T.C.
MANİSA CELAL BAYAR UNIVERSITY
GRADUATE SCHOOL OF

MASTER's THESIS
DEPARTMENT of COMPUTER ENGINEERING

DEFECT CLASSIFICATION OF ELECTRONIC BOARDS BY DEEP LEARNING

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MANİSA–2024

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2024

COMMITMENT

I declare that this thesis was written in Manisa Celal Bayar University, Faculty of Engineering, Department of Computer Engineering in accordance with academic and ethical rules, and all the literature information used is included in the thesis with reference.

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ÖZET

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Bu tez kapsamında, baskılı devre kartlarındaki üretim hatalarının derin öğrenme ile tespitine yönelik olarak bir çalışma gerçekleştirilmiştir. Literatürde bu konudaki çalışmalar genellikle eksik bileşen ve lehim kusurlarına bağlı hatalara yoğunlaşmıştır. Bu tezde, Vestel Beyaz Eşya Sanayi örneği üzerinden yola çıkarak bir durum değerlendirmesi yapılmış ve eksik bileşen ve lehim hatalarına ek olarak literatürde göreceli olarak az çalışılmış¸ ters polarite ve yanlış¸ hizalama hatalarının tespitine yönelik olarak da çalışılmıştır. Bu bağlamda, Vestel'e ait çeşitli üretim bantlarından elde edilmiş¸ hatalı ve hatasız PCB'lere ait toplamda 783 görüntü elde edilmiştir. Bu görüntülerin sayısı çeşitli veri artırımı teknikleriyle 1407'ye çıkarılmıştır. Daha sonrasında, derin öğrenmeyle nesne tespiti için bir YOLOv5 modeli oluşturulmuştur. Model başarımı kesinlik, duyarlılık, ortalama kesinlik değerlerinin ortalaması ve birleşim üzerinde kesişim metrikleri üzerinden değerlendirilmiş¸ ve kesinlik için 0,694-0,912 arası, duyarlılık için 0,857-0,877 arası, mAP için 0,865-0,931 arası, IoU için 0,735-0,786 arası başarım performanslarına ulaşılmıştır.

Anahtar Kelimeler: Baskılı Devre Kartı Hata Tespiti, Derin Öğrenme, Ters Polarite, YOLOv5, Entegre Devre, Konnektör.

2024, 48 sayfa

ABSTRACT

M.Sc. Thesis

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Within the scope of this thesis, a study was carried out to detect production defects in printed circuit boards using deep learning. Studies on this subject in the literature generally focus on defects due to missing components and soldering errors. In this thesis, a situation assessment was made based on the case of Vestel Beyaz Eşya Sanayi, and in addition to missing components and soldering errors, a study was also carried out to detect reverse polarity and misalignment defects, which are relatively less studied in the literature. In this context, a total of 783 images of defective and defect-free PCBs obtained from various production lines of Vestel. The number of these images was increased to 1407 using various data augmentation techniques. Afterwards, a YOLOv5 model was builded for object detection with deep learning. Model performance was evaluated through precision, sensitivity, mean average precision and intersection over union metrics and the following performances are achieved: precison [0.694-0.912], recall [0.857-0.877], mean average precision [0.865-0.931] and intersection over union [0.735-0.786].

Keywords: Printed Circuit Board, Deep Learning, Reverse Polarized, Yolov5, Integrated Circuit, Connector.

2024, 48 pages

ACKNOWLEDGEMENTS

This thesis is the product of a challenging and lengthy process in which many people, including the company I work for, have contributed to and supported me. I would like to thank everyone who guided me and supported me on this challenging journey.

First of all, I would like to thank my supervisor, Prof. Dr. Tuğba Özacar Öztürk, for her patience, guidance and support throughout this research. Her expertise has been a great source of inspiration for me.

I would like to express my gratitude to the faculty members of the Department of Computer Engineering for their valuable lectures and suggestions, which greatly contributed to the development of my thesis.

The research conducted at Vestel Elektronik Sanayi ve Ticaret A.Ş. facilities and the knowledge sharing provided by Vestel Elektronik Sanayi ve Ticaret A.Ş. have significantly contributed to improving the results of my thesis. I would like to express my sincere gratitude for the support provided.

Finally, I would like to thank my family and loved ones. I am grateful for your patience, understanding and motivation throughout this process.

This thesis was finalized with your support.

Best regards,

Damla İLGEN
Manisa, 2024

LIST OF ABBREVIATIONS

PCB	Printed Circuit Board
AOI	Automatic Optical Inspection
IC	Integrated Circuit
YOLO	You Only Look Once
QC	Quality Control
NMS	Non-Maximum Suppression
mAP	Mean Average Precision
P	Precision
R	Recall
IoU	Intersection over Union
DNN	Deep Neural Network
SVM	Support Vector Machine
FBC	Flexible Printed Circuit Board
CAD	Computer Aided Design
SMD	Surface Mount Device
CAM	Class Activation Mapping

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1. INTRODUCTION

The plates on which the electrical connections are provided with copper paths between the electronic circuit elements placed on it are called electronic cards of printed circuit boards (PCBs). The main purpose of these boards is to keep the electronic circuit elements together and to provide the electrical connection between them. PCBs can be single-sided, double-sided, 3-layer, 4-layer or multilayer. This depends on the project and the resources available. Today, PCBs have a great importance and are used widely in many fields. PCBs are the basic building components of many electronic devices such as cell phones, computers and televisions. PCBs are required for many other functions such as engine control, entertainment systems and security systems. Automation systems in factories, control panels, sensors and other industrial equipments also usually include PCBs. PCBs have a critical role in today's technological developments due to their flexibility, allowing for the design of more complex and customized circuits and making electronic devices more compact.

PCBs, are among the most crucial parts of electronic goods. As production technology advances, the structure of PCBs becomes more complex, making PCB quality checking crucial. The conventional techniques for detecting PCB defects are expensive, time-consuming, and error-prone to mistakes [1].

PCBs, are a part of practically every kind of electronic equipment. The integrated circuit and semiconductor technologies have advanced quickly, allowing for the reduction of PCB size to extremely small dimensions. As a result, high-precision and quick fault detection on PCBs are essential. [2] examines over 100 relevant publications from 1990 to 2022 in order to investigate different PCB failure detection techniques.

In this thesis, we develop a model to detect the following two types of defects in PCBs manufactured at Vestel using deep learning methods: **(a)** IC Direction Defect **(b)** Connector Defect. The reason we chose these two defect is their high frequency of occurrence.

Next section describes PCB production at Vestel Beyaz Eşya Sanayi, the errors encountered during the production process and the proposal presented in this thesis for the detection of these errors. Section 3 examines the studies carried out in the literature on image-based detection of PCB defects. In Section 4, the work carried out within the scope of this thesis is explained. Details of the preliminary studies, building of the dataset, processing of the dataset for deep learning, and finally the development of a problem specific custom YOLOv5 model are explained in this section. Chapter 5 proposes the evaluation the proposed deep learning model. Evaluation metrics, evaluation of the model and discussion of evaluation results are presented in this section. In chapter 6, the results of the thesis are evaluated and possible future studies are presented.

2. PROBLEM DEFINITION: THE CASE OF PCB DEFECT DETECTION IN VESTEL

2.1. Manufacturing and Installing the PCBs

PCBs at Vestel Beyaz Eşya Sanayi are utilized in fields such as Electric Charging Units, White Goods, TVs, Lighting, Automotive, Batteries, Automation Systems, Industrial Devices, etc.

PCBs are designed and manufactured by an external company and delivered to the factory. Then, PCBs are assembled at Vestel Electronics factory. Typesetting of PCBs electronic cards are then subjected to various tests and the cards are delivered to other Vestel factories. Once the cards have been turned into products, product testing is carried out.

It is important to ensure that PCBs sent to other factories are defect-free. Any error in the PCB may cause the product to operate with low performance or not operate at all. After the product has been manufactured, removing the PCB from the product can damage the PCB and other elements of the product. This process is time consuming and costly if other materials are damaged. Overlooking an error that can be easily corrected on the PCB may result in delivery of a defective product to the customer and a decrease in customer satisfaction and brand value. Figure 2.1 shows the steps of the PCB manufacturing process.

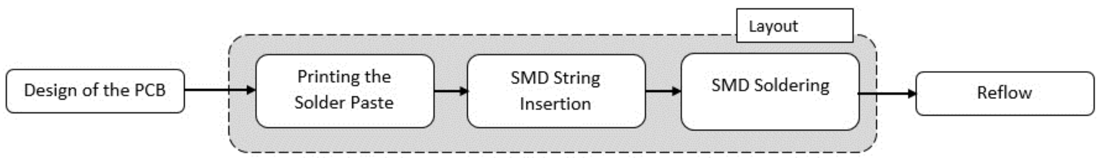

Figure 2.1 The PCB Manufacturing Process.

A. Design of the PCB: is the first stage in the process of manufacturing printed circuit boards. This design includes the layout of circuit elements, circuit paths and connection points. The PCB design is usually performed using CAD software. It is necessary to prepare the design for manufacturing. This stage involves reviewing the design, revising it if necessary and optimizing it for the manufacturing process. Details such as scaling, detection of transitions between layers, widths of traces, etc. are reviewed. After this, preparations are made for the layout stage.

B. Layout: is the process of converting the design of a circuit board into a physical PCB. The layout stage has a great importance in PCB production. Layout involves the location of a circuit board's components, the tracing of trace paths, the organization of layers, and many other elements that determine its overall electrical and mechanical performance. Good layout provides a PCB that is suitable for production. This can increase the efficiency of soldering operations, reduce production costs and decrease the defect rate in the production process. A defective layout can seriously affect the performance, reliability and producibility of the circuit. Therefore, details such as component location, trace paths and layer layout are important to ensure the proper functioning of a circuit board.

   a. **Printing the Solder Paste:** is the first step in the PCB installation. The cream solder appears as gray and the person who will do the typesetting must apply cream solder evenly everywhere. This process is performed with special stencils for the circuit board being used. A thin stainless steel stencil is placed on the PCB, then the solder paste is applied evenly to the desired areas with the help of a soldering machine.

   b. **SMD String Intersection:** is the process of placing the components on the board. This process was done manually with tweezers. The person doing the layout would manually place the components by selecting them in the past. Today, this process is done more accurately, quickly and consistently by automated machines. After applying the solder cream on the PCB, the PCB is moved to the layout machine. The components in the layout machine are automatically placed on the PCB without touching them.

   c. **SMD Led Soldering:** involves SMD soldering and solder paste pressing.

C. Reflow: is the most widely used method of attaching surface mount components to printed circuit boards (PCBs). The aim of the process is to form acceptable solder joints by first pre-heating the components/PCB/solder paste and then melting the solder without causing damage by overheating.

Before installing the PCB on the product, a product tree is created according to the project. It is determined which component should be placed on which coordinate. SMD layout machines place the components on the PCB in according to design documents using a pre-written program. Before the installation process begins, the machine's camera determines the coordinates of the reference marks on the board for accurate positioning on the PCBs.

2.2. Test Procedure

This thesis proposes an approach to detect two of the "polarized component misplacement" errors frequently encountered in PCBs. Therefore, it is important to understand the testing procedure for detecting PCB defects at Vestel. Polarized components are the components that must be mounted in a certain direction. These components includes diodes, transistors, integrated circuits and electrolytic capacitors, connectors, ICs (Integrated Circuit), etc. Mounting polarized components in the opposite way can affect or completely break the functionality of the circuit. For example, when the IC is mounted reversely, it may cause the circuit to operate in an undesired way or become completely non-functional. Components mounted in the wrong orientation can become overheated or even be physically damaged. This can cause the circuit to become unstable or in the long-term may cause the circuit to burn out. Such mistakes are often likely to affect the operation of a specific component on the circuit or the overall performance of the circuit. Therefore, the correct mounting of polarized components is an important detail that needs to be considered during the PCB layout and soldering stage.

Rework is the decision to make the rejected products suitable by an additional process according to an pre-approved method. Repair is the decision to carry out an operation after a rejection decision according to an approved written method that does not ensure the product's suitability but will enable it to perform its desired function. Rework and repair cause significant time, labor and economic loss.

At the Vestel Electronics Plant, orders are opened on a customer basis and the quantity of an ordinary order varies between 200-10.000 pieces. In other words, incorrect layout in a mass production means that a large amount of electronic cards are subjected to rework and repair processes. If the manufactured product is not in compliance with the contract, purchase order, specification or technical drawing conditions, "Repair" and "Rework" decisions cannot be made without customer approval. In case of customer disapproval, the electronic cards become unusable and cause a serious cost loss. For example, the cost of ICs and connectors varies according to their fields of usage. On average, IC costs range from 2$ to 300$.

