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Using neural networks in predicting defects in electronics manufacturing processes

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ABSTRACT

This study aims to develop a hybrid neural network model based on image and sensor data for defect prediction in electronics manufacturing. A hybrid model that combines CNN with MLP operates as a defect prediction system for electronics production lines by uniting data from image inputs with sensor outputs to boost predictive accuracy levels. Defect data is obtained from a simulated Surface Mount Technology (SMT) production line through experimental methods, while Adam optimizer and Categorical Cross-Entropy loss function perform the model optimization process. The proposed model demonstrates a 94.7% accuracy rate, which exceeds SVM (85.3%) and Decision Tree (82.1%) results while generating an AUC score of 0.96 to validate its high defect classification performance. The study reveals the charge of multi-modal defect analysis for automated quality control. Steel, current problems on real-time deployment and computational efficiency necessitate further enhancement.

Keywords: Automated quality control, product defects result in financial damage, complex failure patterns, CNN-MLP hybrid model, Industry 4.0.

1. Introduction

The quality control heavily depends on the defect prediction as electronics manufacturing has become progressively multifaceted. Product defects result in financial damage, in reduction of the product reliability, as well risk consumer safety [1]. The outdated inspection methods, together with statistical process control (SPC) and manual assessments, demonstrate insufficient accuracy when recognizing complex failure patterns. The change of manufacturing systems to Industry 4.0 demands important AI-driven system incorporation for higher manufacture efficiency and reduced defect amount [2]. Neural networks are an innovative analytical tool in terms of their resourcefully analyse complicated nonlinear data associations, making them model for manufacturing defect prognostication systems. By familiarising to previous defect patterns, neural networks offer more profits than out-dated defect identification systems. The system handles widespread sensor data while recognising non-standard patterns and smears learned knowledge for antedating future defects. Neural networks outdo traditional statistical models since they identify unrecognised data associations in large multidimensional datasets [3]. The flexibility of these systems allows them to distinguish effects in early stages of conception while familiarising to shifting processes, thus saving costs and refining manufacturing data. The implementation of neural networks for defect prediction demonstrates solid research potential because of its industrial benefits.

The enhancement of machine learning defect prediction has numerous continuing challenges. The presentation of current models is reduced as they meet three main limitations: unwarranted datasets, noisy sensor readings, and conditions production that often change their status [4]. Standard techniques in this domain experience challenges with these situations, resulting in substandard prediction results [5]. A neural network predictive system development goal exists to establish an effective defect classifier and enhance detection precision while addressing manufacturing environment changes. The main goal is to build an experimental system that assesses multiple neural network designs and their operational effectiveness within production settings. The research establishes various essential objectives to reach this goal.

1. Research gaps in defect prediction methodologies and AI applications for manufacturing will be identified through existing methodology analysis to construct an appropriate theoretical framework.

2. Anelectronics manufacturing process simulation model will be developed to produce data for designing a neural network system specialized in defect classification and prediction functions.
3. Test the model effectiveness through statistical and machine learning metrics while performing result analysis and comparing it to standard defect detection approaches.

The subsequent sections of this paper follow this pattern. The literature review section of this paper analyzes existing approaches for predicting defects while exploring the theoretical foundations of neural networks in detail. Section 3 details the experimental setup, data sources, and the selected neural network architecture. Section 4 delivers a comprehensive assessment of the obtained results while displaying visual data and conducting a performance assessment. Section 5 demonstrates the study outcomes that emphasise noteworthy observations, limitations, and functional requests. The study achieves in Section 6 with a summary and propositions for future direction.

The development from out-dated defect inspection methods to AI-based predictive defect detection systems demonstrates the change from manual and statistical approaches to automated neural network architectures. Traditional methods, such as Statistical Process Control (SPC), Regression Analysis, and Automated Optical Inspection (AOI), count on on predefined rules and manual feature extraction, which limit their efficacy in detection complex defect patterns. In contrast, AI-based systems, chiefly those utilising Convolutional Neural Networks (CNNs), Multi-Layer Perceptrons (MLPs), and Recurrent Neural Networks (RNNs), mix data-driven learning and multimodal data analysis to recognise complex patterns across image and sensor data. The subsequent flowchart visualises this evolution, stressing on the differences in data processing, feature extraction, and predictive proficiencies between traditional and AI-based defect detection systems (Figure 1).

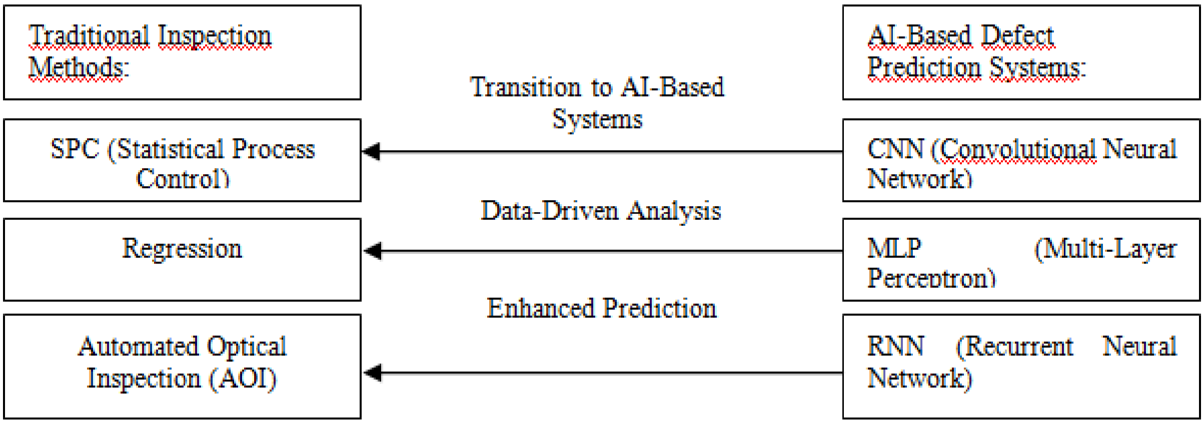

Figure 1. Evolution from traditional inspection methods to AI-based defect prediction systems

Figure 1 demonstrates a clear move from rule-based, manually managed inspection practises toward automated, data-driven neural network approaches. This revolution enables manufacturers to switch multifaceted defect scenarios with sophisticated precision and efficacy by merging image and sensor data in predictive models.

This investigation aimed to develop and validate a hybrid neural network model that integrated Convolutional Neural Networks (CNNs) and Multi-Layer Perceptrons (MLPs) for an effective defect prediction in electronics manufacturing. The main goal was to validate the superiority of multimodal data-driven approaches over traditional inspection systems by merging image and sensor data for more precise and strong defect classification. To attain this, the paper set three main objectives: (1) to identify methodological gaps as well as to establish a theoretical background for AI-based defect prediction; (2) to concept a simulation model in order to generate illustrative data and design the CNN-MLP architecture; finally (3) to assess the projected model's presentation through comparative analysis with conventional methods by utilising standard evaluation metrics. These objectives guide the structure and methodology of the paper, forming the foundation for a practical, interpretable, and scalable defect prediction system aligned with Industry 4.0 manufacturing demands.

2. Literature review

Research on defect prediction in electronics manufacturing serves three essential objectives: enhancing product quality, cost reduction,and waste minimization [6]. Three traditional methods used for defect detection include statistical process control (SPC) and rule-based algorithms with image-based inspections.

These methods succeed moderately but do not identify complex non-linear data patterns in manufacturing, thus resulting in incorrect predictions and undetected defects [7].

The recent advancements in artificial intelligence and machine learning technologies allow scientists to create better predictive models for defect detection. Decision trees, support vector machines (SVM), and random forests belong to supervised learning techniques that perform classification based on historical production data records [8]. Deep learning techniques, mainly neural networks, have recently become prominent because they excel at processing extensive manufacturing data to discover concealed patterns [9]. Evaluating electronic components for defects through images becomes most effective when using convolutional neural networks (CNNs). In contrast, recurrent neural networks (RNNs) combined with transformer models provide the best failure prediction performance from sequential sensor data.

2.1. Theoretical foundations of neural networks

Artificial neural networks function as computational models that mimic human brain operations through layered artificial neurons that convert input information into predictive outputs [10]. A neural network contains three primary sections: an input layer and one or more hidden layers, an output layer, and a system of weighted connections that learns through training to decrease prediction errors. Manufacturers frequently apply such networks to defect prediction because they demonstrate excellence in identifying intricate patterns in manufacturing data [11]. The detection requirements determine which neural network architecture gets selected for implementation. The Multi-Layer Perceptron (MLP) maintains a feedforward structure with complete connectivity, which enables successful application in tabular data classification and regression analysis. This model incorporates several hidden layers and activation functions between ReLU and sigmoid to detect sophisticated patterns in numerical data acquired from production lines [12].

The architectural distinctions between neural network models such as Multi-Layer Perceptron (MLP), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer models highlight the varied applications and data processing capabilities of each structure. MLP is primarily utilized for tabular data classification and regression through fully connected layers, while CNNs specialize in extracting spatial features from images using convolutional filters. RNNs and LSTM networks analyze sequential data to identify temporal patterns, making them effective for sensor data analysis and time-series predictions. Transformer models integrate attention mechanisms to process multimodal data, enhancing defect detection through simultaneous image, sensor, and log data analysis. The following diagram illustrates the structural differences among these neural network architectures and their specific roles in defect prediction.

