCB quality remains crucial. Literature highlights significant advancements in PCB fault detection. Key contributions from various studies emphasize traditional image processing and modern deep learning models, particularly convolutional neural networks (CNNs). A recurring theme is the need for extensive datasets, with future directions focusing on augmenting datasets and improving detection of smaller components.

(Zakaria et al., 2020) explore defects during the solder paste printing process, introducing Solder Paste Inspection (SPI) and Automatic Optical Inspection (AOI) as essential tools. They delve into machine learning approaches to enhance detection efficiency, aiming to improve production yields and reduce rework costs.

(Cho et al., 2023) present a predictive framework for semiconductor memory module tests, addressing imbalanced outcomes through multimodal fusion of tabular and image data. This framework optimizes testing strategies, demonstrating its real-world efficacy and reflecting the broader trend of leveraging advanced technologies to boost productivity in semiconductor manufacturing.

In multimodal machine learning, diverse data sources are used to improve model performance and diagnostic accuracy. (Huang et al., 2020) advance pulmonary embolism (PE) diagnosis by integrating CT imaging with electronic health record (EHR) data, demonstrating the superiority of a late fusion model over imaging-only or EHR-only models.

Similarly, (Tang et al., 2022) enhance pulmonary nodule classification by combining structured and unstructured data. Their models outperform those using only unstructured data, highlighting the importance of integrating patient demographics and clinical characteristics with medical images for more accurate diagnoses.

(Yang et al., 2022) provide an overview of multimodal learning, discussing methods like early fusion, late fusion, and hybrid fusion. They address challenges in fusing multimodal features efficiently and explore model-based fusion methods such as multiple kernel learning (MKL) and neural networks (NN) to enhance feature representation.

(Yan et al., 2021) focus on breast cancer classification using multimodal data. They propose integrating pathological images with Electronic Medical Records (EMR), emphasizing the benefits of denoising autoencoders over dimensionality reduction. Their feature-level fusion method achieves higher accuracy by combining images and structured data, surpassing models using only structured data or images.

3.1 A Comprehensive Analysis of the Production Line

To gain a comprehensive understanding of the production line dynamics, a detailed overview of its constituent processes is essential, with a specific focus on the initial three stages (Zakaria et al., 2020). This targeted approach facilitates early detection of potential issues in Printed Circuit Boards (PCBs) production.

The initial stages under scrutiny include Laser Marking PCB, Solder Paste Printing, and Solder Paste Inspection, each playing a crucial role in ensuring the quality and functionality of the final product. By concentrating efforts on these foundational steps, a proactive approach is adopted to swiftly identify and rectify any anomalies in the PCB manufacturing process.

The journey of PCB assembly begins with the insertion of a "blank" PCB into the initial machine, devoid of any unique identifiers or data. Subsequently, the Laser Marking PCB Process takes precedence in the manufacturing sequence.

The Laser Marking PCB process holds significant importance across all production plants, focusing on traceability for utilized parts and materials in Bosch products. Its objective is to standardize PCB and panel processing within the Surface Mount Technology area, assigning unique identifiers generated by the Manufacturing Execution System to both panels and their corresponding individual PCBs.

Upon completion of the Laser Marking PCB process, the PCB proceeds to the Solder Paste Printing machine. This machine applies solder paste to the PCBs, with the quality of this application significantly impacting overall PCB performance. The Solder Paste Printing process involves stringent measures to ensure precise application of solder paste to the PCBs in line, directly influencing the usability of the final product.

Following Solder Paste Printing, the Printed Circuit Board undergoes Solder Paste Inspection to verify and ensure the quality of the solder paste application. This process serves as a critical checkpoint to detect defects or irregularities in the solder paste before advancing to subsequent manufacturing phases.

The primary objective of Solder Paste Inspection is to evaluate the accuracy and uniformity of solder paste deposition on the PCB surface, crucial for preventing defects such as solder bridges or insufficient solder. Advanced optical systems and specialized inspection equipment scan and analyze the solder paste, facilitating precise examination of volume, alignment, and distribution across the PCB.

In addition to these processes, efficient management and storage of data generated during Laser Marking PCB, Solder Paste Printing, and Solder Paste Inspection are imperative. Tabular data from these stages is organized into different tables and stored in the Hadoop cluster through a pre-established pipeline, ensuring systematic and accessible data for future analyses.