Therefore, for a qualified electronic board inspection, detection and classification of the defects is an important step in the production process. In general, PCB defect detection approaches can be classified into two categories: direct inspection by a human operator and camera-based machine vision methods.

In operator-based inspection, operators easily perform visual checks using simple instructions. The manual control method is more suitable for a small number of electronic boards. As the number of boards increases, they need to be controlled by a mechanical device. Operator-based inspection is an error-prone, costly and time-consuming process. Operators may miss some errors due to fatigue, distraction or other factors. Checking large and complex PCBs may require more time, which can cause slowdowns or delays in the production process. People may have different interpretations and standards. In other words, since each operator does not have the same experience, different operators may reach different test results on the same card. For these reasons, more modern and accurate inspection methods such as automation technologies and image processing systems may be preferred.

Automated optical inspection (AOI) can be more efficient than manual inspection, providing advantages such as higher accuracy and faster inspection. This method is especially preferred when the number of PCBs to be checked is high. Component number and soldering quality are controlled with optical inspection machines. By taking high-resolution photographs of PCBs, optical inspection machines detect defects on the boards. This provides the ability to see details such as small stains, broken connections or soldering defects.

Although faster than manual inspection, it can sometimes miss defects, especially on complex and detailed boards. For this reason, optical inspection machines should be adjusted on a model-by-model basis. Lighting affects the visibility of details on the card. The angle, intensity and color of the light source should be adjusted. Lighting from different angles can make certain defects better exposed. Parameters such as the camera resolution, focus settings, exposure time and speed determine the image quality and the visibility of the details. These settings must be optimized to ensure that details are displayed clearly and accurately.

The operators play a critical role in ensuring that optical inspection machines produce more accurate results. Their experience and skills are essential for increasing the efficiency of the machines and detecting the right defects. They are responsible for starting and operating the optical inspection machines properly. This includes basic configurations such as machine power-up, lighting and camera settings. Operators analyze and evaluate the data produced by the machines. They evaluate this data to detect potential defects, filter out misleading data and draw the right conclusions. Optical inspection machines often require individual settings for each PCB, because each board can be different. However, this depends entirely on the complexity, design and manufacturing process of the board.

At Vestel Beyaz Eşya Sanayi, after the optical controls, the quality team checks the accuracy of the orientation of the components by sampling the cards. In mass production, only a certain number of cards are checked due to the high number of orders. The quality team performs these checks by visual inspection. This method has many disadvantages. Performing repetitive operations for many hours can cause distraction and fatigue. This can increase the possibility of making mistakes. The human eye may not be as accurate as the fine and continuous measurements made by machines. This can cause small details that require examination under a microscope to be missed. Humans work more slowly than machines. Eye inspection can therefore take more time in the production process, which can reduce overall efficiency. The sampled cards may not have any errors detected, but due to a changed feeder during the typesetting process, they may have been re-typed incorrectly.

2.3. Proposed Approach

This thesis proposes an approach to detect two of the "polarized component misplacement" errors frequently encountered in PCBs. As a case study, the proposed approach is applied to improve the test procedure of Vestel Beyaz Eşya Sanayi, which is described in the previous section.

After analyzing the test procedure of Vestel, we made the following observations:

1. IC and connector components are included in approximately all PCB models,
2. Manual inspection of IC and connector components takes about 50% of the entire inspection,
3. The consequences of IC and connector failures carry a higher risk than other component failures.

In light of all these observations, we define two polarized components; we define two polarized components; integrated circuits (ICs) and connectors. Integrated Circuit (IC), is a collection of electronic components, which are combined in one package (IC) and soldered on the PCB. PCB connectors are mounted on the PCB and are typically used to transfer signals or power from one PCB to another, or to transfer to or from the PCB from another source within the unit. In this case, the circuit may not function properly or may not function at all. An IC inserted in the wrong orientation may damage other components in the circuit. Improper polarity or reverse voltage application may cause the IC and other connected components to malfunction. This may cause overheating and loss of performance.

A misplaced connector can also have negative consequences. Especially with connectors that transmit power or data, misplacement can cause safety risks.

This study, we propose an approach for model-based identification of defective areas on PCBs and classification of these defects (IC Direction Defect, Connector Defect) using deep learning. Deep learning methods are highly effective for image processing/recognition and can be effective in recognizing and analyzing complex patterns. In this way, the manual inspection process performed by the quality control team will be automated and the error rate will be minimized. We have identified four labels for classification;

- **IC:** represents the properly mounted IC individuals.
- **Connector:** represents the properly mounted connector individuals.

- **IC Direction Defect:** polarity indicates the symmetry of a component. It is a directional flow of electrons from one pole to the other. The components are either polarized (with polarity) or non-polarized (without polarity). Non-polarized components are as simple as they get. They can be connected either way and will work correctly. Polarized components can be connected only one way in a circuit for them to work. The current must go from anode to cathode. If the current goes the other way, at best it will just stop the circuit. At worst, it could result in burned components. ICs belong to the class of polarized components. An integrated circuit will usually have a notch or an etched dot to indicate the first pin (Figure *2.2*). IC Direction Defect represents the IC individuals that are mounted incorrectly.

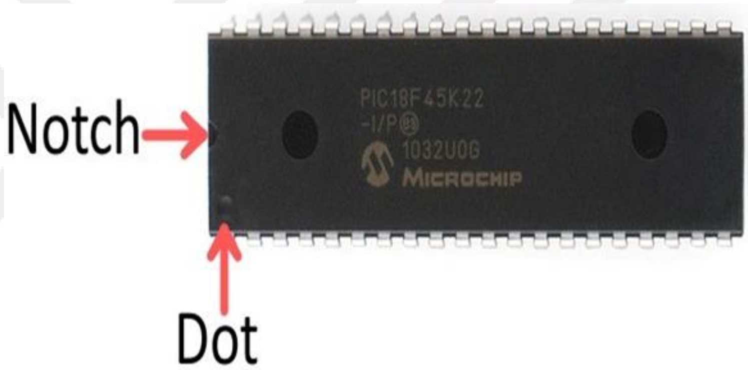

Figure 2.2 The Notch or an Etched Dot to Indicate the First Pin.

- **Connector Defect:** includes **(a)** shifted connectors, **(b)** reversely mounted connectors, **(c)** missing connectors (Figure *2.3*).

(a) shifted connector **(b)** reversely mounted connector **(c)** missing connector

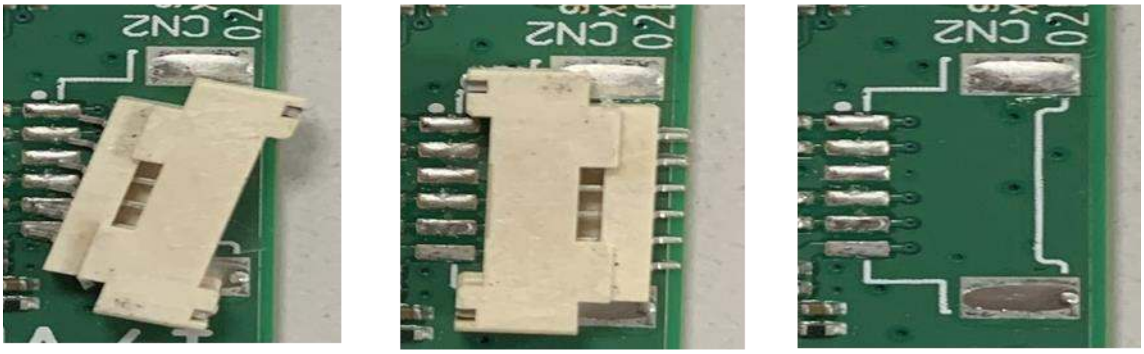

Figure 2.3 Three Types of Connector Defects.

Schematics usually use arrows, triangles, circles or special symbols to indicate the orientation of ICs and connectors in PCB designs. We builded the dataset by manually labeling the photos using Tzutalin's well-known annotation tool, LabelImg [3]. These symbols are an indication of the direction in which the component should be positioned.

Figure 2.4 Labelling with LabelImg.

We labelled the dataset, using the bounding box method for labelling (Figure 2.4). Bounding boxes determine the outermost point of the object on the image. We can classify the object and determine its position. Using this method, we labelled the PCB images. Our aim is to detect and classify reverse polorized ICs and Connectors.

Examples of defect types are given in Figure 2.5 and Figure 2.6. In Figure 2.5, the first and second images show examples reverse polorised connectors, while the third picture shows a connector whose position was shifted during typesetting. Figure 2.6 shows examples of reverse polorized ICs. In this case, the symbol on the PCB and the symbol direction on the IC do not match.

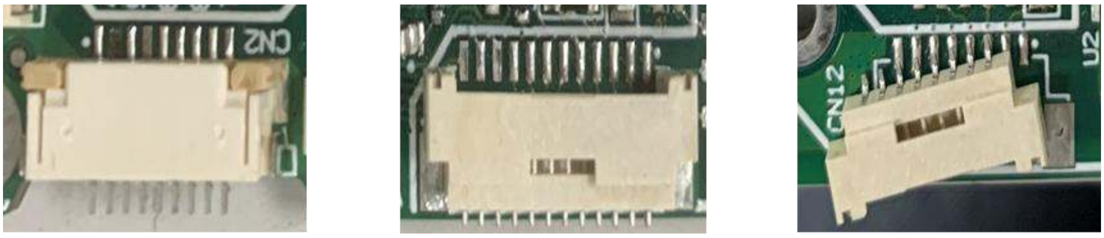

Figure 2.5 Examples of Connector Defect.

Figure 2.6 Examples of IC Defect.

YOLO, which stands for "You Only Look Once", is a deep learning model used for object detection. In literature, this model is also used for the detection and classification of solder joint defect on PCBs [4]. In this study, we also use YOLOv5s for the detection and classification of defect types. This model is designed to detect objects in an image with a single pass and is particularly effective for real-time applications. YOLOv5 is the fifth generation of YOLO, written in Python programming language [5]. YOLOv5 is the successor of YOLOv4 and has a number of enhancements. YOLOv5 offers generally better performance in the object recognition task. It features high sensitivity, lower error rates and faster processing capabilities. Figure 2.7 shows the architecture of the original YOLOv5 Network [6]. YOLOv5 is now the most potent object detection method available [6].

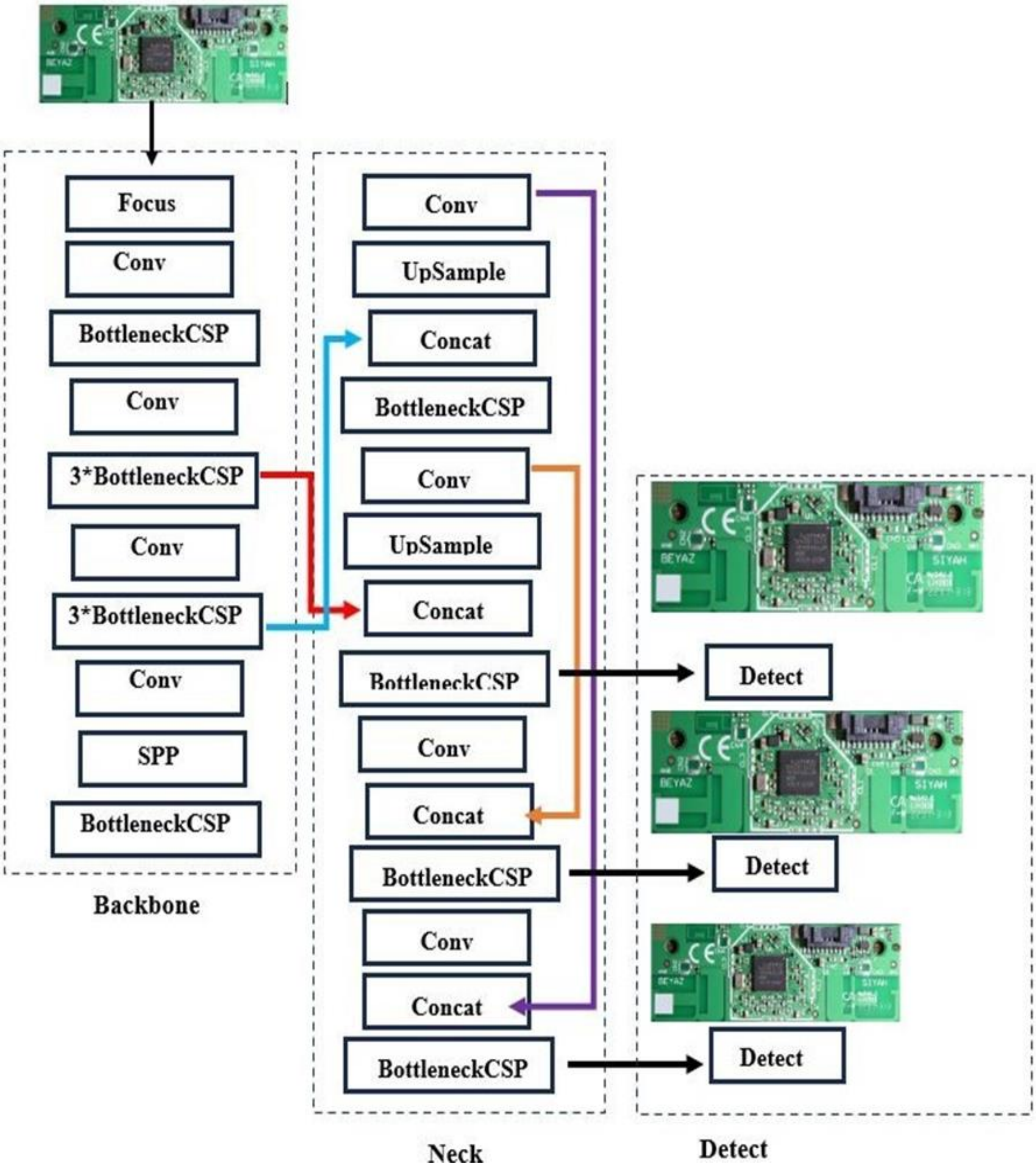

Figure 2.7 Architecture of Original YOLOv5s Network.