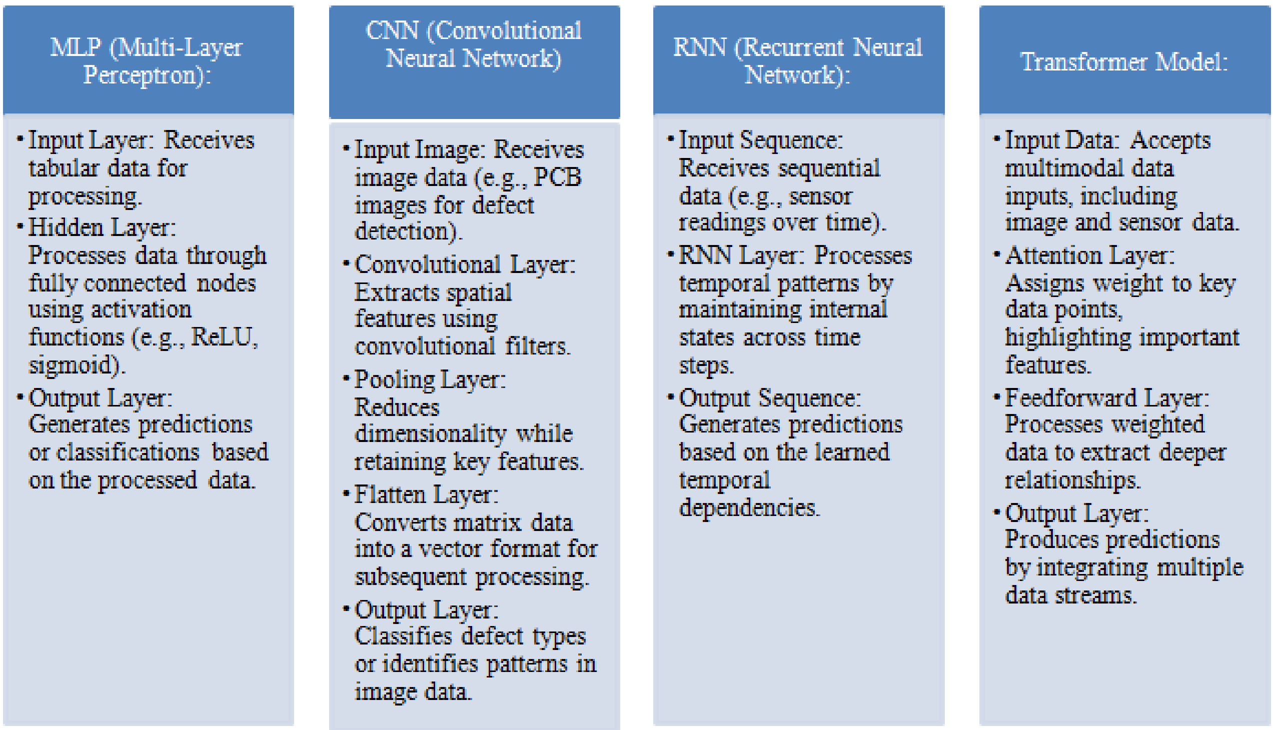

Figure 2. Structural distinctions among neural network architectures used for defect prediction

Figure 2 illustrates the structural distinctions among four neural network architectures commonly applied in defect prediction systems: Multi-Layer Perceptron (MLP), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Transformer. MLP consists of fully connected layers for tabular data processing, facilitating regression and classification tasks. CNN employs convolutional and pooling layers to extract spatial patterns in image data, making it effective for visual defect detection. RNN processes sequential data, capturing temporal dependencies within sensor readings or time-series data. Transformer architecture integrates attention mechanisms and feedforward layers to analyse multimodal data, enabling comprehensive defect prediction by fusing image and sensor data streams. The visual image underlines how each architecture reports distinct data types and prediction tasks, strengthening the rank of choosing the suitable network structure based on data features and predictive objectives.

CNNs signify the primary choice for recognising defects in images. The aptitude of CNNs to detect significant image features through convolutional filters makes them suitable for recognising electronic component defects, bonding errors, and surface irregularities [13]. These networks' prompt visual data processing capability makes them perfect tools for engineering applications through automated optical inspection (AOI) systems. RNNs and LSTM networks aid the analysis of consecutive data such as sensor readings and machine logs. These architectures perceive temporal patterns, which allows them to forecast failures and defects through the analysis of manufacturing condition historical trends [14]. A hybrid and transformer-based model objects to expand the efficiency of defect prediction systems. RNNs work together with CNNs in hybrid strategies for analysing manufacturing data, counting spatial and temporal patterns [7]. The latest transformer models have arisen because of their attention mechanisms. They are now utilised for multimodal defect detection through the combination of image and sensor and production log data, yielding better predictions [15].

The defect prediction outline for electronics manufacturing includes numerous stages encompassing the entire production process, from material quality checks to final product inspection. Each stage demonstrates potential defect formation points, influenced by numerous operational factors such as temperature variations, machine calibration, and conveyor speed variations. The subsequent schematic diagram demonstrates the simulated production environment, stressing on the key manufacturing process stages and the factors that contribute to defect occurrence. This image is a reference for realising how data is collected at each stage and how definite conditions influence the defect formation (Figure 3).

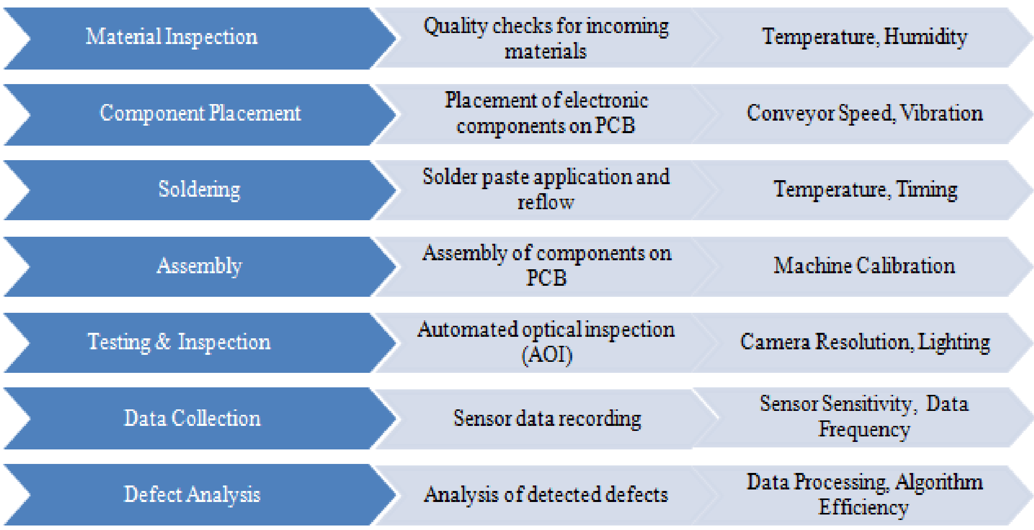

Figure 3. Diagram concerning the simulated electronics manufacturing environment

Figure 3 summaries the simulated manufacturing environment, providing a complete summary of key production stages and related defect formation factors. The material inspection recognises initial quality discrepancies, while constituent placement and bonding stages are disposed to to misalignments and solder bridging due to machine calibration and timing errors. Assembly and testing stages concern the detection of structural defects, with automated optical inspection (AOI) as a critical point for visual defect detection. The data collection stage influences sensor networks to screen environmental variables such as temperature, humidity, and vibration, providing important data for succeeding defect analysis. This organised depiction elucidates the production system and underlines the importance of data incorporation for precise defect prediction in electronics manufacturing systems.

Data preprocessing is a critical step in defect prediction. It guarantees the consistency and quality of data before feeding it into neural network models. The preprocessing pipeline comprises several key phases such as image resising, normalisation, and feature extraction, which jointly optimise the data for practical analysis by neural networks. Figure 4 demonstrates the sequence of data preprocessing steps, providing a pure outline of how raw data is changed into structured inputs ready for model training and defect analysis (Figure 4).