A schematic representation provides a visual depiction of a segment of the production line, serving as a foundational reference for further discussion on the intricacies of Laser Marking PCB, Solder Paste Printing, and Solder Paste Inspection processes.

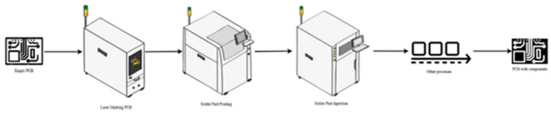

Figure 1: Production Line First Three Processes.

4 DATA UNDERSTADING

This phase is pivotal in laying the groundwork for building a multimodal classification model for fault prediction in PCBs. This section involves a thorough exploration and analysis of the dataset, including both structured data and images of PCBs

4.1 Laser Marking PCB

The LMP process is essential to the workflow but does not alter the components of the printed circuit board (PCB). It involves scanning the QR code on the PCB and logging the information into the system. Most data generated by the LMP process relates to system metadata rather than the PCB's intrinsic attributes. PCB-specific characteristics are usually captured in the SPP or SPI datasets, which detail the manufacturing and inspection processes.

A key data point is the 'panelmatId' column, indicating the PCB supplier. Extracting the 'supplierId' from the panelMatId field requires preprocessing. The panelMatId includes the supplier number and extraneous details, following a format like '123456SB32321', where digits before 'SB' denote the supplier number. For supplier analysis, the panelMatId data structure was deconstructed, and a new column was created to isolate the supplier number.

Due to security, supplier values will not be disclosed, but a broader analysis of the attribute will be conducted to understand its characteristics and implications.

Table 1: LMP Data Distribution.

Attribute	Count	Null	Distinct
supplierId	10838198	0	1018 (<1%)

4.2 Solder Past Printing

The SPP process contrasts with the LMP process by significantly transforming the printed circuit board (PCB). While the LMP process involves no alterations to PCB components, SPP introduces changes through various parameters and structured data collected from machines. Operators play a key role in SPP by selecting these parameters, influencing the manufacturing outcome. Unlike LMP, which captures mainly system-related metadata, SPP records crucial characteristics intrinsic to the PCB.

During the denormalization process, new variables 'year', 'month', and 'day' were derived from 'eventCreatedAt' to enhance data access speed by partitioning data storage. The resulting DataFrame contains 2,048,448 records and 70 fields/columns. Due to the large size of the dataset, only the most relevant features indicated by operators and domain knowledge are discussed in this section.

Table 2: SPP Data Distribution.

Attribute	Count	Null	Distinct
sppProg1Name	2048488	0	13 (<1%)
sppMaxFiducial Mark Deviation	2048488	0	80(<1%)
sppPrintingPressureF orwards and sppPrintingPressureB ackwards	2048488	0	14(<1%)
sppPrintingSpeedFor wards and sppPrintingSpeedBac kwards	2048448	0	6 (<1%)
sppPrintingDist ance	2048448	0	9 (<1%)
sppSeparationS peed	2048448	0	6 (<1%)
sppSnapOff	2048448	0	8 (<1%)
spptemperature	163398	1885050	62 (<1%)
spphumidity	163398	1885050	184 (<1%)
sppCleaningInte rval	2048448	0	7 (<1%)
sppNumOfPan elsSinc eLastCleaning	2048448	0	16 (<1%)
sppToolId	2048448	0	149 (<1%)

To explore the interrelationships between variables, a correlation matrix analysis using the Pearson correlation coefficient was conducted. This coefficient, ranging from -1 to 1, measures the linear relationship between two continuous variables. Values close to 1 indicate a strong positive correlation, values near -1 indicate a strong negative correlation, and values around 0 suggest no linear correlation. The correlation matrix provided insights into variable dependencies, enhancing understanding of their interactions and potential predictive capabilities.