3. LITERATURE REVIEW

3.1. PCB Defect Classification

Many defects/faults arise during the production of PCBs due to the extreme difficulty in achieving accuracy in the mechanical and chemical processes. The performance of electronic items deteriorates as a result of these fabrication defects. [7] examines various defects in PCBs categorized under Through hole and SMD. Data collection and analysis processes were conducted to understand the frequency and causes of these defects. The defects on the PCB are generally classified into soldering defects and non-soldering defects. Non-soldering defects include wiring track faults, Wrong Polarity, Missing Components, and Misaligned components. Programming errors or component mounting in reverse order can also result in reverse mounting errors. Additionally, improper component feeding can result in mounting errors. Defects in Component Alignment are caused by soldering errors and profile problems. Defect Classification Tree in [7] is represented in Figure *3.1*.

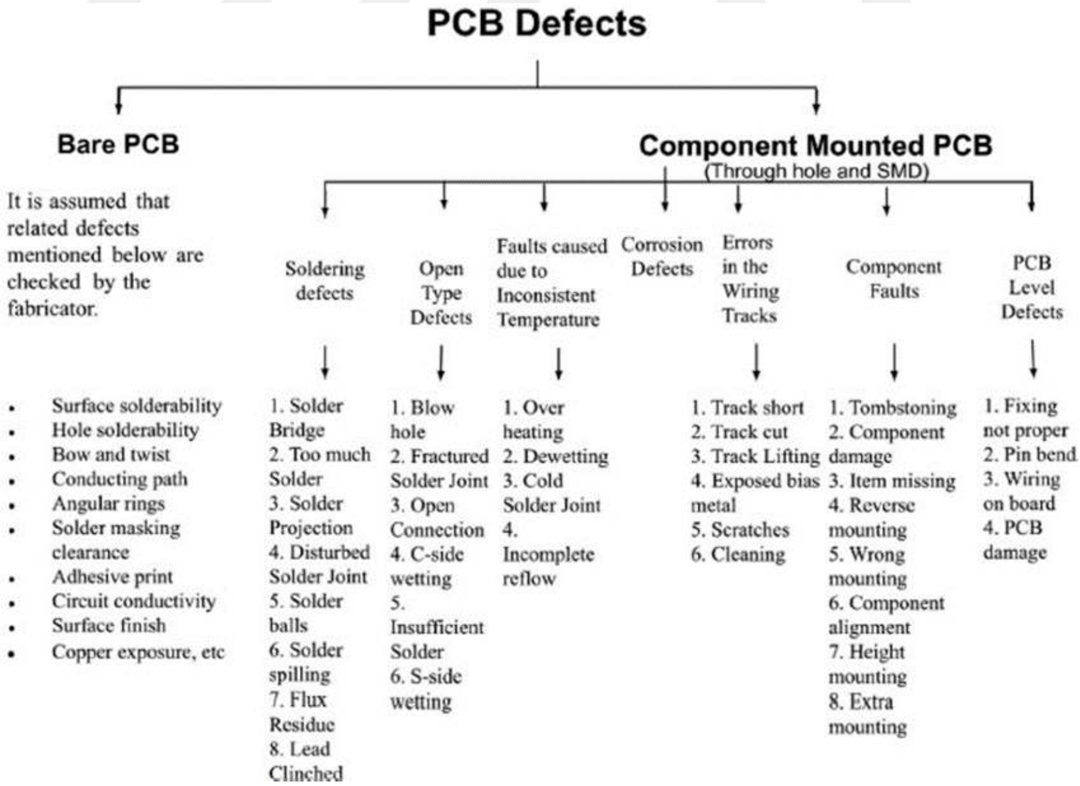

Figure 3.1 Defect Classification Tree

When the errors detected within the scope of this thesis are classified with the method proposed in [7];

a) "IC Direction Defect" is in the defect class no 4 ("Reverse Mounting") under "Component Faults".

b) "Connector Defect" can be included in one of the following defect classes; defect class no 3 ("Item Missing") under "Components Faults", defect class no 4 ("Reverse Mounting") under "Components Faults" or defect class no 6 ("Component Alignment") under "Components Faults".

3.2. PCB Defect Detection

There are current studies on PCB typesetting errors and the use of deep learning approaches to control these errors. In this section, some important studies on this subject will be summarized and evaluated.

[8] proposes a deep learning model that can identify different sorts of defects (Component shifted, Insufficient solder, Component sideward, Tombstoning, Non-wetting). This model achieved a precision rate of 96.96% for defect-free products and recall rate of 94.29% for defective products.

In [9], a defect detection system based on machine learning and deep learning techniques is proposed. To extract and categorize the features of the defects (missing hole, mouse bite, open circuit, short, spur, spurious copper) on the PCB images HOG+SVM, HOG+KNN and YOLO-v4 algorithms were trained. The success rates of categorization of defects were 74.62% with YOLO-v4, 47.83% with HOG+SVM, and 39.86% with HOG+KNN. Consequently, it has been observed that the success rate of the YOLO outperformed the other methods.

[10] presents a deep learning-based tool for classifying PCB components for the purpose of reusing components from scrap PCBs. [10] uses hierarchical algorithms and YOLOv5. It has been seen that the combined method has a great recognition accuracy and precision in the classification and localization of circuit board components. The proposed hybrid approach is able to identify types: Stm32, MCU51 and other main control chips. The algorithm’s performance is 38% higher than the original YOLOv5 model.

[11] created a defect detector based on YOLOv3, which applies a process to examine the chips of surface-mount device light emitting diodes (SMD LED). The model identifies missing components, incorrect placement, inverse polarity, missing wires and defective surface in addition to an inspection process of identifying defect-free products. YOLOv3-dense was produced to use for the Darknet-53 backbone as replacing densely linked convolutional networks (DenseNet) to increase the defect detector's performance. It has been seen that the mean test precision (mAP) measured by YOLOv3-dense was 33.69% higher than the class activation mapping (CAM) localization of a convolutional neural network (CNN). The test mAP was also 14.98% higher than that of traditional YOLOv3.

[12] proposes a modern PCB inspection system using a convolutional autoencoder with a skip-connected link. A deep learning model is developed for detecting defects, including missing hole, mouse bite, missing hole, open circuit, short, spur and spurious copper. To locate the defective region, the decoding images were contrasted with an input image. To enhance the model's success rate, suitable augmentation was implemented on the datasets. For datasets comprising both defective and non-defective samples, a basic unsupervised autoencoder model has exhibited the ability to accurately detect up to 98% of defects while maintaining a false pass rate of less than 1.7%.

[13] proposes an integrated detection framework for solder joint defects in the context of AOI of PCBs. YOLO was used to automatically detect hundreds of small and tightly aligned soldered joints on PCB images.

In [14], a method based on references is proposed for studying and training an end-to-end convolutional neural network (CNN) to classify defects, including missing hole, mouse bite, open circuit, short, spur and spurious copper. Unlike traditional approaches that require pixel-by-pixel processing, it finds defects and classifies them with neural networks. An end-to-end CNN model based on the reference comparison method is used to classify the defects. To learn more efficiently, not only convolutional layers are used, but instead dense shortcuts inspired by Densenet are used to achieve high accuracy with relatively few layers.

[15] presents an intensive SIFT and CNN based method to accurately evaluate the grey-scale image features of a PCB and detect defects (Disconnection,

Connection, Projection and Crack). In the proposed method, no reference image is used, intensive SIFT is used for the detection of effective key points in the defective region. If there was a defect, intensive SIFT and SVM tests were performed to eliminate it. In a sample of 200 test images, the classification accuracy was 98.5% for the cropped image and 83.5% for the whole image.

In [16], a new approach is proposed to improve the accuracy of the defect classification (Disconnection, Connection, Projection and Crack). The proposed approach introduces the defect detection which corresponds to the color image and concept of random sampling using multiple SVMs. To choose the most effective feature combination, data and characteristics for several subsets are applied using random sampling and feature selection. Each Support Vector Machine (SVM) recognizes a subset of characteristics and the final discrimination is determined through a weighted voting method.

Aiming to reduce the problems of low efficiency, high false detection rate and high omission rate of FPC (Flexible Printed Circuit Board) defect detection, [17] tries to apply the deep learning algorithm and feature pyramid network to detect defects for the first time. This approach builds multiscale characteristics by utilizing the deep neural network's (DNN) built in multiscale pyramid hierarchy structure. The experiments confirmed that the reasonable anchor design can obtain a more accurate Intersection over Union (IoU) score and can accurately detect defects, including open circuit, short circuit, scratch, foreign body on the surface.

In [18], a CNN is trained to classify a defective or defect-free PCB. In this study, a grand total of 41,387 images were utilised and categorised into three distinct datasets: training, validation and test. Over 88% accuracy was achieved and the number of misclassified defective PCBs was minimised.

[19] suggests an integrated framework for the detection of solder joint defects. Both Localisation and Classification tasks were taken into account. For the localisation part, a generic deep learning method has been used, which to can be easily ported to different PCB configurations and soldering technologies, while at the same time ensuring real-time speed and high accuracy. Because it requires domain-specific knowledge, an active learning method was proposed for the classification part to reduce the labeling workload. The experiments demonstrate that the model

can be conveniently transferred to various PCB layouts and attains precise detection outcomes, processing less than 0.34 seconds per PCB image.

[20] proposes a method for defect detection (disconnection, connection, projection and crack) and classification of electronic circuit board by extracting key points without reference images. After extracting keypoints from the image of the electronic circuit board, a patch image is cropped using the position and other keypoint data that was found. The cropped images are used as input to CNN (Convolutional Neural Network) and 4096-dimensional features are obtained in the final layer of the full connected layers. SVM (Support Vector Machine) is introduced for learning and classification using CNN features.

[21] proposes a machine vision-based device to automatically disassemble and recycle the CPU on a mobile phone circuit board in an effort to address the issue of recycling the circuit boards of used mobile phones.

In [22], missing hole, mouse bite, open circuit, short, spur, and spurious copper defects on the printed circuit have been detected. According to the results obtained, success accuracies of 74.62% were obtained with YOLOv4, 47.83% with HOG+SVM and 39.86% with HOG+KNN.

[23] introduces the application of a convolutional neural network (CNN) for LED chip defect inspection. A class activation mapping method that built in the CNN was proposed to localize defective regions. The proposed CNN based defect inspector, LEDNet, showed impressively high performance with an error rate of 5.04%.

[24] uses Michelson-like contrast (MLC) enhancement and multiscale adaptive Fourier analysis (MAFA) to develop an automatic SMD-LED defect detection system. The proposed system detects the common and important defects in LED package components, including missing component, no chip, wire shift and foreign material. The system provides a recognition rate of 98.25%.

[25] proposes a basic and simple method, called the subtraction method, to locate and detect defects on PCBs in the fastest way. A live image acquisition and examination of the circuit board were conducted under this method. The digital image processing method was utilized on images. Subtraction method was used to

comparise and match reference image and defective image of circuit boards. Using this method, it is possible to detect and classify missing holes and paths.