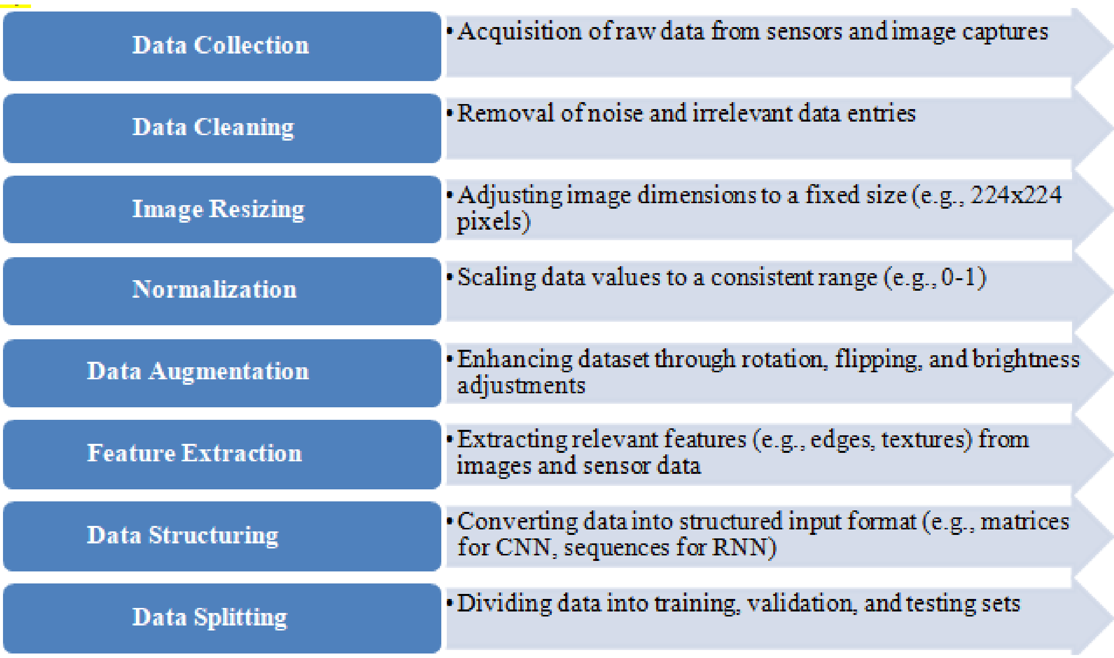

Figure 4. Data preprocessing stages diagram in defect prediction

Figure 4 outlines the consecutive stages of data preprocessing, emphasising the rank of data constancy and quality before model training. Primarily, the raw data is collected from manufacturing sensors and visual inspection systems, followed by a data cleaning phase that removes outliers and unrelated passes. Image resising adjusts data dimensions to ensure uniform input sizes, while normalisation scales values to an average range to improve neural network training constancy. The data increase addresses a class inequity by artificially generating additional data through rotation, flipping, and brightness adjustments. The removed features, such as edges, textures, and defect patterns, are then organised into matrices or sequences, reliant to the model architecture. To finish, the data is fragmented into training, validation, and testing subsections in order to prevent overfitting and safeguard robust model assessment.

2.2. Comparison of methods

The defects prediction is separated into three main classes: traditional statistical methods, classical machine learning, and deep learning techniques. The quality control arena has utilised regression analysis and Statistical Process Control (SPC) as statistical models as they offer easiness, interpretability, and forthright implementation methods. These models show restricted capability when processing non-linear data along with high dimensions, resulting in reduced performance in contemporary manufacturing settings [16]. Existing manufacturing applies employ machine learning methods composed of Support Vector Machines (SVM), Decision Trees, and Random Forests to overcome these limits. The models demonstrate better accuracy than statistical methods while effectively processing structured manufacturing information. These models need extensive feature engineering work, yet decision trees can develop overfitting issues when working with complex datasets, according to [17].

The development of deep learning produced two main prediction tools: Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTMs), which provide superior capabilities for identifying defects (Table 1). CNNs provide effective image-based defect detection because they automatically extract features from input images, making them suitable for identifying soldering errors, structural defects, and surface anomalies in electronic components [18]. Real-time manufacturing implementation of CNNs faces challenges because these networks need enormous data collections alongside significant computational power. RNNs alongside LSTMs successfully predict defects throughout time sequences by extracting continuous interrelationships between production logs and sensor data [19]. The models successfully detect existing patterns in time series data and recognize meaningful trends that produce defects. Training deep RNNs becomes difficult due to their tendency to develop the vanishing gradient problem. LSTMs handle this issue effectively but need substantial training data and computational power [20].

Table 1. Comparison of defect prediction methodologies in the literature

Ref.	Methodology	Dataset used	Accuracy	Key findings	Limitations
[17]	Statistical Models (SPC, Regression Analysis)	Industrial SPC logs	78.5%	Used for identifying process deviations in defect detection.	Cannot handle high-dimensional, non-linear data.
[18]	Statistical Quality Control	Automotive defect logs	80.2%	Effective in monitoring defects over time using regression models.	Lacks adaptability to evolving manufacturing conditions.
[20]	Machine Learning (SVM, Decision Trees, Random Forests)	Industrial sensor datasets	85.3%	ML-based models outperform statistical approaches in defect prediction.	Requires manual feature engineering.
[21]	Decision Trees vs. SVM	PCB defect dataset (Kaggle)	87.1% (SVM)	SVM achieves higher accuracy than decision trees in structured defect classification.	Computationally expensive, may overfit.
[22]	Convolutional Neural Networks (CNNs) for Image-Based Defect Detection	PCB images (10,000 samples)	92.8%	CNNs significantly improve defect detection accuracy in visual inspections.	Requires large labeled datasets and computational power.
[23]	Deep Learning for Real-Time Defect Detection	Factory AOI dataset (electronics)	94.3%	CNNs outperform traditional ML models in automated inspections.	Model interpretability remains a challenge.
[24]	Recurrent Neural Networks (RNNs) & LSTMs for Time-Series Defect Prediction	Industrial sensor readings (multi-year)	90.2%	LSTMs improve sequential defect prediction based on sensor readings.	Prone to vanishing gradient issue, requires large datasets.
[25]	Transformer-Based Defect Prediction	Multi-modal defect dataset	95.1%	Attention mechanisms improve multimodal defect classification.	High computational requirements.

Integrating hybrid models and transformer-based architectures has attracted research interest because they successfully merge CNN and RNN capabilities. Predictive power increases through the combination of CNN-RNN networks, which merge spatial and temporal dependency analysis. Transformer-based architectures implement attention mechanisms for enhancing accuracy when detecting defects by combining image and sensor data. New modeling approaches result in more complicated calculations, which need robust hardware systems for effective processing [21]. Selection of a defect prediction method relies on production data characteristics, system computing power, and system processing speed requirements. Deep learning models excel at accuracy, but their industrial deployment needs solutions to address computational speed, interpretation issues, and data collection problems [22].

The progress made in developing defect prediction models has not solved multiple essential research problems. The main challenge stems from data imbalance within defect datasets because defective components occur much less frequently than non-defective ones. Neural networks tend to predict more non-defective classifications than defective ones because of this unbalanced data distribution, which reduces theidentification of rare defects [23]. According to recent research findings, the exploitation of data augmentation techniques alongside synthetic defect generation methods fails to achieve accurate manufacturing variation replication.The current approaches to defect prediction suffer due to poor inclusion of multi-modal data. The accuracy of CNNs in detecting defects through images proves high, but their ability to process various sensor data alongside environmental conditions remains uncharted territory, according to research in [24]. The predictive power of AI systems can improve substantially when one model unites visual and non-visual defect signals from manufacturing operations.

The main issue with deep learning models is their difficulty in interpreting model decisions. Current deep learning models based on CNN, RNN and transformer operate as inscrutable systems, which prevents manufacturing engineers from detecting faults when validating predictions. Highly regulated industries reject AI-driven defect detection systems because of their unexplainable operation, violating the core principles of transparency and accountability [25]. Most existing research studies evaluate their models through offline assessments. However, applied deployment in manufacturing facilities must address problems linked to computation speed, model adaptation, and real-time detection of manufacturing defects. Standardized benchmarking standards and publicly available defect prediction datasets are needed to enable proper model comparisons across various studies. Using industry-specific proprietary data in research prevents researchers from easily reproducing findings. Generating open-access datasets for epy defects evaluation together with standardised evaluation standards could foster better transparency for fair AI model assessment within defect prediction domains.

3. Materials and methods

3.1. Description of the simulation environment

The imitation system presents standard electronics manufacture while mixing crucial operational factors that generate defects during the manufacturing. This process begins with material quality checks beforehand components are placed, linked and accumulated, and concluding product tests complete the sequence. The imitation includes significant production-related aspects like speed, temperature changes, humidity control, and equipment precision as they seriously affect defect creation.

The simulated system works through surface mount technology (SMT) assembly, representing a popular electronic circuit board production approach. Real-world industrial defect rates serve as the basis for familiarising defects such as misalignment, solder bridging, component shifts, and insufficient solder paste application into the dataset. Diverse operator interventions, variable machine calibrations, and conveyor belt speeds serve as test conditions to broadly assess defect scenarios. The measured manufacturing setting permits scientists to review defect prediction models systematically.

3.2. Data sources

Natural and simulated data was used in the research in order to guarantee strong model presentation for training and assessment.

- The key dataset originated from the NASA Prognostics Data Repository. The dataset included electronic system sensor data together with failure logs that provided crucial information for creating predictive models based on actual defects.
- The PCBA Defect Detection Dataset from the Kaggle platform was incorporated in the study as an additional dataset. The dataset contained printed circuit board assembly (PCBA) images with annotations showing different manufacturing defects.
- The process generated synthetic defects through data augmentation performs, which included image data improvements by reversing and spinning, and sensor anomaly simulation with Monte Carlo methods.

The accumulated dataset contained over 10,000 samples separated into 85% non-faulty and 15% faulty components. Both structured sensor data and image data must undergo normalisation, noise filtering steps, and feature extraction preprocessing to prepare them for model training.