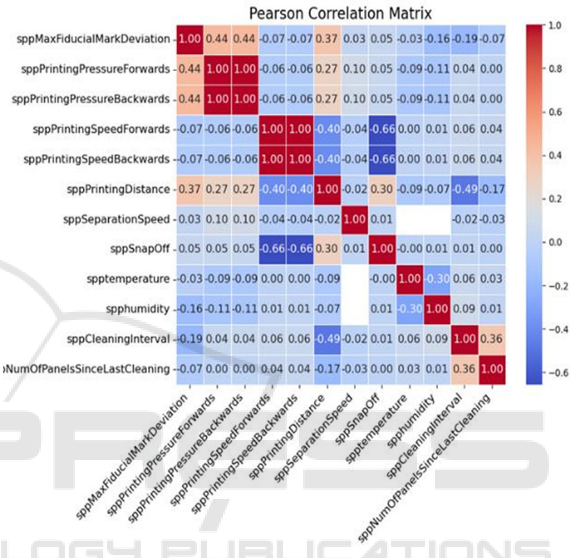

Figure 2: SPP Features Correlation.

The correlation matrix analysis revealed significant correlations between attributes such as sppPrintingPressureForwards and sppPrintingPressureBackwards, and sppPrintingSpeedForwards and sppPrintingSpeedBackwards, likely due to consistent operator settings. Most variables, however, showed minimal correlation, indicating independent behavior. Notably, sppCleaningInterval had a moderate correlation with sppPrintingDistance, but their distinct functions suggest no direct causal relationship.

4.3 Solder Past Inspection

The SPI generates significantly more data than SPP by capturing information at both the board and pad levels. This comprehensive dataset provides valuable insights into soldering quality, necessitating careful preprocessing for meaningful analysis. The SPI dataset contains 2,988,850,335 entries due to the expansion of arrays for boards and pads, which dramatically increases data volume and requires substantial computational resources.

The dataset's vast size constrains analysis, requiring significant processing power and time, and posing challenges in storage, speed, and computational complexity. Strategic sampling approaches are necessary to make analysis feasible while leveraging the SPI data's rich insights.

Images critical for quality assessment are meticulously stored locally, with data utilization focused on images identified by SPI as defective PCBs. These images undergo manual operator review to validate SPI findings, adding a verification layer to the analysis pipeline.

The SPI system captures a broader array of data than SPP, with key attributes derived from previous analyses and domain knowledge. These attributes are essential for understanding and optimizing the soldering process, as summarized in the following table, reflecting their significance for informed decision-making and process improvement.

Table 3: SPI Data Distribution.

Attribute	Count	Null	Distinct
spiMessageTrigger	2988850335	0	2 (<1%)
spiProg1Name	2988850335	0	12(<1%)
spiProposedPanelResult	2988850335	0	3 (<1%)
spiFinalPanelResult	2988850335	0	4 (<1%)
spiProposedBoardResult	2988850335	0	2 (<1%)
spiFinalBoardResult	2988850335	0	3 (<1%)
spiBadMarkedBoard	2988850335	0	2 (<1%)
spiFailureDescription	2988850335	0	11 (<1%)
spiProposedPadResult	2988850335	0	4 (<1%)
spiFinalPadResult	2988850335	0	5 (<1%)
spiPadType	2988850335	0	3 (<1%)

The label, derived from the final stage of production, represents the ultimate outcome for each PCB. It encompasses various scenarios encountered during manufacturing. Some PCBs flagged as defective by the SPI are deemed acceptable by operators, allowing them to continue through production, potentially resulting in both acceptable and defective outcomes. Conversely, some PCBs identified as acceptable by the SPI may have varying final statuses upon reaching the end of the line. Notably, no PCBs are classified as defective by both the SPI and operators; such PCBs are scrapped and do not receive component insertion. This label distribution is highly imbalanced, as shown in the following table, reflecting the diverse outcomes observed throughout the production line.

Table 4: Label Distribution.

Label	Count
Good	25838604
Not Good	797141

5 MODELING

The modeling phase marks a pivotal stage in the research, where diverse modeling techniques are meticulously chosen and implemented, with a focus on calibrating their parameters to attain optimal values. This phase is characterized by the exploration of various scenarios encompassing different approaches, input models, preprocessing techniques, and other pertinent variables.

Notably, four scenarios were meticulously crafted using structured data, each tailored to specific research objectives and hypotheses. Additionally, two scenarios were developed to incorporate multimodality, leveraging both images and structured data, thus enriching the analysis and capturing nuanced insights from multiple perspectives.

5.1 First Scenario

The journey begins with thorough data preprocessing, crucial for preparing the data for classification. Feature selection is pivotal, with relevant attributes chosen from data obtained from previous processes such as SPP, SPI, and LMP. These features cover various PCB aspects, including dimensions, materials, components, and results from electrical and functional tests.