[26] aimed to provide a systematic review of deep learning-based bearing fault diagnosis. Three popular deep learning algorithms Auto Encoder, Constrained Boltzmann Machine and Convolutional Neural Network that can be used to diagnose a bearing fault were used.

In [27], a neural network-based automatic visual inspection system for the diagnosis of missing footprints on PCBs is presented. There are five types of footprint components classified. Footprints on the board are detected by capturing images of the board and performing a difference operation on the reference image and the captured image. Three different types of geometrical features are extracted from each footprint component. The neural network method is used to classify five classes of solder pastes (good, excess, insufficient, horizontal displacement, vertical displacement) and a high recognition rate is achieved (100% good, 93.4% for horizontal displacement, vertical displacement and excess and 91.7% for insufficient).

[28] uses two categories of Machine Learning (ML) and Deep Learning (DL) techniques to classify consumer electronics. ML models include Naïve Bayes with Bernoulli, Gaussian, Multinomial distributions, and Support Vector Machine (SVM) algorithms with four kernels of Linear, Radial Basis Function (RBF), Polynomial, and Sigmoid. While DL models include VGG-16, GoogLeNet, Inception-v3, Inception-v4, and ResNet-50. These models are used to classify three laptop brands, including Apple, HP and ThinkPad.

[29] introduces an automated component recognition system for PCBs using a Convolutional Neural Network (CNN). This work also detects the location of the defects on PCB components. In the first place, a simple convolutional neural network based component recognition classifier is developed. Since training a convolutional neural network from scratch is expensive, transfer learning with pre-trained models was performed instead. To evaluate which model is most appropriate for component identification, pre-trained models like VGG16, DenseNet169 and InceptionV3 are used. Transfer learning with VGG16 gives a best result of 99% accuracy with the capability of recognising up to 25 different components. Following this, object

localization is performed using a faster region-based convolutional neural network (R-CNN). The best mean average precision (mAP) obtained for the defect localization system is 96.54%.

[30] focuses on how a simplistic image subtraction could adequately aid manufacturers in the realm of quality control. The system can swiftly identify faults in PCB with the image subtraction method, taking between 0.856 to 2.68 seconds depending on the situation.

No	Year	Method	Success Rate Of
[8]	2023	AI deep learning model	accuracy rate of 95%
[9]	2022	HOG, SVM, KNN, YOLOv4	47.83% SVM, 39.86% KNN, 74.62% YOLOv4
[10]	2022	combination of hierarchical algorithms and YOLOv5	reliability rate between 92% and 97%
[11]	2021	CNN+CAM, YOLOv3, YOLOv3-Dense	CNN+CAM 61.59%, YOLOv3 80.30%, YOLOv3-Dense 95.28%
[12]	2021	Convolutional autoencoder, Skip-connected convolutional autoencoder	Convolutional autoencoder 95%, Skip-connected convolutional autoencoder 98%
[13]	2020	YOLO	mAP 0.951%
[14]	2019	CNN	97.74%
[15]	2018	Dense SIFT and CNN	98.5%
[16]	2014	SVM	Proposed (Gray Scale) 84.40%, Proposed (Color) 93.45%
[17]	2021	Deep Learning, DNN, Convolutional Neural Networks	CNN 95.1%
[18]	2018	CNN	88%
[19]	2020	YOLO	95%
[20]	2017	CNN	detection accuracy of 82.64%, classification accuracy of 70.80%
[21]	2020	Machine Vision	NA
[22]	2023	YOLOv7	98.74%
[23]	2018	CNN	NA
[24]	2016	MLC	recognition rate of 98.25%
[25]	2017	Image Subtraction Method	NA
[26]	2019	CNN	NA
[27]	2011	Neural networks	97.26% for training and 97.23% for testing
[28]	2021	MLML and Deep Learning techniques	VGG-16 77%, GoogLeNet 92%, ResNet-50 60%
[29]	2019	CNN	accuracy rate of 99%
[30]	2017	OPENCV with Image Subtraction Method	accuracy rate of 80%

4. MATERIALS AND METHODS

4.1. Preliminary Studies

We started the thesis study by analyzing how the production process is set up and how a faulty card is examined. Detecting PCB defects before the PCB becomes a final product, prevents cost and time losses. Since defects in PCBs will affect the performance and functionality of the final product, early detection and correction of defects in the design and production of PCBs improves the overall quality of the product. Quality control, testing and verification play an important role in this process.

We observed that some stages of quality control rely on human interpretation. After optical inspection, the directional components on the PCBs were manually checked by quality control staff. Manual control in mass production may cause delays in production and reduced accuracy in error detection. Besides, manual control may not be as accurate as automated approaches.

For component defects related to the mounting direction, we planned to perform defect classification using deep learning methods instead of manual inspection by sampling. The research process started by first collecting defective and defect-free PCB images. We then labelled the images and created files in YOLO format. We expanded our dataset using data augmentation methods.

In our model, we decided to use the YOLOv5 algorithm. YOLOv5 is a deep learning model for image-based object detection. After determining the algorithm we would use, we trained the model with the training dataset we created and evaluated it on the test dataset. Figure 4.1 shows the steps of the process we followed.

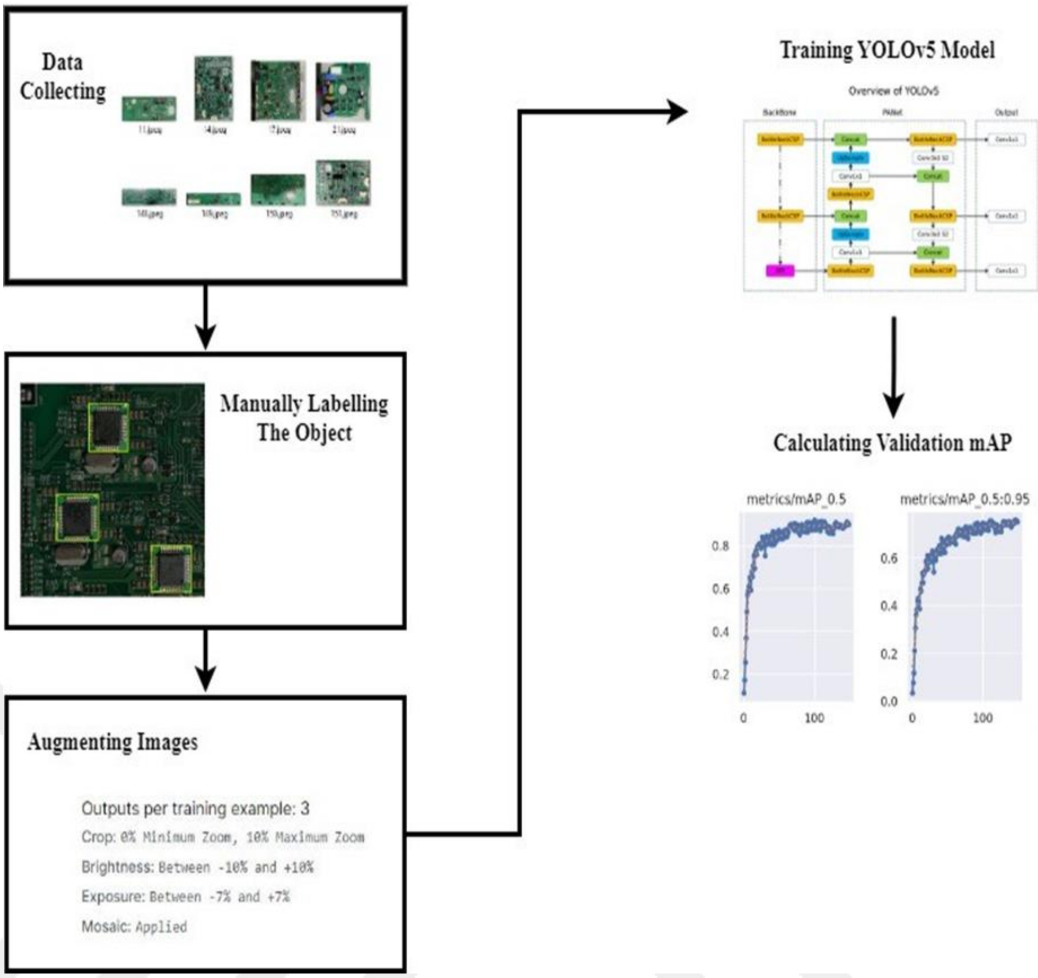

Figure 4.1 Defect Detection Process.

4.2. Building the Dataset

Deep learning models are usually trained by feeding them data. The generalization ability of these models is directly related to the quality and diversity of the training dataset. A larger and more diverse dataset allows the model to perform better. Therefore, the model needs qualified and representative data to learn the correct patterns and relationships. Insufficient or misleading data can cause the model to learn incorrectly and produce incorrect results. During data collection; steps such as cleaning, organizing and processing data have a great impact on the training and performance of the model.

We started the preliminary studies of the thesis with the analysis of the production process. In order to increase the generalization ability of the deep learning model and help the model learn different design features and component layouts, we used variable PCBs from different production areas such as white goods, electrical chargers, TV, lighting, automotive, battery and automation systems. The reason for choosing these areas is that their monthly production volumes are high. A mistake in mass production has many negative consequences. Correcting or replacing defective products requires additional time and resources due to the high volume of production. Delays in the production process harm resource management and prevent on time deliveries. Therefore, quality control processes are of great importance. However, quality control processes also require time, labor and cost. Within the scope of this thesis, a solution has been presented to increase efficiency in controlling the two most common defects in order to reduce cost of the testing processes in Vestel Beyaz Eşya Sanayi. Based on the analysis results and interviews with employees in the testing unit, these defects are identified as "IC Direction Defect" and "Connector Defect".

Figure 4.2 shows the steps of the data building process. In the following sections, the studies carried out to build the necessary dataset and deep learning model to solve the problem.

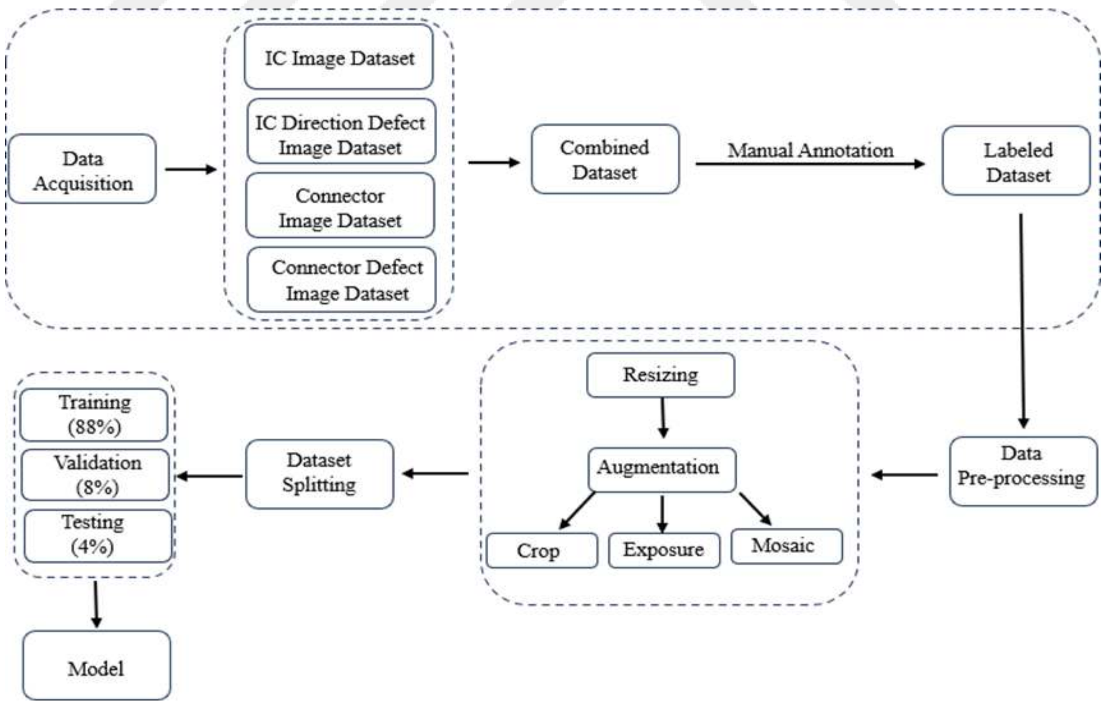

Figure 4.2 Steps of the Data Building Process.