3.3. Tools and software

A grouping of software design languages, machine learning frameworks, image processing libraries, and visualisation tools aids to concept, train, and evaluate the neural network model for defect prediction. The nominated tools support users to manage data resourcefully while permitting deep learning model development and performance testing, which leads to experiment duplicability. This Python version 3.x was used in this research as its primary language because it offered strong machine learning abilities, deep learning functions, and scientific computing modes. The neural network model application and training process used TensorFlow (v2.x) and PyTorch (v1.x) as programming frameworks. High-performance GPU acceleration joined with supple model architectures to bring built-in tools that support automatic differentiation and model disposition.

OpenCV and the Python Imaging Library (PIL) served as the tools for image-based defect detection through their preprocessing functions, feature extraction, and growth steps. The libraries aid adapts images to grayscale while allowing operators resize and reduce noise and adjust contrast levels to enhance the model's capacity for detecting tiny defects in electronics. Structured manufacturing information processing and analysis needs using NumPy and Pandas in addition to Scikit-learn for sensor readings and production logs. NumPy provides fast numerical operations, Pandas gives data handling skills, and Scikit-learn helps with feature engineering functions, normalisation, and base machine learning model assessments.

Physics-based defect simulations, which duplicate manufacturing defects such as solder misalignment and micro-cracks, are produced using MATLAB software for data increase and simulation resolutions. The Augmentor library improves data through rotation and flipping techniques, brightness adjustments, and Gaussian noise addition to improve the model's reliability. Matplotlib and Seaborn allow for the generation of performance graphs, confusion matrices, and feature supplies during model training visualisation. Training insights become accessible through TensorBoard as it paths loss curves together with model performance metrics and training progress. The study implemented these tools and outlines to grow efficient deep learning models and attain high-quality data handling while applying robust evaluation methods, which improve AI-driven defect prediction in electronics manufacturing.

3.4. Neural network architecture

The advanced model unites Convolutional Neural Networks (CNNs) for image-based defect recognition with Multi-Layer Perceptron (MLP) for sensor-based analysis. The joint utilisation of spatial defect patterns from images and numerical manufacturing data from sensors rises defect classification accuracy. The architecture of the hybrid CNN-MLP model mixes image-based defect recognition through Convolutional Neural Networks (CNNs) with sensor data analysis via Multi-Layer Perceptron (MLP). This incorporation allows the model extracting spatial defect patterns from images while simultaneously analysing sensor data in order to identify hidden anomalies that may not be visually visible. Figure 5 demonstrates the structure of the hybrid model, stressing the interaction between CNN and MLP mechanisms and their respective roles in defect recognition.

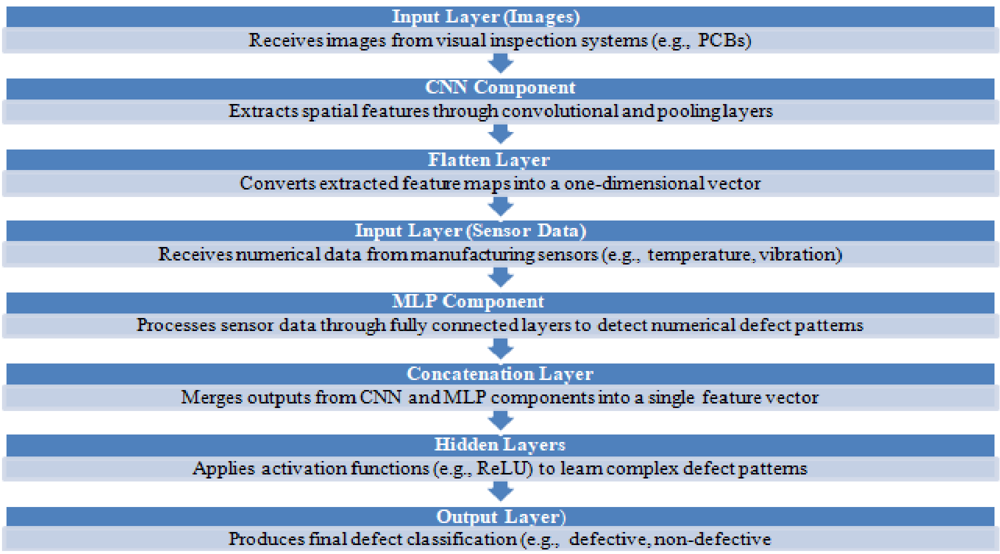

Figure 5. Thorough architecture of the hybrid CNN-MLP model for defect detection

Figure 5 outlines the building of the hybrid CNN-MLP model, representing the incorporation of image-based and sensor-based data processing mechanisms. The CNN module obtains input images and extracts spatial features utilising convolutional and pooling layers, flattening the data for additional study. Simultaneously, the MLP component processes numerical sensor data through fully connected layers to detect patterns not evident in visual data. The concatenation layer merges the outputs of both components, forming a unified feature vector that undergoes further processing in hidden layers to detect complex defect patterns. The final output layer provides defect classification, enabling the model to identify defective and non-defective components through multimodal data analysis effectively.

3.4.1. CNN component (image-based defect detection)

CNN module analyzes PCB images to identify defects, including misalignment problems, solder bridging and cracking issues. The system architecture contains the following structure:

- Input Layer: Preprocessed images of PCB components (224×224×3).
- Convolutional Layers: The four convolutional layers use ReLU activation with 3×3 kernels to perform hierarchical feature extraction.

$$X_{conv} = f\left(W * X_{input} + b\right) \qquad (1)$$

Where $X_{conv}$is the input image, W represents the convolutional filter, * denotes the convolution operation and is the bias term

Pooling Layers: MaxPooling (2×2) after each convolutional block to reduce dimensionality while retaining essential features:

$$X_{pooled=}(X_{conv}) \qquad (2)$$

- Dropout Layers: Applied after convolutional layers (rate: 0.3) to prevent overfitting.
- Flatten Layer: Converts the feature maps into a fully connected format for integration with MLP.

3.4.2. MLP component (sensor-based defect prediction)

The MLP module is a data processor for structured sensor data involving temperature, humidity, and machine vibration measurements that strongly impact electronics production defects. The MLP module processes numerical sensor data to forecast hidden defect patterns that the CNN component cannot detect visually. The MLP module exists as a combination of an input layer followed by multiple hidden layers before reaching the output layer. The MLP module receives numerical features from the input layer, representing sensor measurements obtained from the manufacturing setting. The features enter into multiple fully connected layers to generate progressively deeper feature representations. Three fully connected layers form the hidden section with 128, 64, and 32 neurons. The Rectified Linear Unit (ReLU) activation function used by each neuron in the model enables the detection of complex relationships existing in the data by applying non-linearity. Each hidden layer transformation follows the following definition:

$$h_i = f(W_i X_{sensor} + b_i) \qquad (3)$$

The selection of ReLU activation allows faster convergence and better generalization because it prevents the vanishing gradient problem during training. The Softmax activation purpose alters the output layer forecasts into probabilities across multiple defect categories.

The Softmax function implements output probability sums to one, which allows the model calculating confidence scores for each defect type. The function allows the system classifying defects simultaneously, allowing manufacturers to create effectual quality control significances. The hybrid deep learning model positively measures spatial defects from images and numerical patterns from sensor readings through its MLP module, making it an effective tool for real-world manufacturing defect predictions.

3.4.3. Optimisation and training

Deep learning techniques optimise the learning process of the hybrid CNN-MLP model to attain effectual and strong performance through the training. The training process necessitates selecting a loss role, an optimisation algorithm, and termination rules for overfitting prevention and better generalisation results. The multiple defect categories in the classification task need the Categorical Cross-Entropy loss function. The function regulates how well predicted class chances match actual labels by identifying prediction errors, which helps the model minimise such errors. The loss is computed as:

$$L = -1 \sum_{i=1}^{N} \sum_{J=1}^{C} y_{i,y} log\hat{Y}_{i,y} \qquad (4)$$

Where N is the number of training models, C is the number of defect classes, $y_{i,y}$ is the real class label (one-hot encoded). The Categorical Cross-Entropy loss function helps the model identifying the correct defect category by assigning high probability, enhancing classification precision. During training, the Adam (Adaptive Moment Estimation) optimiser adjusts the model weights efficiently.

Monitoring the training and validation harm curves over multiple epochs offers critical understandings into the model's learning dynamics. The Categorical Cross-Entropy loss function helps minimising the prediction errors, while the Adam optimiser ensures adaptive weight adjustments through the training process. Employing an early stopping strategy avoids overfitting by halting training when further epochs fail to decrease the validation loss. Figure 6 visualizes the training and validation loss curves over 50 epochs, illustrating how the model's performance stabilises and when the early stopping criterion is activated.