Normalization techniques ensure selected features are on a comparable scale, facilitating the learning process for classification algorithms. Additionally, categorical features are encoded into numerical values for efficient processing.

The classifier is then trained using various machine learning algorithms, chosen based on data type, problem complexity, and interpretability needs. K-fold cross-validation evaluates algorithm performance and prevents overfitting, ensuring robustness and generalization to unseen data. To address data imbalance in PCB classification, oversampling techniques increase the representation of faulty PCBs in the training dataset, enhancing the algorithm's accuracy in classifying such instances.

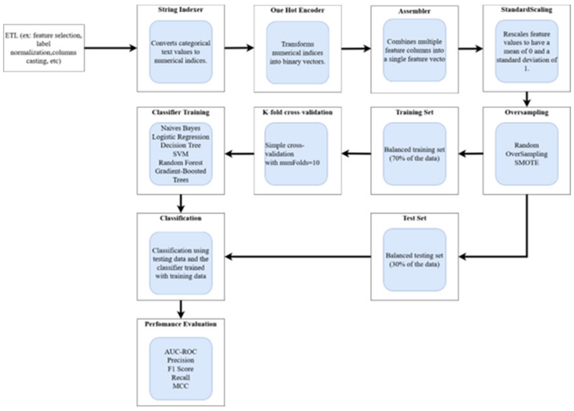

Figure 3: First Scenario Example Pipeline.

5.2 Second Scenario

In the second scenario, the process closely resembles the first one, with a focus on accurate data preprocessing and effective feature selection derived from previous processes such as SPP, SPI, and LMP, as outlined in the paper. These features are curated based on domain expertise and insights from earlier research stages. Normalization techniques ensure the comparability of selected features across the dataset, enabling classification algorithms to effectively learn from the data.

However, instead of employing oversampling techniques to address data imbalance, undersampling techniques are utilized in this scenario. Undersampling involves reducing the size of the majority class samples to match the minority class samples, achieving a more balanced dataset. This approach aims to mitigate the impact of data imbalance on classification performance and enhance the model's ability to accurately classify both good and faulty PCBs, especially in scenarios where the occurrence of faulty PCBs is rare.

5.3 Third Scenario

In the fourth scenario, a refined approach was taken, involving data filtration based on program and supplier specifications. By segmenting the dataset according to unique program-supplier pairs, several advantages were realized.

Firstly, this segmentation resulted in a significant reduction in data volume, streamlining computational requirements and allowing for more efficient resource allocation. Additionally, the focused dataset facilitated the exploration of a wider range of modeling techniques, including the incorporation of XGBoost models, known for their effectiveness with structured data. Moreover, the targeted segmentation helped mitigate imbalance within the dataset, ensuring more equitable class representation and improving classification accuracy. By prioritizing critical program-supplier combinations, resources could be directed towards areas with the greatest impact on operational performance and PCB quality.

5.4 Fourth Scenario (Multimodal)

In the sixth scenario, we employed a multimodal approach, incorporating both structured data and images to enhance our classification process. To streamline processing, we worked with a one-month data sample, minimizing computational demands while capturing the dataset's essence.

We used an early fusion technique, integrating information from both structured data and images at the input level. This allowed us to combine features extracted from structured data with those derived from images before feeding them into the classification model.

To execute early fusion, we began by preprocessing both types of data to extract relevant features and ensure compatibility. We extracted features from structured data, selecting or engineering them to represent key PCB characteristics. Concurrently, we used convolutional neural networks (CNNs) to extract features from images, capturing visual patterns and information.

Next, we concatenated the features from structured data and images into a single feature vector. This combined feature vector, representing the fused input data, incorporates information from both modalities. We then trained a classification model using this fused feature vector, employing common machine learning algorithms or neural network architectures.

5.5 Fifth Scenario (Multimodal)

In the sixth scenario, we adopted a multimodal strategy by combining structured data and images to enhance our classification process. To manage computational resources, we worked with a one-month sample of data, ensuring manageable processing demands while capturing the dataset's essence.

Unlike the early fusion method used previously, in this scenario, we employed a late fusion approach. Late fusion involves separately processing structured data and image data through distinct pathways in the model before merging the outputs at a later stage.