4.2.1. Data Collection

At this stage, as a first step, the necessary data sources were defined. It was determined which models were produced on which production lines. PCB images were then collected at regular intervals. Photographs of defective and defect-free electronic cards coming from the production lines including White Goods, Electrical Charging Unit, TV, Lighting and Battery projects were collected manually using a camera and a smartphone. In addition, images taken from optical inspection machines were also used. We made sure the board had directional ICs and connectors. We considered the quality and resolution of the collected images and the accuracy of factors such as focusing and lighting. We paid attention to data diversity to make deep learning models more efficient and reliable. A model trained on a variety of examples in different conditions and scenarios will have higher performance in a real-world scenario. If the diversity of the dataset was low, we could run the risk of overfitting.

We collected 370 connector and 413 IC images containing defective and defect-free samples. Table 4.1 presents the specifications of the dataset.

Table 4.1 Data Specifications Table.

Specifications table	
Subject	Computer science, Electronic Testing
Specific subject area	YOLOv5, Object Detection, Deep Learning
Type of data	Image, txt file
How data were acquired	Images were acquired manually using a camera, a smartphone and optical inspection machines.
Data format	Raw digital image (JPG format), Annotation file (txt format)
Parameters for data collection	The dataset consists of 370 images of connectors and 413 images of ICs, including both defective and defect-free samples. Through augmentation, the original set was expanded to a total of 1407 images.
Data source location	Vestel Electronics R&D Center, 45030 Keçiliköy OSB/Yunusemre/Manisa, Turkey

4.2.2. Data Annotation

Data annotation, also known as data labelling or data marking, is an important step in the preparation of dataset used to train machine learning and artificial intelligence models. Data annotation process involves assigning the correct labels or tags to data points in order to identify and classify the objects.

During the data annotation process, after taking defective and defect-free photographs of the PCB images, we converted all of the images into JPG format. We used the popular LabelImg annotation tool to manually label images. LabelImg is a free and open-source tool for labeling image-based datasets. It is often used for tasks such as object detection or object recognition. It makes it easy to edit the size, position and label of the objects. LabelImg allows us to export labeled data in various file formats. In particular, it supports popular formats such as Pascal VOC, YOLO and COCO.

To annotate the image using LabelImg, we first opened the image with this program (Figure 4.3). We then manually drew the bounding-box, which corresponds the smallest rectangle that defines the boundaries of the relevant component in the image. Figure 4.4 and Figure 4.5 show the example bounding-boxes from the dataset. The coordinates of the upper left corner of this rectangle, the length and width of the rectangle are automatically stored in different formats by LabelImg. Each component is labelled as "Connector", "IC", "Connector Defect" or "IC Direction Defect".

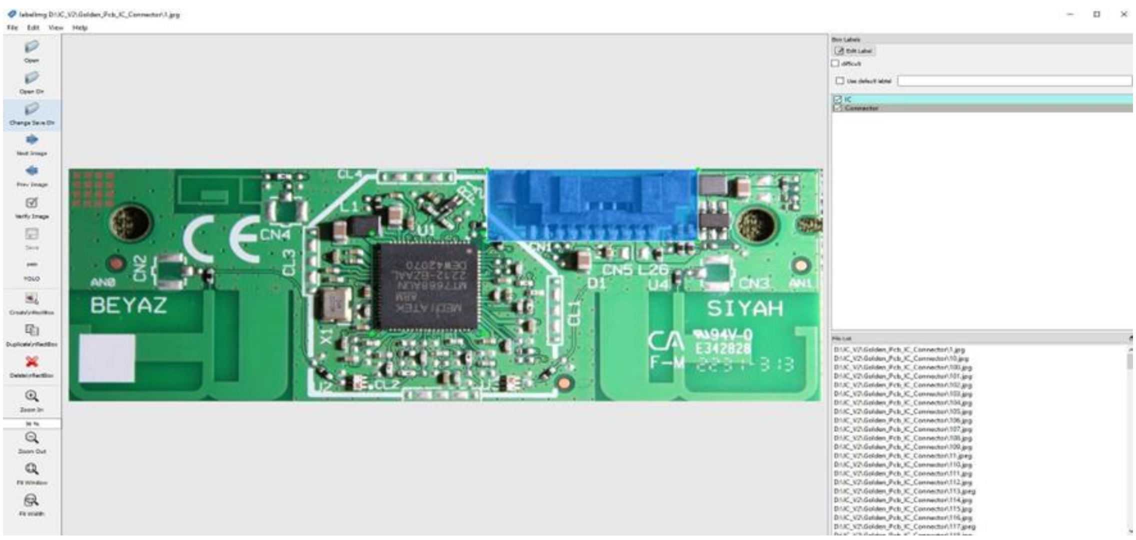

Figure 4.3 An Example Labelling in LabelImg Format.

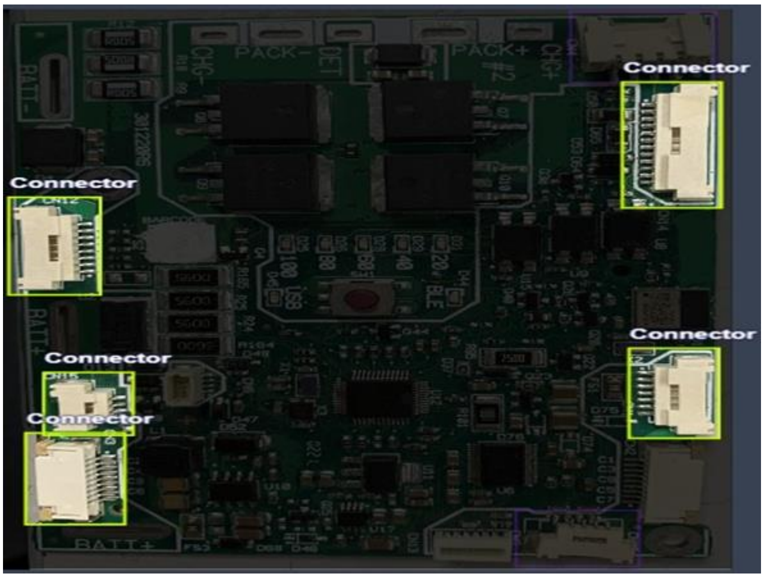

Figure 4.4 An Example Image of Defect-Free Connector from the Dataset.

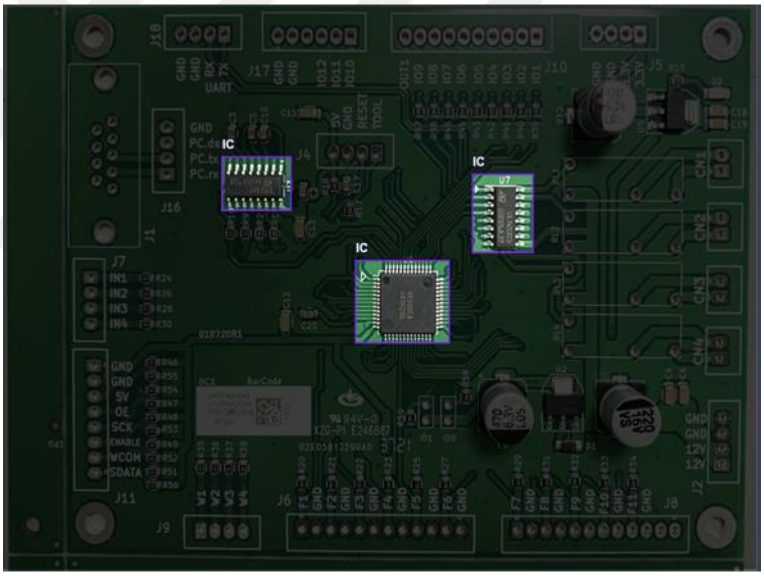

Figure 4.5 An Example Image of Defect-Free IC from the Dataset.

After checking the quality of the labels, we converted the labellings into YOLOv5 format that best suits our model. Figure 4.6 shows an example labelling, which is stored in a txt. file in YOLOv5 format.

The leading "0", "1", "2", "3" refer to the indices of the labels IC, Connector, IC Direction Defect and Connector Defect, respectively. This is followed by the x and y coordinates of the labelled object and the width and height of the box. Figure 4.7 shows an example labeling for each class in the dataset.

```
0 0.163121 0.096602 0.191883 0.069855
0 0.597912 0.098490 0.196217 0.064191
3 0.379827 0.292480 0.194641 0.067023
3 0.161545 0.287288 0.204098 0.096916
2 0.382191 0.092826 0.196217 0.093140
2 0.596927 0.296728 0.198582 0.093140
1 0.819149 0.294210 0.212766 0.090623
1 0.818755 0.097860 0.215130 0.090623
1 0.945626 0.581812 0.079590 0.278162
```

Figure 4.6 An Example Labelling in YOLOv5 Format.

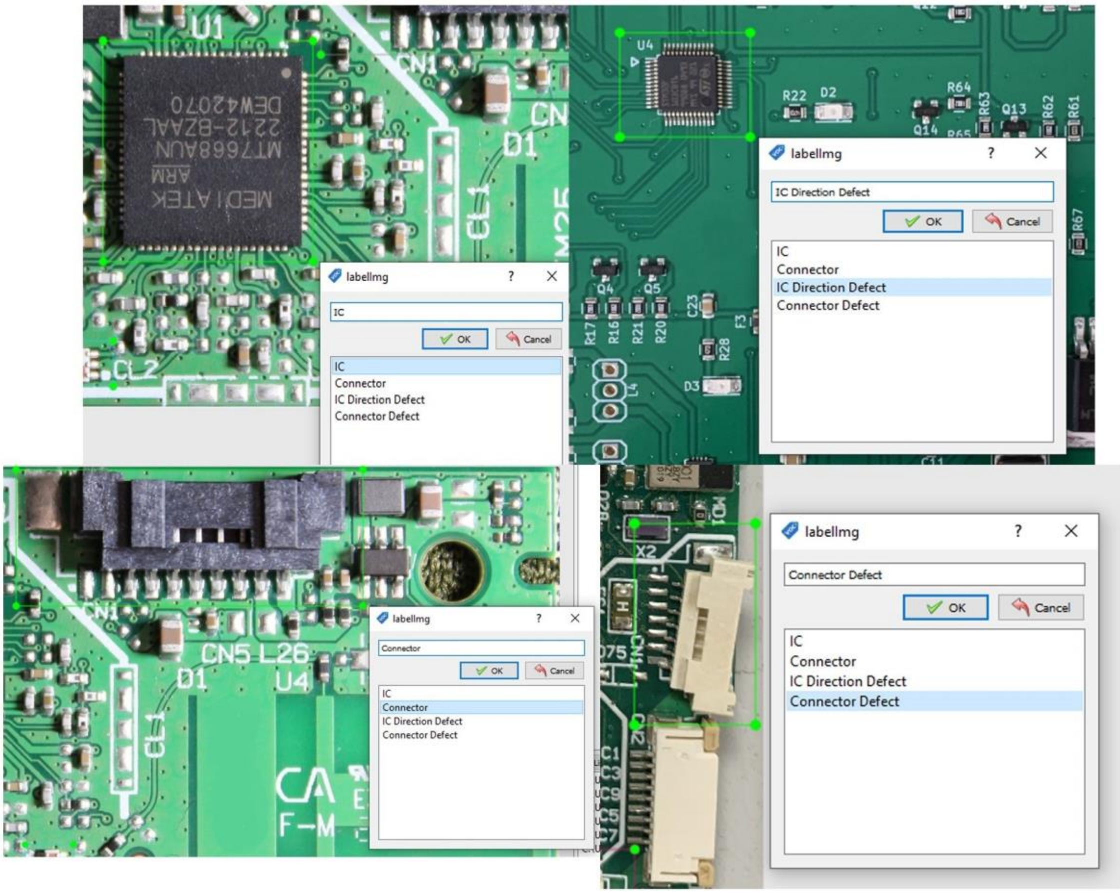

Figure 4.7 Annotating the Defects using LabelImg.

Figure 4.8a shows an example of a reverse polarized IC. The dot on the IC and the dot on the PCB are not in the same direction. Figure 4.8b shows an example of reversely mounted connector. Examples of defect-free "IC" and "Connector" labels are shown in Figure 4.9a and 4.9b.