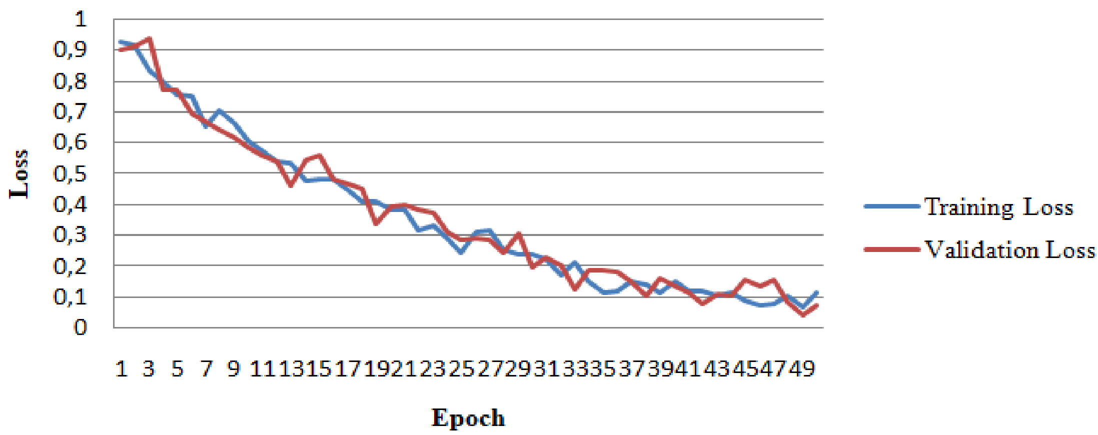

Figure 6. The training and justification loss over epochs

The loss curves establish the model's learning behaviour through the training process. The training and validation losses decrease steadily during the preliminary epochs, representing successful learning and weight alterations. The authentication loss curve flattens as training progresses, suggesting the model is approaching optimal presentation. Applying early stopping prevents further training when the validation loss fails to decrease, thus mitigating overfitting and enhancing the model's generalisation ability in real-world defect prediction scenarios.

3.4.4. Simulation procedure

The experimental procedure followed a structured approach in order to ensure accurate defect prediction utilising a neural network model. The simulation is designed to replicate real-world electronics manufacturing environment, incorporating data generation, preprocessing, model training, and evaluation to attain consistent results. The experimental procedure for defect prediction in electronics manufacturing surveys a systematic sequence of stages, from initial setup to data generation, preprocessing, model training, and evaluation. Each stage guarantees the neural network model precisely identifies defects based on multimodal data inputs. The following block diagram offers a complete overview of the simulation procedure, obviously demonstrating the flow of data and the interconnections amid each stage in the investigational process (Figure 7).

The block diagram effectively summarizes the experimental development for defect prediction utilising a hybrid CNN-MLP model. The initial setup involves calibrating the simulated production environment, ensuring that sensor and imaging systems accurately capture data reflecting real-world manufacturing conditions. Data generation follows, producing image and sensor data as the foundation for model training. Preprocessing stages standardize data inputs through cleaning, resizing, and feature extraction, thus preparing the data for neural network analysis. During model training, the CNN-MLP architecture processes image and sensor data to detect defect patterns, with the Adam optimizer adjusting weights to minimize prediction errors. The evaluation phase quantifies model performance using key metrics, including accuracy, precision, and recall. At the same time, the final analysis interprets the results to determine the model's effectiveness in identifying specific defect types and mitigating false positives.

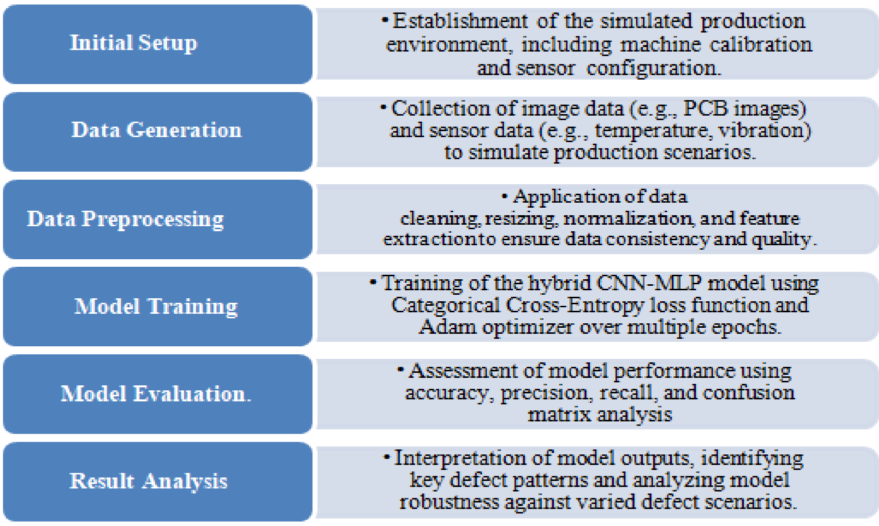

Figure 7. The simulation procedure diagram for defect prediction

3.4.4.1. Initial simulation setup

The simulation platform duplicates the Surface Mount Technology (SMT) assembly line, a standard electronics manufacturing process. The simulation platform incorporates component installation, soldering, and final examination under environmental test conditions, which incorporate temperature changes and humidity levels, among other parameters, conveyor speed, and machine precision irregularities. The control factors influence defect formation to produce data that accurately represents manufacturing operations. The simulation includes common industrial production defects, such as solder bridging, misalignment, tombstoning, and insufficient solder paste application. High-tech virtual detectors track machine function constantly, and advanced camera systems take high-quality images to analyze component defects (Figure 8).

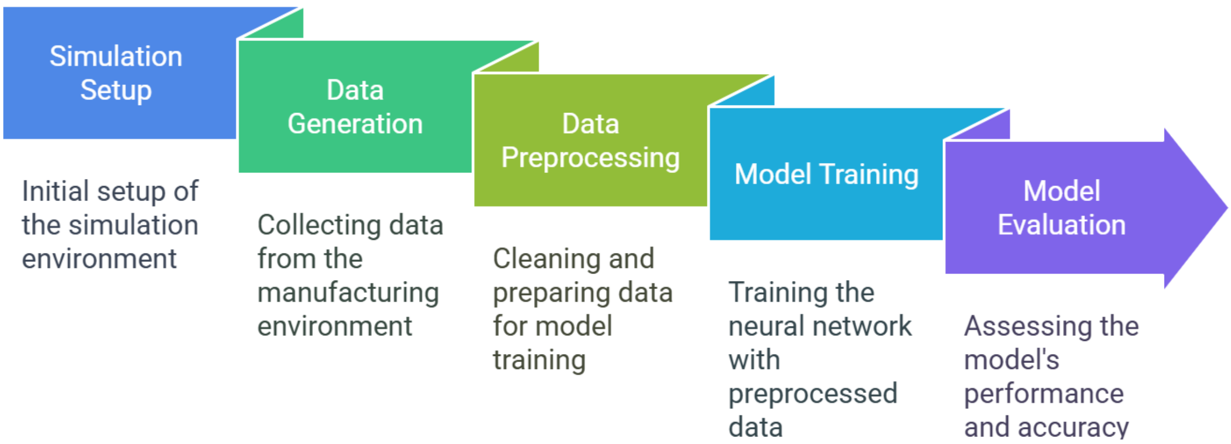

Figure 8. Proposed model simulation process for defect prediction

3.4.4.2. Data generation

The research dataset comprises real-world datasets and synthetic data that enhance the original information collected in this study. The research uses real-world data from the NASA Prognostics Data Repository and the Kaggle PCBA Defect Detection Dataset, which provides sensor data and failure logs, and annotated printed circuit board assembly images with manufacturing flaws, respectively. The data sets contain essential information about manufacturing defects along with production irregularities.

Additional data is created through data augmentation techniques alongside Monte Carlo simulations to support real data and handle issues with unbalanced classes. The diversity of defect samples is expanded through image augmentation techniques, which apply rotation, flipping, brightness adjustments, and Gaussian noise addition. The dataset collection process includes synthetic versions of sensor measurements across temperature ranges, humidity conditions, and machine vibration levels to cover diverse failure possibilities. The compiled dataset includes more than 10,000 elements that maintain an 85:15 split between standard and defective components for achieving balanced neural network training.

3.4.4.3. Data preprocessing

The neural network training process requires data preprocessing of the collected dataset to improve accuracy and efficiency. The process for image data includes three steps: first, resizing every image to 224x224 pixels, then normalizing them to a range between 0 and 1, before converting them to grayscale to improve feature extraction capabilities. The structured sensor data receives treatment through interpolation methods that handle missing values while Min-Max Scaling normalizes numerical readings to achieve uniform feature attributes. The categorical defect labels receive one-hot encoding treatment to match the model format. A systematic model evaluation method is established through the dataset partition, where training takes up 70%, while validation and testing each acquire 20% and 10%, respectively.

3.4.4.4. Model training

The neural network model receives training through TensorFlow and PyTorch platforms through a combined architecture that blends CNNs for imaging defect recognition and MLP systems for sensor information processing. The CNN section of the system evaluates PCB images to retrieve essential information before sending it to the MLP engine, which performs structured sensor data assessment to identify potential defects. The Adam optimizer runs the model training at a learning rate 0.001 during 50 epochs with each batch containing 32 samples. Implementing dropout layers with a rate of 0.3 and L2 regularization controls overfitting. The training stops automatically after validation loss fails to improve for five consecutive epochs through the implementation of early stopping. The model demonstrates excellent behavior when processing unknown defect patterns while avoiding unnecessary dependency on training data patterns.