To implement late fusion, we first preprocessed both types of data independently, extracting relevant features and ensuring compatibility with our classification model. Structured data underwent feature selection or engineering to highlight pertinent PCB characteristics, while image data underwent feature extraction using techniques such as convolutional neural networks (CNNs) to capture visual patterns.

Subsequently, we fed the processed structured data and image data through separate pathways in the classification model. Each pathway independently learned representations from its respective data modality, leveraging machine learning algorithms or neural network architectures optimized for each data type.

Finally, the outputs from both pathways were merged or concatenated at a later stage, creating a combined representation of the data that captured the complementary information from both modalities. This fused representation was then used as input to the final classification layer of the model.

6 RESULTS

Table 5: Model Predictions Results.

Scenario	Model	Precision	Accuracy	Recall
1	Gradient-Boosted Trees (SMOTE)	0.8889	0.8326	0.0070
2	Gradient-Boosted Trees (Random Undersampl ing)	0.8614	0.8769	0.0067
3	XGBoost	0.87786	0.9476	0.0350
4	Early Fusion	0.9394	0.9389	0.1530
5	Late Fusion	0.9114	0.8732	0.1023

The results presented in the table stem from rigorous exploration of various methodologies aimed at developing robust classification models for distinguishing between good and faulty Printed Circuit Boards (PCBs). Each scenario represents a unique experiment characterized by distinct combinations of sampling techniques, machine learning algorithms, and data fusion strategies.

It's crucial to emphasize that all experiments underwent meticulous optimization involving an exhaustive search for hyperparameters. This optimization ensured that the models were finely tuned to the dataset's characteristics and the classification problem's specific requirements. Evaluations were conducted in a controlled environment provided by Bosch, leveraging GPU clusters, particularly in scenarios involving image processing. This environment ensured consistency and reliability in assessing model performance.

The primary objective throughout these experiments was to optimize precision, prioritizing the minimization of false positives. Achieving high precision was crucial as it ensured the classification system exhibited a high level of certainty and generated minimal entropy. This approach stemmed from the understanding that misclassifying a good PCB as faulty could be costlier than accurately identifying multiple faulty PCBs. Therefore, the focus was on developing models that could confidently distinguish between good and faulty PCBs while minimizing the risk of false positives.

The best-performing scenario is Scenario 4, "Early Fusion," with an impressive precision of 0.9394 and an accuracy of 0.9389. While the recall value is relatively lower at 0.1530, indicating that the model may miss some faulty PCBs, the high precision suggests a strong ability to correctly identify faulty PCBs while minimizing false positives. This precision-focused approach is vital in manufacturing, as misclassifying a good PCB as faulty can be more costly than correctly identifying faulty ones. The success of Scenario 4 underscores the effectiveness of the "Early Fusion" technique and its potential for optimizing precision in classification tasks.

7 CONCLUSIONS

Our exploration of fault prediction scenarios in PCB manufacturing has yielded insightful findings, particularly in our best-performing scenario and our approach to reducing model complexity through structured data filtration.

In our best scenario, Early Fusion, we achieved impressive results with a precision of 93.94%, accuracy of 93.89%, and recall of 15.30%. This outcome underscores the effectiveness of combining multimodal data (images and structured data) to enhance fault prediction accuracy. Leveraging both visual and structured information allowed us to capture nuanced patterns and correlations, leading to more robust predictions. This holistic approach represents a significant step forward in fault detection in PCB manufacturing, aligning with the principles of Industry 4.0 and bolstering quality control efforts.

Conversely, our exploration of filtering structured data to reduce model complexity (Scenario 4) sheds light on the importance of targeted data preprocessing. By filtering data based on program and supplier characteristics, we were able to streamline the modeling process and focus on critical subsets of data. This approach not only mitigated the challenges posed by imbalanced datasets but also facilitated the utilization of advanced modeling techniques such as XGBoost. The resulting decrease in model complexity led to improved computational efficiency and enhanced interpretability, essential factors in real-world deployment scenarios.

In summary, our research underscores the significance of adaptive modeling strategies and targeted data preprocessing techniques in fault prediction in PCB manufacturing. By embracing interdisciplinary collaboration and leveraging advanced data science methodologies, we are poised to drive meaningful advancements in quality control and operational efficiency within the electronics manufacturing industry, ushering in a new era of innovation and reliability.

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