(a) IC Direction Defect **(b)** Connector Defect

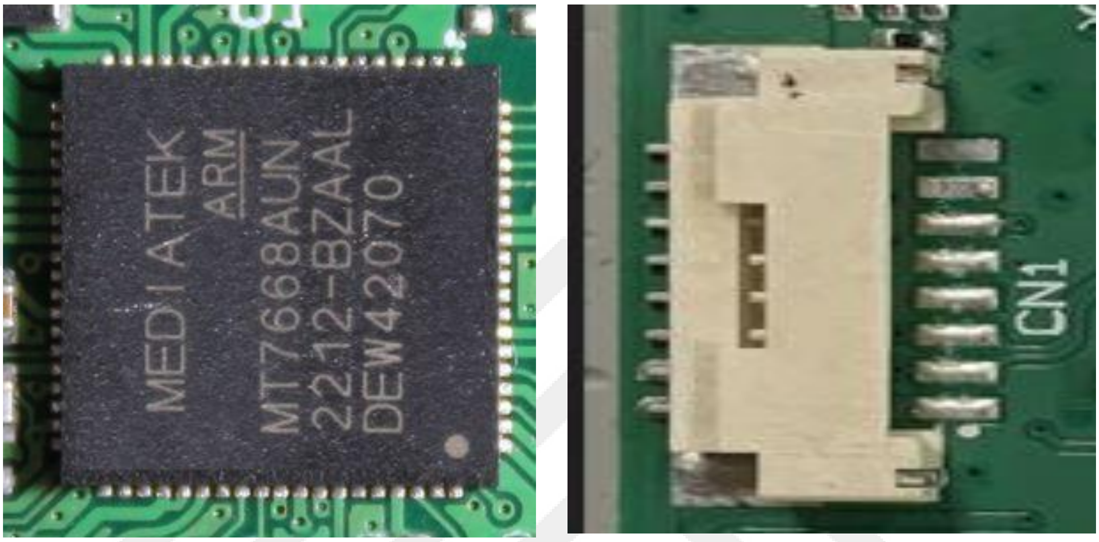

Figure 4.8 Examples of Defective PCBs.

(a) Defect-free IC **(b)** Defect-free Connector

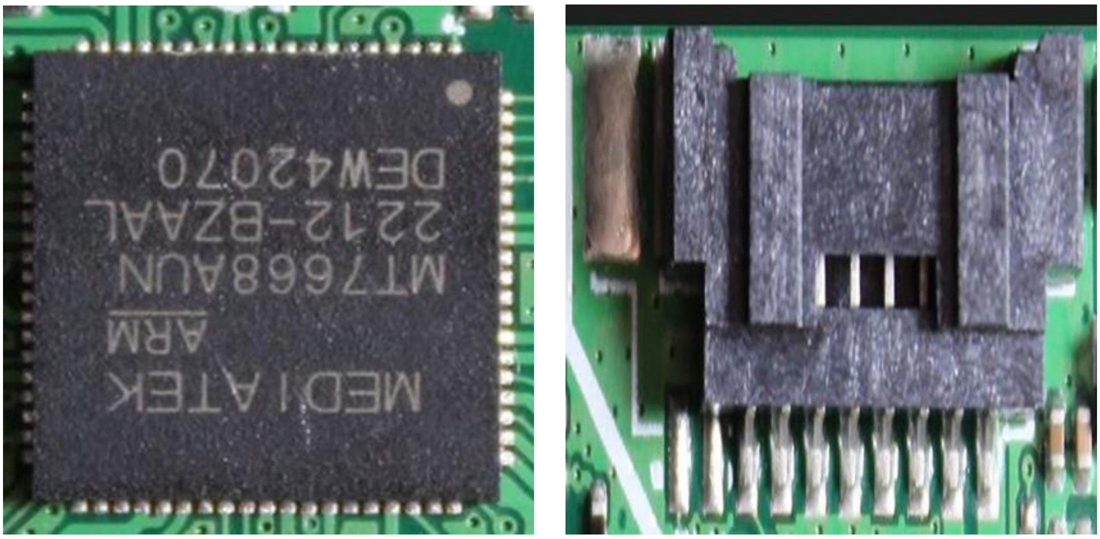

Figure 4.9 Examples of Defect-Free PCBs.

4.2.3. Data Augmentation

The photos were labeled and then uploaded to "Roboflow" for augmentation. Roboflow [31] is a platform that facilitates data augmentation for image data. By automating data augmentation processes, it enables the creation of diverse dataset for machine learning models. It allows you to experiment with different boosting techniques for different datasets and better train your models.

Data augmentation increases the diversity of the training dataset, allowing the model to learn different variations and scenarios. This can help the model perform better on more general, real-world data. Modern machine learning models require large amounts of high-quality annotated data. Data collection and annotation are time and resource consuming tasks. Data augmentation is a technique of artificially increasing the training set by creating modified copies of a dataset using existing data [32].

Data augmentation can make the model more general and reliable. However, it is important to do this in a balanced and correct way. Over-augmentation can cause the model to over-fit, while under-augmentation can prevent the model from adapting to different data situations. Therefore, data augmentation should be done carefully and applied in a balanced way to improve the quality of the training process. In this study, the model was repeatedly trained by applying varying augmentation methods to the dataset. The following methods were used to augment the dataset;

1. **Crop:** Crop an image at a random position. Since the object(s) of interest we want our models to learn aren't always fully visible in the image or not at the same scale in our training data, this improves the generalization of our model. By applying the crop method between 0% minimum zoom and 10% maximum zoom, we have diversified the dataset by selecting or cropping a specific region of the image and creating new images with smaller sizes. This can be an image containing a smaller fragment of the original image with a different perspective or size.
2. **Exposure:** Increase or decrease the brightness of an image. This helps make our model more robust to changes in lighting and camera

settings. By changing the light levels with the exposure method in the range of -7% and 7%, we increased and decreased the contrast by adjusting the light and dark areas of the image. This allows the model to adapt better to different lighting conditions.

3. **Mosaic Augmentation:** Combine different images together. This improves the model's performance by strengthening the algorithm's resistance to the objects' surroundings. In other words, the mosaic method allows the model to encounter different arrangements of objects, backgrounds and angles. This can help the model adapt to more general and varied situations. At the same time, it allows the creation of richer datasets that include different relationships, positions and sizes of objects in the dataset. We applied the mosaic augmentation by applying the following steps:
    1) Choose four different images randomly from the dataset,
    2) Combine the selected images into a single large image using mosaic stitching.

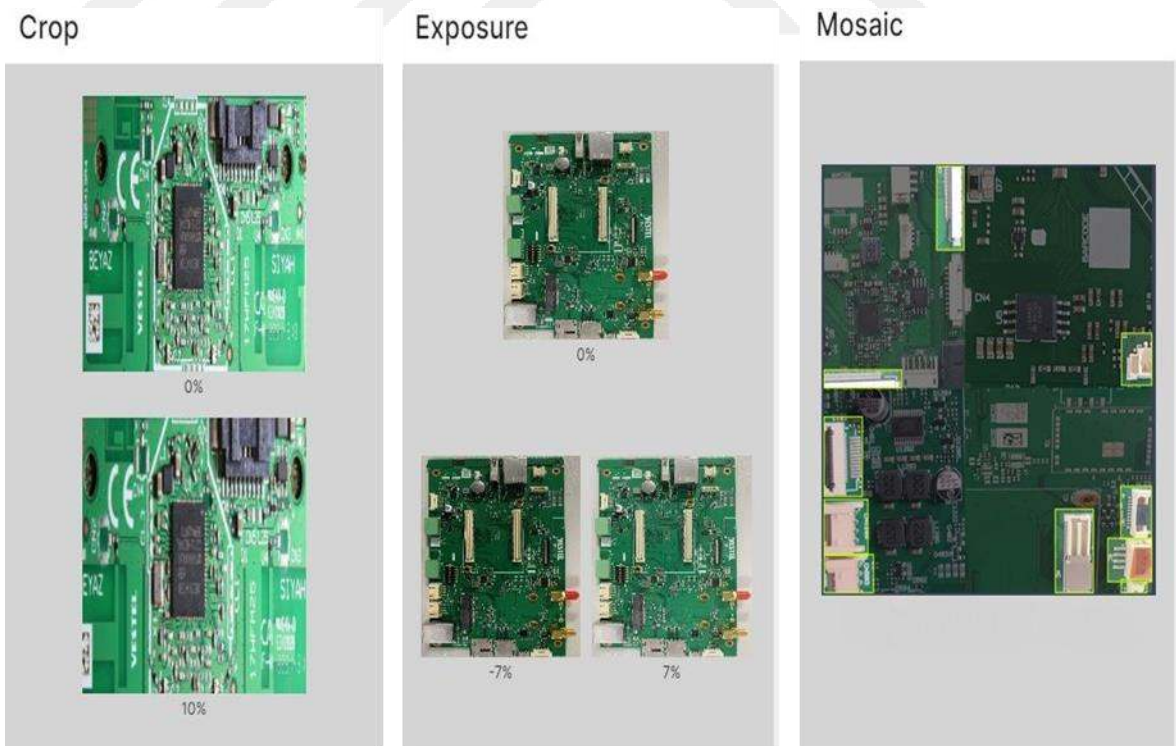

Figure 4.10 Data Augmentation Methods.

4.3. Building a Custom YOLOv5 Model

YOLO, or You Only Look Once, is one of the most widely used deep learning-based object recognition algorithms on the market. Training YOLOv5 typically involves using pre-trained weights as a starting point, and then training new weights based on the custom dataset. This process can vary, often depending on the size and variety of the training dataset and the accuracy of the model.

In this thesis, we create a dataset of PCB images containing defective and defect-free ICs and connectors and train a custom YOLOv5 model to recognise objects in our dataset. We followed the steps below in order:

1. The data set is collected and the data set is labeled for use in training the model. The images in which the objects are labeled and the label files of these objects are used to train the model. Labels provide reference points that the model uses to produce accurate results. For example, labels such as the types, locations, and bounding box information of objects in an image help the model recognize those objects. Labels guide the model in learning and help identify the patterns needed to produce desired results. In this thesis, we used the LabelImg platform for labeling in YOLOv5 format. We used the labels “IC Direction Defect” for reverse polarized ICs, “Connector Defect” for defective connectors and “IC” and “Connector” for defect-free ICs and connectors, respectively. Then, we divide the dataset into three essential subsets: the training set (88%), the validation set (8%) and the test set (4%) (Figure 4.11).

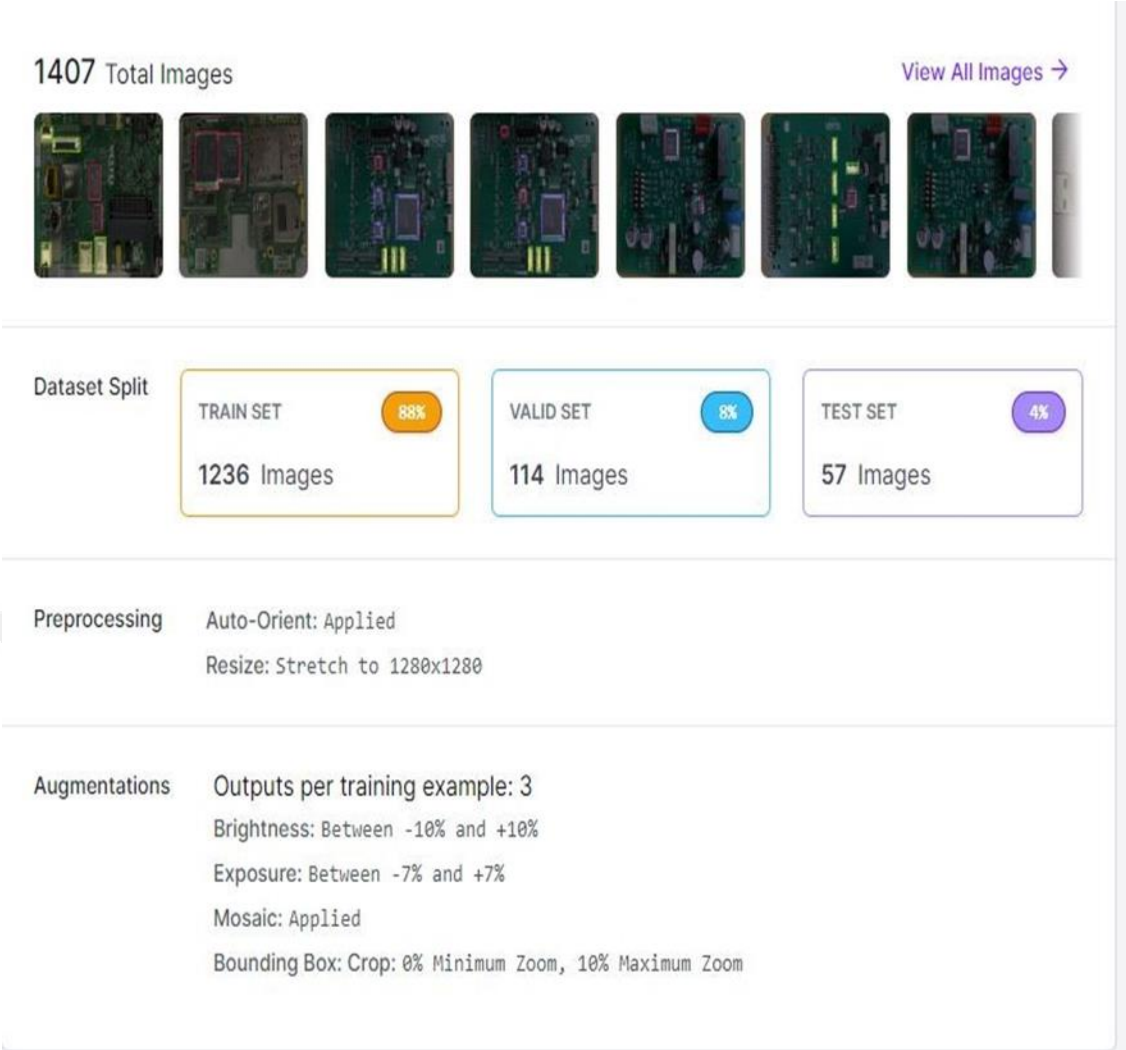

Figure 4.11 Splitting of the Dataset.