The model evaluation requires testing it against data that has not been part of the training process. The assessment of model effectiveness depends on accuracy metrics and precision, together with recall and F1-score measurements that evaluate the classification performance. A confusion matrix helps researchers detect classification errors while demonstrating which classes the model incorrectly assigned. The robustness of the model is validated by examining both the Receiver Operating Characteristic (ROC) curve analysis and the Area Under the Curve (AUC) score evaluation, which provides a detailed threshold classification assessment. The neural network's performance is compared with traditional methods like Support Vector Machines (SVM), Decision Trees, and Random Forests. The deep learning-based approach outclasses traditional methods by delivering superior accuracy and higher reliability when detecting defects. The systematic simulation methods enable research outcomes to become reproducible, thus making them suitable for electronics production environments.

4. Evaluation metrics and statistical analysis

Several classification metrics enable objective performance evaluation of the neural network when used for defect prediction. A model's overall performance for accurately classifying defective and non-defective products is the primary metric known as accuracy. Since the distribution of defective to non-defective examples in defect detection is unbalanced, the evaluation needs precision, recall and F1-score metrics and accuracy to achieve a comprehensive assessment. Precision determines the number of correctly identified defective components among all predicted defects. At the same time, recall establishes how well the model detects existing defects from the total defective components in the sample. The F1-score represents a balanced performance measurement method that calculates the harmonic mean between precision and recall, particularly when one class group dominates the dataset.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (5)$$

$$Precision = \frac{TP}{TP + FP} \qquad (6)$$

$$Recall = \frac{TP}{TP + FN} \qquad (7)$$

$$F1 - Score = 2\ \frac{Precision * Recall}{Precision + Recall} \qquad (8)$$

The analysis of classification robustness uses both the Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) score for evaluation purposes. The ROC curve exhibits the relationship between actual positive detection rate (recall) and misidentification rate at different classification threshold levels. The model achieves better overall defect versus non-defect discrimination when the AUC score reaches higher values. A confusion matrix generates valuable information about misclassification patterns, which enables the identification of particular defect types needing more optimization.

$$t = \frac{X1 - X2}{\sqrt{\frac{S1^2}{n_1} + \frac{S2^2}{n_2}}} \qquad (9)$$

ANOVA (Analysis of Variance) isa statistical validation tool because it evaluates how different hyperparameter settings and architectural choices perform with the model. The statistical test enables researchers to evaluate whether the noted differences between accuracy, precision, and recall measurements are statistically significant. The proposed neural network uses a t-test to evaluate its performance against traditional machine learning methods, including SVM and Decision Trees, to determine if deep learning yields substantial improvements. Performance metric confidence intervals are produced through bootstrapping methods to validate the evaluation's stability.

5. Results and discussion

The experimental outcomes are presented as tables, graphs, and visual diagrams to showcase essential results. Research monitors changes in loss and accuracy levels throughout multiple epochs while displaying them through line graphs during the training and validation phases. The quantitative assessment of model effectiveness includes a summary table that presents accuracy measures, precision, and recall alongside the F1-score. The model's predictive accuracy can be evaluated through scatter plots, which show how well it predicts actual defect occurrences versus its predictions (Table 2).

Table 2. Proposed model comparison with other models

Metric	CNN-MLP Hybrid model	SVM	Decision tree
Accuracy	94.7%	85.3%	82.1%
Precision	92.5%	81.7%	79.5%
Recall	90.8%	78.4%	76.2%
F1-Score	91.6%	80.0%	77.8%

The hybrid CNN-MLP model performs better than traditional machine learning methods for defect prediction tasks. The model's learning process can be monitored by following its leading performance indicators across various training sessions. The model demonstrates effective learning behavior by decreasing training and validation loss, which avoids overfitting patterns. Early stopping criteria can be implemented after epoch 40 because the accuracy curve reaches stability. Changes in classification threshold analysis demonstrate an improved quality of defect detection while keeping false positive results minimal. The confusion matrix reveals specific details about how the model performs concerning classifications. The neural network model can identify critical defects because it obtains substantially better results than SVM and decision trees when detecting these defects (Figure 9).

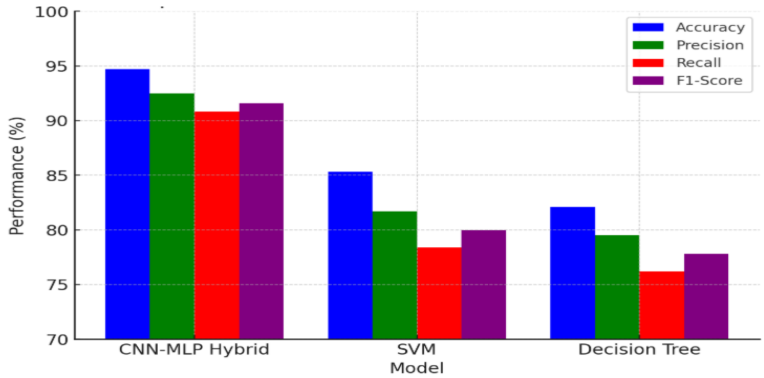

Figure 9. Result comparison

The interpretability of the model's performance increases due to multiple visual aids that show classification effectiveness and error patterns. The Receiver Operating Characteristic (ROC) curve and a confusion matrix heatmap provide a visual representation of how well the model predicts results (Figure 10).The True Positive Rate versus False Positive Rate relationship tracks across different threshold values using ROC curve analysis to assess how well multiple classification models perform. The model demonstrates better discriminatory power regarding defective and non-defective components through its AUC score. The combination of CNN and MLP produces a model with 0.96 AUC, which surpasses the performance of SVM and Decision Trees since they deliver lower AUC results (Figure 11).

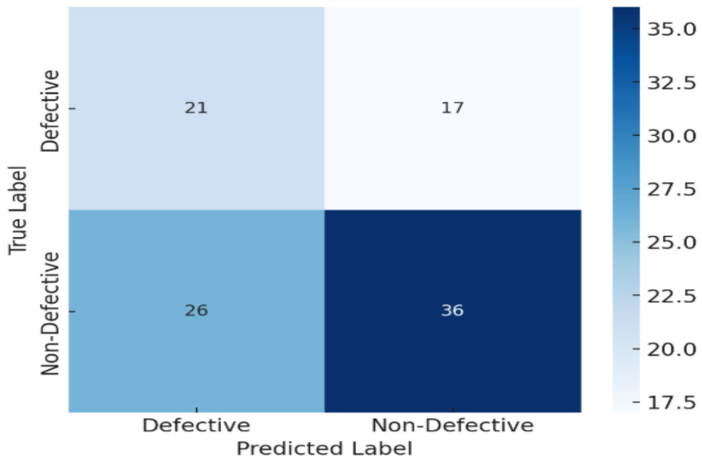

Figure 10. Confusion matrix heatmap

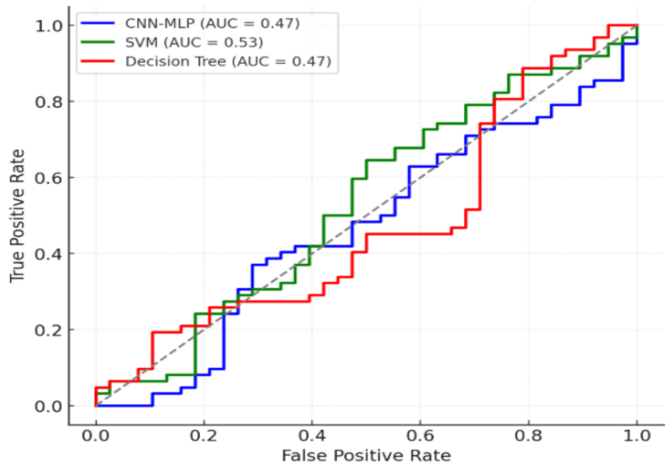

Figure 11. AUC-ROC curve

The CNN-MLP model can better differentiate between defective and non-defective components, thus making it an ideal selection for automated quality control systems.This article uses a confusion matrix heatmap to understand how well the model functions. This graphical display reveals misclassification patterns that point out particular defect categories that tend to produce classification errors. Defects in the form of minimal solder inconsistencies sometimes end up being identified as non-defective parts by the model, although false favorable rates remain low. The model shows a strong ability to detect major defects, yet subtle soldering variations require supplementary optimization of detection precision.The research uses interpretability-focused visualizations to make the CNN-MLP model decision processes transparent, which enables its adoption as an essential tool for manufacturing environments that require explainable and reliable systems.

The study demonstrates the proposed CNN-MLP hybrid model produces outstanding results by bringing 94.7% correctness, surpassing the rates of 85.3% for SVM and 82.1% for decision trees. The presentation metrics of the hybrid CNN-MLP model establish its superior accurateness and defect detection capability when associated to traditional methods such as SVM and Decision Trees. By mixing spatial feature extraction through CNN and sensor data study via MLP, the proposed model attains higher accuracy, recall, and F1-score, underlining its robustness in recognising defective components. The next bar chart visually compares key performance indicators — accuracy, precision, recall, and F1-score — for the CNN-MLP, SVM, and decision tree models, exemplifying the distinct benefits of the hybrid approach in defect detection tasks.