2. After the labeling process, the data was transferred to Roboflow and the data set was augmented by applying cropping, brightness, exposure and mosaic enlargement methods. Roboflow made it easier to manage these processes. The number of images in the dataset, which was 783 in total (413 ICs, 370 connectors) before the data augmentation process, increased to 1407 after the process.
3. Google Colab [33] was used for model training and evaluation purpose. We used the free Google Colab environment provided by Google. Before starting the model training, the necessary files for YOLOv5 need to be downloaded to the virtual machine through Colab. The command required for this process is shown in Figure 4.12. The dataset was downloaded to Google Colab using the

Roboflow generated URL as a zip folder. A development environment is created for the training. It provides a cloud-based Jupyter notebook [34] environment. It can be used to conduct research, perform data analysis, train machine learning models or develop various projects using the Python programming language. To build and train the model, we installed the necessary dependencies for Pytorch [35], an open source Python library. It contains many tools for working with artificial neural networks and is very popular in the field of deep learning. Figure 4.13 shows the details of training the YOLOv5 model. In this figure, "Batch size" refers to the number of training instances in the batch. "Epochs" controls the number of complete passes through the training dataset. During training, images have to be reshaped to the same size. "Image size" selects the size of the images to train on.

```
#clone YOLOv5 and
!git clone https://github.com/ultralytics/yolov5  # clone repo
%cd yolov5
%pip install -qr requirements.txt # install dependencies
%pip install -q roboflow

import torch
import os
from IPython.display import Image, clear_output  # to display images
```

Figure 4.12 Downloading Required Files for YOLOv5.

```
!python train.py --img 1280 --batch 16 --epochs 150 --data {dataset.location}/data.yaml  --weights yolov5s.pt --cache
```

Figure 4.13 The Details of Training the YOLOv5 model.

During the training of the model, we resized the images to different dimensions, including 416x416, 512x512, 1024x1024 and 1280x1280. Each dataset was repeatedly retrained by changing the img, batch and epoch parameters.

4. Test and evaluate the YOLOv5 model.

5. EVALUTION

Experiments were conducted using YOLOv5 on real images containing defective and defect-free samples.

During testing and training, the sizing values of the original PCB images are modified according to the scale configured in the testing parameters. YOLO's original configuration is set to 416x416 pixels. In this study, resized versions of the image at 416x416, 512x512, 1024x1024 and 1280x1280 pixel scales were used. YOLOv5 was used to learn and evaluate two cases: **(a)** defect classification if the sample is defective, **(b)** component classification if the sample is defect-free. The evaluation was carried out on four metrics; Precision (P), Recall (R), Average Precision (mAP) and Intercept on Union (IoU).

5.1 Evaluation Metrics

In this study, we measured accuracy, precision, and recall ratios, which are commonly used metrics for evaluating the model's performance. The usage of these measures in deep learning applications is confirmed by [36]. These measures are defined as follows:

Accuracy: The ratio of correctly predicted samples to the total number of samples; where true positives (TP) represent the number of positive samples correctly predicted, true negatives (TN) represent the number of negative specimens correctly predicted and total samples represent the total number of data samples.

$$Accuracy = \frac{TruePositives + TrueNegatives}{TotalSamples}$$

Precision (P): Indicates how many of the samples predicted to be positive are actually positive, where false positives (FP) represent the number of positive samples predicted incorrectly.

$$Precision = \frac{TruePositives}{TruePositives\ +\ FalsePositive}$$

Recall (R): Indicates how many true positive samples were correctly detected, where false negatives (FN) represent the number of negative samples that were predicted incorrectly.

$$Recall = \frac{TruePositives}{TruePositives\ +\ FalseNegatives}$$

F1 Score: The F1 score represents the harmonic mean of precision and recall values. Using a harmonic average, as opposed to a simple average, ensures that extreme cases are not missed.

$$F_1\ Score = \frac{2\ x\ Precision\ x\ Recall}{Precision + Recall}$$

Mean Average Precision (mAP): mAP is the Average Precision (AP) for each class and then average over a number of classes.

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i$$

Intersection over Union (IoU): IoU is a metric commonly used in deep learning, particularly in object detection tasks, to evaluate the performance of models. This metric measures how much the predicted region by the model overlaps with the ground truth region.

$$IoU = \frac{Unionof\ PredictedRegionandGroundTruthRegion}{Intersectionof\ PredictedRegionandGroundTruthRegion}$$

These metrics contribute to a more detailed evaluation of the model's performance in a classification problem. Nevertheless, when employed individually, they may be incomplete or even misleading in certain cases. Therefore, it is advisable to assess different metrics collectively to obtain a comprehensive understanding of the model's performance.

5.2 Evaluation of the Model

We compared detection performances using Precision (P), Recall (R), Mean Average Precision (mAP) and Intersection over Union (IoU) metrics, under different image resolution configurations (416x416, 512x512, 1024x1024 and 1280x1280). We found that YOLO's performance in detecting small objects was unsatisfactory when using the initial resolution setting. Therefore, we increased the resolution to 1280x1280 and this change resulted in the expected improvement in accuracy and provided the best results. Although the processing time increased, it did not exceed acceptable limits.

Results of the model created for YOLOv5 are presented in , Table 5.1, Table 5.2, Table 5.3 and Table 5.4 , respectively.

Table 5.1 Accuracy Results when Image Resolution is 416x416.

Class	P	R	mAP	IoU	Processing time
All	0.79	0.725	0.762	0.629	4s
Connector	0.899	0.853	0.898	0.704	4s
Connector Defect	0.829	0.625	0.636	0.564	4s
IC	0.637	0.659	0.698	0.567	4s
IC Direction Defect	0.794	0.764	0.817	0.682	4s

Table 5.2 Accuracy Results when Image Resolution is 512x512.

Class	P	R	mAP	IoU	Processing time
All	0.843	0.771	0.813	0.669	6s
Connector	0.913	0.853	0.898	0.703	6s
Connector Defect	0.971	0.75	0.802	0.673	6s
IC	0.641	0.736	0.723	0.608	6s
IC Direction Defect	0.847	0.746	0.827	0.692	6s

Table 5.3 Accuracy Results when Image Resolution is 1024x1024.

Class	P	R	mAP	IoU	Processing time
All	0.896	0.802	0.907	0.763	11s
Connector	0.929	0.8	0.923	0.758	11s
Connector Defect	1	0.804	0.922	0.776	11s
IC	0.759	0.78	0.863	0.714	11s
IC Direction Defect	0.895	0.824	0.919	0.804	11s

Table 5.4 Accuracy Results when Image Resolution is 1280x1280.

Class	P	R	mAP	IoU	Processing time
All	0.845	0.865	0.907	0.764	15s
Connector	0.899	0.877	0.931	0.757	15s
Connector Defect	0.873	0.862	0.929	0.778	15s
IC	0.694	0.857	0.865	0.735	15s
IC Direction Defect	0.912	0.865	0.903	0.786	15s

The performance results of the YOLOv5 model are presented in Figure 5.1, Figure 5.2, Figure 5.3, Figure 5.4, Figure 5.5 and Figure 5.6, respectively.

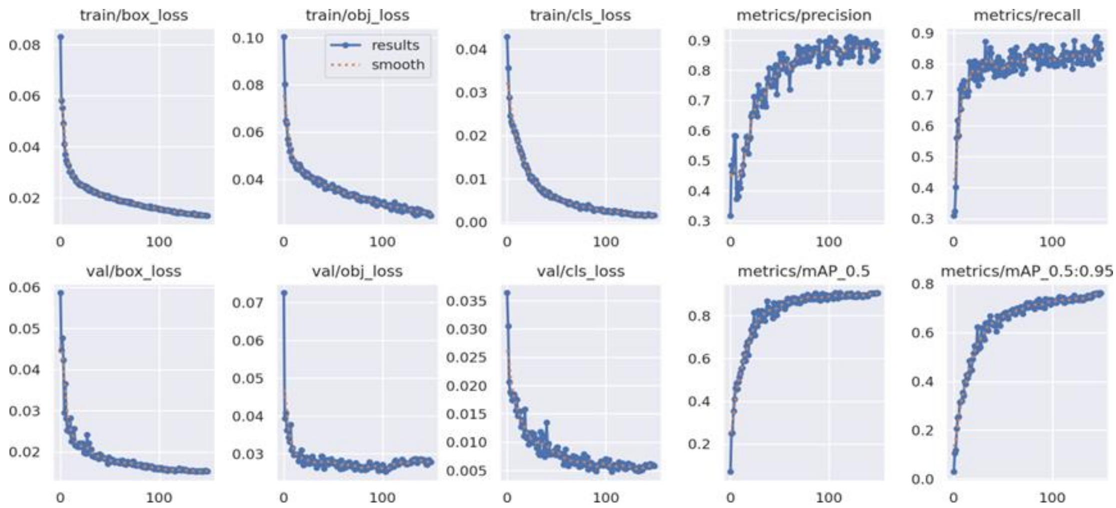

Figure 5.1 The Performance Results of YOLOv5 Training.

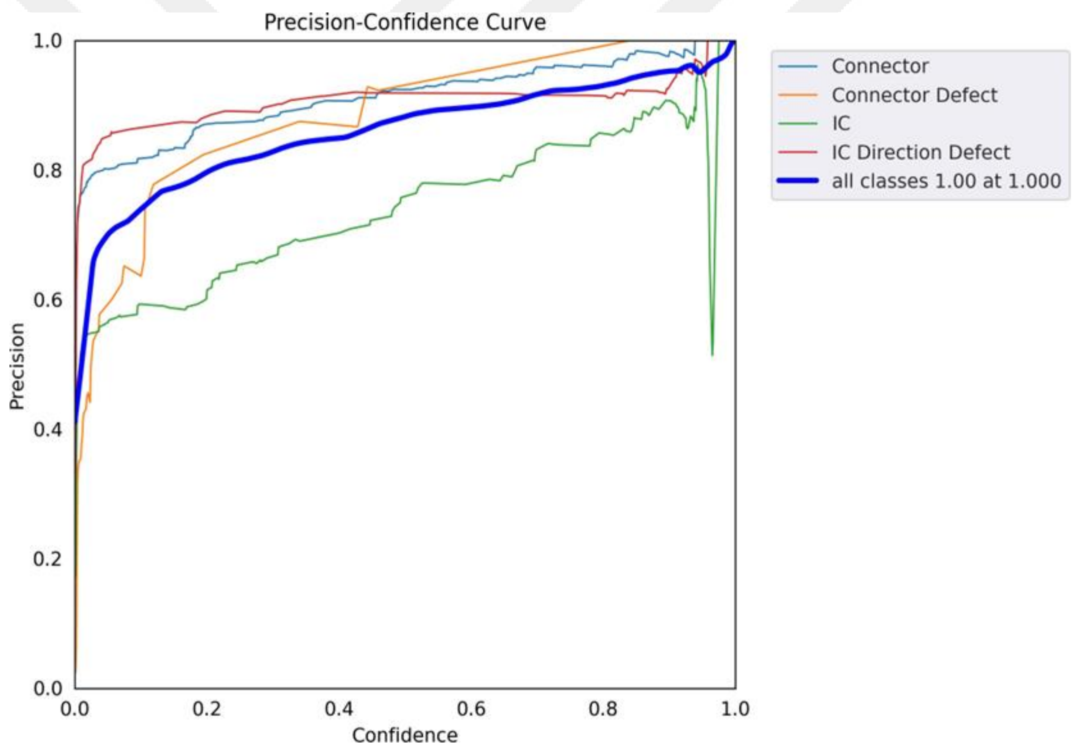

Figure 5.2 P Curve of the Model.