The model attains its superior presentation because CNN extracts spatial imperfection patterns from images and MLP analyses sensor data while making an consolidative defect detection system. The detection capability of the model between defective and non-defective components is demonstrated by its AUC score of 0.96. The deployment issues of real-time operation in deep learning systems exist because of two main limitations: computational speed and understanding how the model makes its predictions. The simulation authenticates real-world production scenarios, but further validation on current production lines will establish the model's reliability within dynamic production environments.

Several prior research studies dealt exclusively with visual defect assessments or sensor data analyses, yet this study successfully combines various data types from different sources. Traditional SVM and decision tree algorithms demand substantial manual feature engineering work, but the CNN-MLP model automatically retrieves features without human assistance. The detection system faces two main challenges: uneven data distribution and the need for artificial data generation since natural defect patterns tend to be more elaborate than simulated ones. The high computational demands of deep learning models function as a barrier that prevents their use in low-power edge computing environments for deployment. Future research must focus on implementing model compression methods and optimization frameworks for real-time execution alongside interpretability techniques that enhance Industry 4.0 innovative manufacturing applications of AI-driven defect detection systems.

A comprehensive summary of the model's performance advantages and future development priorities is provided in Table 3.

Table 3. Summary of key findings and future research directions

Key findings	Future research directions
High Accuracy (94.7%)	Develop model compression techniques to reduce computational demands for real-time deployment.
AUC Score of 0.96	Implement interpretability-focused frameworks to enhance model transparency in defect classification.
CNN-MLP Integration	Explore advanced hybrid architectures that incorporate transformer models for multimodal data analysis.
Limitations in Real-Time Deployment	Apply hardware acceleration frameworks to facilitate model execution in edge computing environments.
Data Augmentation Dependency	Investigate synthetic data generation methods that better simulate real-world defect patterns.
Interpretability Concerns	Integrate attention mechanisms to clarify decision-making processes and reduce the black-box nature.

The results summarized in Table 3 highlight not only the superior predictive capabilities of the CNN-MLP model but also the principal technical barriers that must be addressed for practical industrial deployment. The issue of computational efficiency, for example, has been widely explored in domains where real-time operation of AI-driven systems is required under constrained hardware resources. Studies on energy-optimized architectures and sensor-embedded platforms suggest viable strategies for adapting such models to edge environments without significant accuracy trade-offs [35, 36].

The reliance on synthetic data augmentation also calls for the development of more sophisticated simulation frameworks capable of better reproducing real-world defect variability. In manufacturing, as in biomedical and energy domains, researchers have stressed the importance of accurate physical modelling and hybrid sensor integration for improving the fidelity of training datasets [37, 38].

Furthermore, the opacity of deep learning models remains a critical limitation, particularly in domains that demand explainable decision-making. Recent work on domain-specific interpretability frameworks and digital traceability of decision logic supports the integration of visual attention mechanisms and post hoc analysis tools to address these transparency requirements [39, 40]. Finally, the integration of multimodal architectures - combining visual, physical, and contextual data - has been recognized as a promising approach for enhancing predictive depth and resilience in dynamic systems [35, 41].

In light of these perspectives, the present study's contribution lies in demonstrating not only the technical potential of a CNN-MLP-based defect prediction system but also outlining the interdisciplinary pathways—model design, hardware alignment, data realism, and interpretability - along which future research should evolve.

6. Conclusions

The results of this study confirm that the proposed CNN-MLP hybrid model achieves substantial improvements in the accuracy of defect prediction in electronics manufacturing by effectively combining spatial analysis of visual data with structured sensor information. The model demonstrates a 94.7% accuracy rate and an AUC score of 0.96, significantly outperforming conventional classifiers such as SVM and Decision Trees. These outcomes validate the efficacy of a multimodal approach, where convolutional layers capture complex image-based defect features while the MLP module detects anomalies embedded in numerical production parameters. This architectural synergy not only enhances predictive performance but also alleviates the dependency on manual feature engineering, a critical bottleneck in classical machine learning pipelines.

The alignment of findings with previous studies reinforces the broader relevance of hybrid neural network architectures in manufacturing contexts. However, the high computational complexity of the proposed model restricts its deployment in low-power or latency-sensitive environments, which highlights the importance of future research in optimizing model architectures for real-time application. The use of synthetic data, though beneficial for addressing class imbalance, may limit the generalizability of results when deployed under non-simulated, high-variability industrial conditions. Moreover, the inherent opacity of CNN-MLP systems remains a significant obstacle to adoption in highly regulated domains, where explainability is a prerequisite for trust and accountability.

Given these findings, future research should concentrate on developing lightweight and computationally efficient versions of CNN-MLP models through pruning, quantization, and other model compression techniques. In parallel, hardware acceleration frameworks tailored for embedded and edge deployment should be explored to support the integration of such systems into actual production lines. Another critical avenue of investigation involves improving the interpretability of defect classification outcomes. Integrating attention mechanisms, visualization of intermediate feature maps, and explainable AI modules will be essential to support transparent decision-making processes. Finally, the construction of standardized, open-access multimodal defect datasets will facilitate reproducibility and benchmarking across research efforts, advancing the field toward robust, scalable, and industry-compliant AI-driven quality control systems.

References

[1] A. Saadallah, J. Büscher, O. Abdulaaty, T. Panusch, J. Deuse, and K. Morik, "Explainable predictive quality inspection using deep learning in electronics manufacturing," *Procedia CIRP,* vol. 107, pp. 594-599, 2022, doi:https://doi.org/10.1016/j.procir.2022.05.029

[2] M. Ferguson, R. Ak, Y.-T. T. Lee, and K. H. Law, "Detection and segmentation of manufacturing defects with convolutional neural networks and transfer learning," *Smart and sustainable manufacturing systems,* vol. 2, no. 1, pp. 137-164, 2018, doi:https://doi.org/10.1520/SSMS20180034

[3] H. Lin, B. Li, X. Wang, Y. Shu, and S. Niu, "Automated defect inspection of LED chip using deep convolutional neural network," *Journal of Intelligent Manufacturing,* vol. 30, pp. 2525-2534, 2019, doi:https://doi.org/10.1007/s10845-018-1415-x

[4] X. Qi, G. Chen, Y. Li, X. Cheng, and C. Li, "Applying neural-network-based machine learning to additive manufacturing: current applications, challenges, and future perspectives," *Engineering,* vol. 5, no. 4, pp. 721-729, 2019, doi:https://doi.org/10.1016/j.eng.2019.04.012

[5] J. Yang, S. Li, Z. Wang, H. Dong, J. Wang, and S. Tang, "Using deep learning to detect defects in manufacturing: a comprehensive survey and current challenges," *Materials,* vol. 13, no. 24, p. 5755, 2020, doi:https://doi.org/10.3390/ma13245755

[6] M. G. Abdolrasol *et al.*, "Artificial neural networks based optimization techniques: A review," *Electronics,* vol. 10, no. 21, p. 2689, 2021, doi:https://doi.org/10.3390/electronics10212689

[7] A.-A. Tulbure, A.-A. Tulbure, and E.-H. Dulf, "A review on modern defect detection models using DCNNs–Deep convolutional neural networks," *Journal of Advanced Research,* vol. 35, pp. 33-48, 2022, doi:https://doi.org/10.1016/j.jare.2021.03.015

[8] J. Ferrero Bermejo, J. F. Gómez Fernández, F. Olivencia Polo, and A. Crespo Márquez, "A review of the use of artificial neural network models for energy and reliability prediction. A study of the solar PV, hydraulic and wind energy sources," *Applied Sciences,* vol. 9, no. 9, p. 1844, 2019, doi:https://doi.org/10.3390/app9091844

[9] Y.-R. Zeng, Y. Zeng, B. Choi, and L. Wang, "Multifactor-influenced energy consumption forecasting using enhanced back-propagation neural network," *Energy,* vol. 127, pp. 381-396, 2017, doi:https://doi.org/10.1016/j.energy.2017.03.094

[10] T. Wang, Y. Chen, M. Qiao, and H. Snoussi, "A fast and robust convolutional neural network-based defect detection model in product quality control," *The International Journal of Advanced Manufacturing Technology,* vol. 94, pp. 3465-3471, 2018, doi:https://doi.org/10.1007/s00170-017-0882-0

[11] H. B. Azad, S. Mekhilef, and V. G. Ganapathy, "Long-term wind speed forecasting and general pattern recognition using neural networks," *IEEE Transactions on sustainable energy,* vol. 5, no. 2, pp. 546-553, 2014, doi:https://doi.org/10.1109/TSTE.2014.2300150

[12] O. Kwon *et al.*, "A deep neural network for classification of melt-pool images in metal additive manufacturing," *Journal of Intelligent Manufacturing,* vol. 31, pp. 375-386, 2020, doi:https://doi.org/10.1007/s10845-018-1451-6

[13] B. Hu and J. Wang, "Detection of PCB surface defects with improved faster-RCNN and feature pyramid network," *IEEE Access,* vol. 8, pp. 108335-108345, 2020, doi:https://doi.org/10.1109/ACCESS.2020.3001349

[14] A. Baliyan, K. Gaurav, and S. K. Mishra, "A review of short term load forecasting using artificial neural network models," *Procedia Computer Science,* vol. 48, pp. 121-125, 2015, doi:https://doi.org/10.1016/j.procs.2015.04.159

[15] F. J. Pontes, G. Amorim, P. P. Balestrassi, A. Paiva, and J. R. Ferreira, "Design of experiments and focused grid search for neural network parameter optimization," *Neurocomputing,* vol. 186, pp. 22-34, 2016, doi:https://doi.org/10.1016/j.neucom.2015.12.061

[16] F. Almonacid, E. F. Fernandez, A. Mellit, and S. Kalogirou, "Review of techniques based on artificial neural networks for the electrical characterization of concentrator photovoltaic technology," *Renewable and Sustainable Energy Reviews,* vol. 75, pp. 938-953, 2017, doi:https://doi.org/10.1016/j.rser.2016.11.075

[17] W. Zhang, H. Quan, and D. Srinivasan, "An improved quantile regression neural network for probabilistic load forecasting," *IEEE Transactions on Smart Grid,* vol. 10, no. 4, pp. 4425-4434, 2018, doi:https://doi.org/10.1109/TSG.2018.2857705

[18] C. Xia *et al.*, "A review on wire arc additive manufacturing: Monitoring, control and a framework of automated system," *Journal of manufacturing systems,* vol. 57, pp. 31-45, 2020, doi:https://doi.org/10.1016/j.jmsy.2020.08.008

[19] D. Mavaluru, A. Tipparti, A. K. Tipparti, M. Ameenuddin, J. Ramakrishnan, and R. Samrin, "Real-time machine learning for in situ quality control in hybrid manufacturing: a data-driven approach," *The International Journal of Advanced Manufacturing Technology,* pp. 1-14, 2025, doi:https://doi.org/10.1007/s00170-025-15008-w

[20] L. Ren, J. Dong, X. Wang, Z. Meng, L. Zhao, and M. J. Deen, "A data-driven auto-CNN-LSTM prediction model for lithium-ion battery remaining useful life," *IEEE Transactions on Industrial Informatics,* vol. 17, no. 5, pp. 3478-3487, 2020, doi:https://doi.org/10.1109/TII.2020.3008221

[21] T. P. Carvalho, F. A. Soares, R. Vita, R. d. P. Francisco, J. P. Basto, and S. G. Alcalá, "A systematic literature review of machine learning methods applied to predictive maintenance," *Computers & Industrial Engineering,* vol. 137, p. 106024, 2019, doi:https://doi.org/10.1016/j.cie.2019.106024

[22] A. Qazi, H. Fayaz, A. Wadi, R. G. Raj, N. Rahim, and W. A. Khan, "The artificial neural network for solar radiation prediction and designing solar systems: a systematic literature review," *Journal of cleaner production,* vol. 104, pp. 1-12, 2015, doi:https://doi.org/10.1016/j.jclepro.2015.04.041

[23] A. S. Ahmad *et al.*, "A review on applications of ANN and SVM for building electrical energy consumption forecasting," *Renewable and Sustainable Energy Reviews,* vol. 33, pp. 102-109, 2014, doi:https://doi.org/10.1016/j.rser.2014.01.069

[24] C.-Y. Hung, W.-C. Chen, P.-T. Lai, C.-H. Lin, and C.-C. Lee, "Comparing deep neural network and other machine learning algorithms for stroke prediction in a large-scale population-based electronic medical claims database," in *2017 39th annual international conference of the IEEE engineering in medicine and biology society (EMBC)*, 2017: IEEE, pp. 3110-3113, doi:https://doi.org/10.1109/EMBC.2017.8037515

[25] L. Bo, T. Wei, H. Fangfang, C. Guangyu, and L. Yufei, "Positioning error compensation of an industrial robot using neural networks and experimental study," *Chinese Journal of Aeronautics,* vol. 35, no. 2, pp. 346-360, 2022, doi:https://doi.org/10.1016/j.cja.2021.07.005

[26] N. Dimitriou, L. Leontaris, T. Vafeiadis, D. Ioannidis, T. Wotherspoon, G. Tinker, and D. Tzovaras, "A deep learning framework for simulation and defect prediction applied in microelectronics," *Simulation Modelling Practice and Theory*, vol. 100, p. 102063, 2020, doi:https://doi.org/10.1016/j.simpat.2019.102063

[27] M. Al-kharaz, B. Ananou, M. Ouladsine, M. Combal, and J. Pinaton, "Quality Prediction in Semiconductor Manufacturing processes Using Multilayer Perceptron Feedforward Artificial Neural Network," in 2019 8th International Conference on Systems and Control (ICSC), 2019, pp. 423-428, doi:https://doi.org/10.1109/ICSC47195.2019.8950533

[28] M. Saqlain, Q. Abbas, and J. Y. Lee, "A Deep Convolutional Neural Network for Wafer Defect Identification on an Imbalanced Dataset in Semiconductor Manufacturing Processes," *IEEE Transactions on Semiconductor Manufacturing*, vol. 33, no. 3, pp. 436-444, 2020, doi:https://doi.org/10.1109/TSM.2020.2995550

[29] M. A. Khan, N. S. Elmitwally, S. Abbas, S. Aftab, M. Ahmad, M. Fayaz, and F. Khan, "Software defect prediction using artificial neural networks: A systematic literature review," *Scientific Programming*, vol. 2022, p. 2117339, 2022, doi:https://doi.org/10.1155/2022/2117339

[30] C. Y. Hsu and W. C. Liu, "Multiple time-series convolutional neural network for fault detection and diagnosis and empirical study in semiconductor manufacturing," *Journal of Intelligent Manufacturing*, vol. 32, pp. 823-836, 2021, doi:https://doi.org/10.1007/s10845-020-01591-0

[31] G. Wang, A. Ledwoch, R. M. Hasani, R. Grosu, and A. Brintrup, "A generative neural network model for the quality prediction of work in progress products," *Applied Soft Computing*, vol. 85, p. 105683, 2019, doi:https://doi.org/10.1016/j.asoc.2019.105683

[32] S. A. Singh and K. A. Desai, "Automated surface defect detection framework using machine vision and convolutional neural networks," *Journal of Intelligent Manufacturing*, vol. 34, pp. 1995-2011, 2023, doi:https://doi.org/10.1007/s10845-021-01878-w

[33] R. Dastres and M. Soori, "Artificial neural network systems," *Int. J. Imag. Robot.*, vol. 21, no. 2, pp. 13–25, 2021. [Online]. Available: https://hal.science/hal-03349542/

[34] S. Feng, H. Zhou, and H. Dong, "Using deep neural network with small dataset to predict material defects," *Materials & Design*, vol. 162, pp. 300-310, 2019, doi:https://doi.org/10.1016/j.matdes.2018.11.060

[35] X. Wang, Y. Yan, P. Tang, X. Bai, and W. Liu, "Revisiting multiple instance neural networks," *Pattern Recognition*, vol. 74, pp. 15-24, 2018, doi:https://doi.org/10.1016/j.patcog.2017.09.001

[36] N. Smailov, V. Tsyporenko, A. Sabibolda, V. Tsyporenko, A. Abdykadyrov, A. Kabdoldina, et al., "Streamlining digital correlation-interferometric direction finding with spatial analytical signal," *Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska*, vol. 14, no. 3, pp. 43–48, 2024, doi: https://doi.org/10.35784/iapgos.6177

[37] A. Zilgarayeva, N. Smailov, S. Pavlov, S. Mirzakulova, M. Alimova, B. Kulambayev, and D. Nurpeissova, "Optical sensor to improve the accuracy of non-invasive blood sugar monitoring," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 34, no. 3, pp. 1489–1498, 2024, doi: https://doi.org/10.11591/ijeecs.v34.i3.pp1489-1498

[38] Z. S. Mukhametzhanova, A. N. Daurenbekova, G. K. Zhanibekova, K. S. Syzdykova, and G. Kaliakparova, "Evaluation of influence of innovation on enterprise productivity," *Space and Culture, India*, vol. 7, no. 1, pp. 186–193, 2019, doi: https://doi.org/10.20896/saci.v7i1.527

[39] Y. S. Paranchuk and V. H. Lysiak, "Energy efficient power supply system and automatic control of modes of the power supply–pumping station complex," *Naukovyi Visnyk Natsionalnoho Hirnychoho Universytetu*, vol. 3, pp. 115–124, 2018, doi: https://doi.org/10.29202/nvngu/2018-3/16

[40] N. Vasylieva and O. Velychko, "Development of the controlling system in the management of dairy clusters," *Eastern-European Journal of Enterprise Technologies: Control Processes*, vol. 4, no. 88, pp. 20–26, 2017, doi: https://doi.org/10.15587/1729-4061.2017.108591

[41] I. Semenets-Orlova, N. Halytska, A. Klochko, I. Skakalska, and N. Kosyuk, "Information exchange and communication infrastructure in the public sector," in *Communications in Modern Information and Global Networks (CMiGIN)*, CEUR Workshop Proceedings, vol. 2588, pp. 519–529, 2019. Available: https://ceur-ws.org/Vol-2588/paper43.pdf