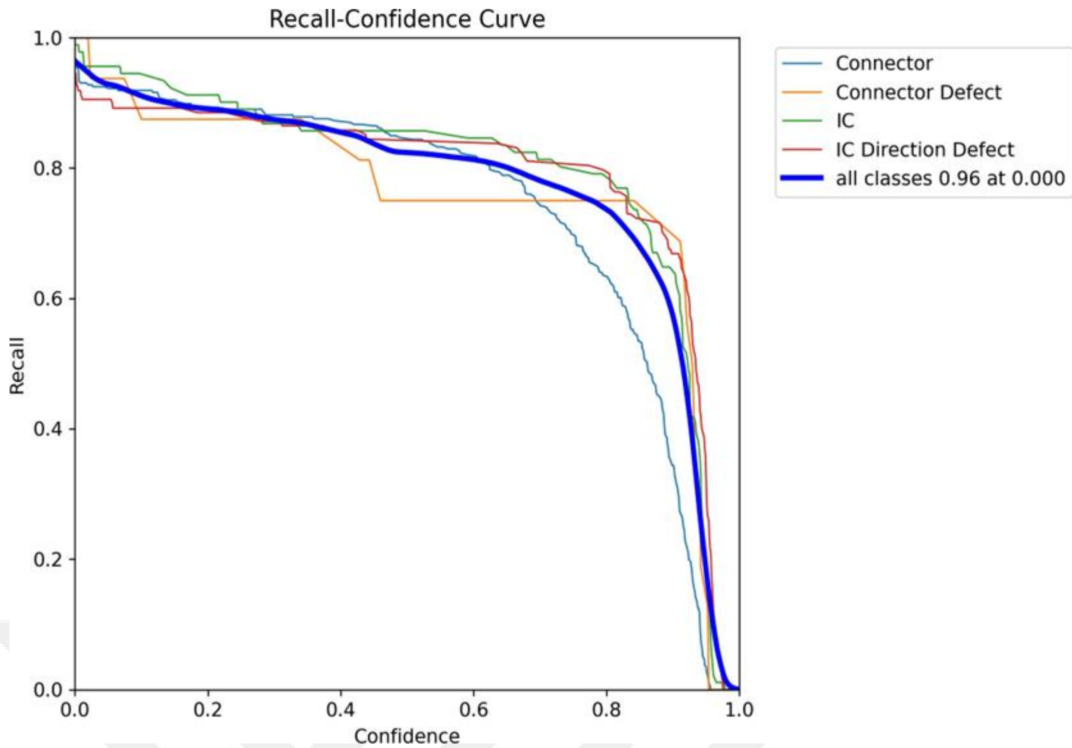

Figure 5.3 R Curve of the Model.

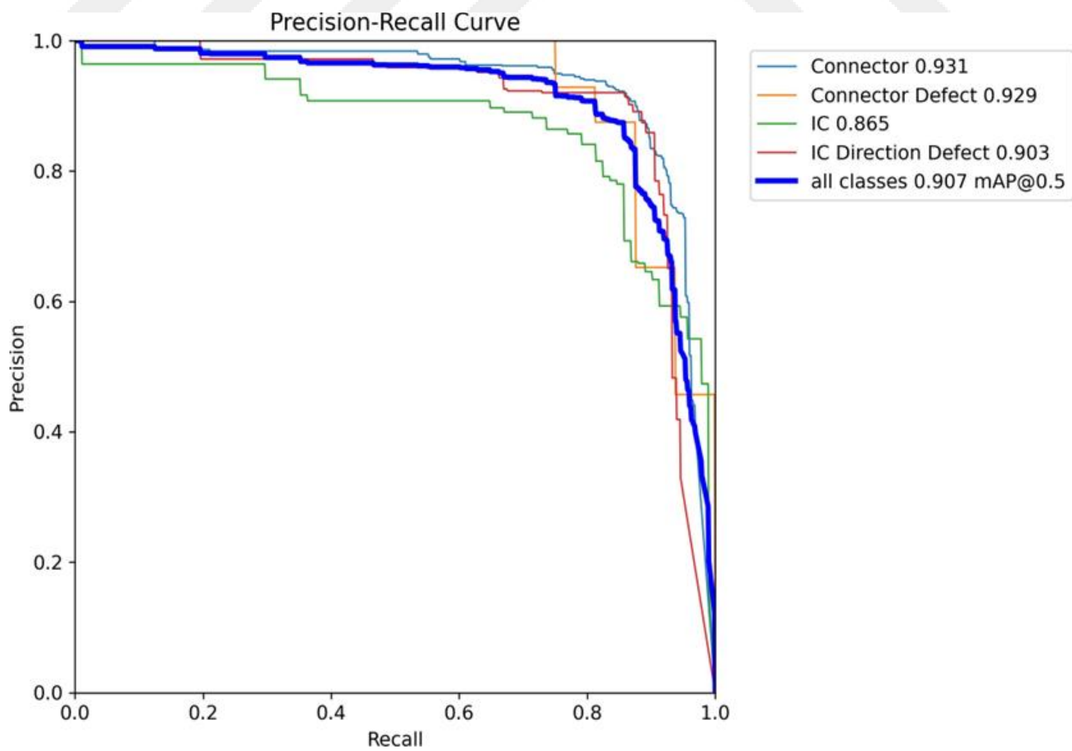

Figure 5.4 PR Curve of the Model.

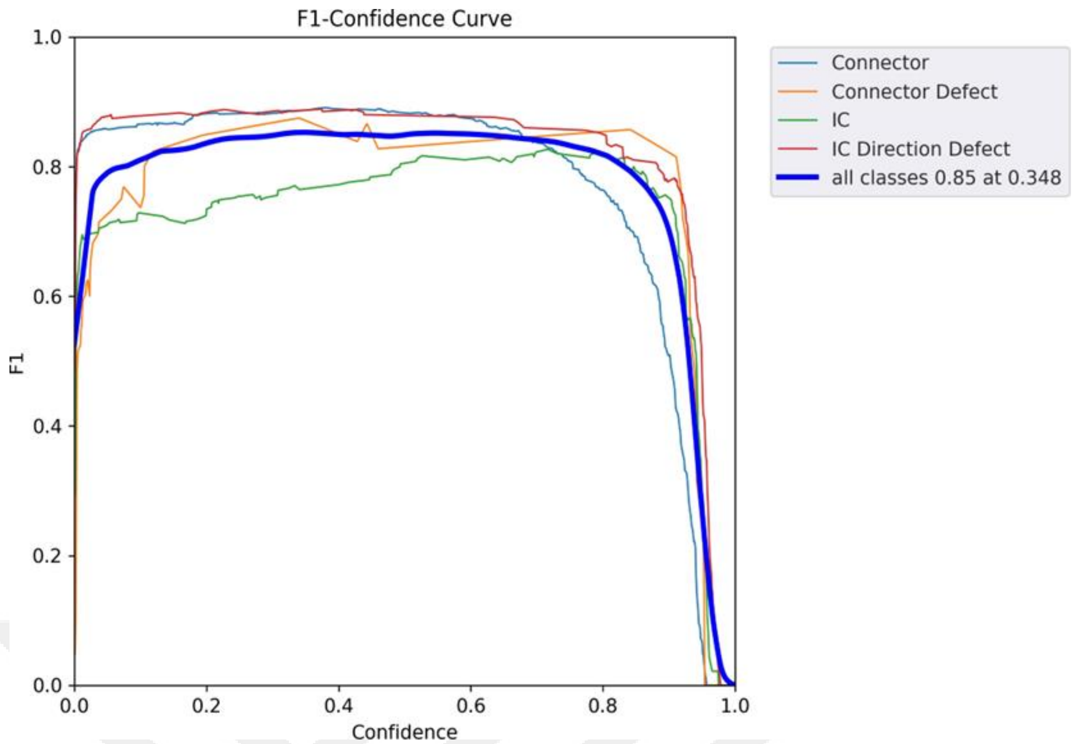

Figure 5.5 F1-Confidence Curve of the Model.

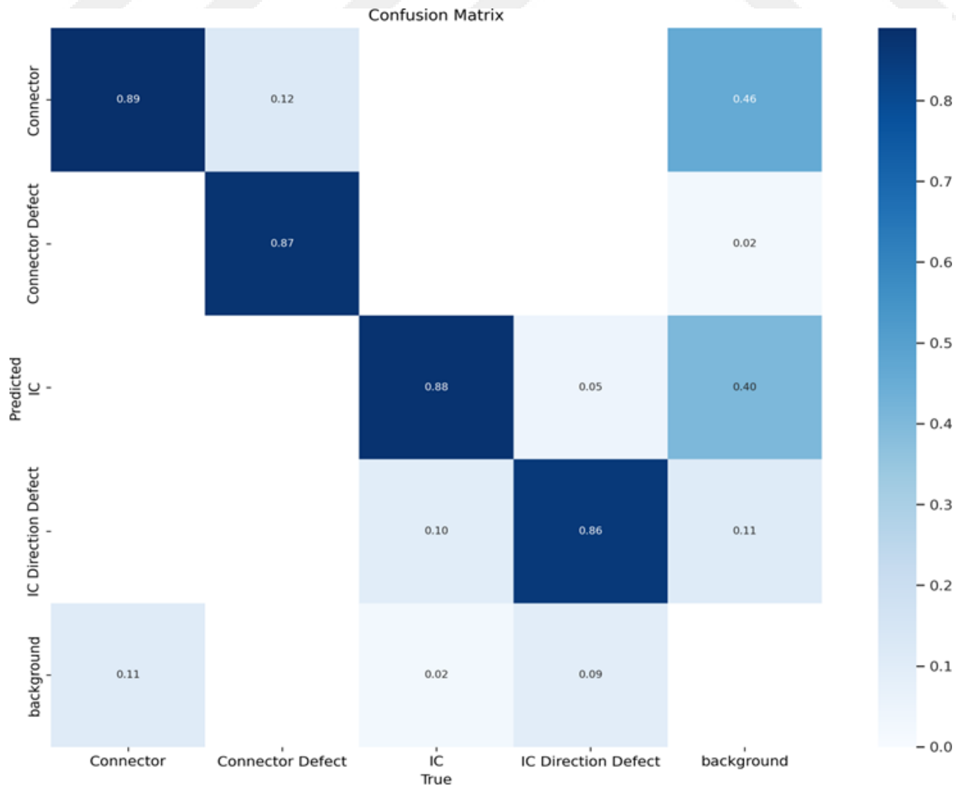

Figure 5.6 Confusion Matrix of the Model.

After completing the evaluation of the YOLOv5 model on training, evaluation and test data, the model was tested on an additional 5 images and the results are represented in Figure 5.7, Figure 5.8, Figure 5.9, Figure 5.10 and Figure 5.11.

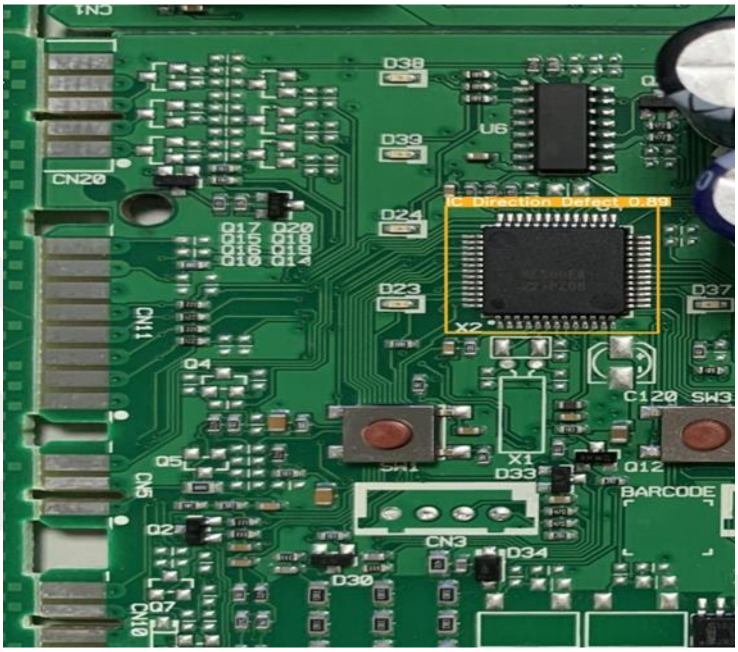

Figure 5.7 Performance of the Model on Sample_Image_1.

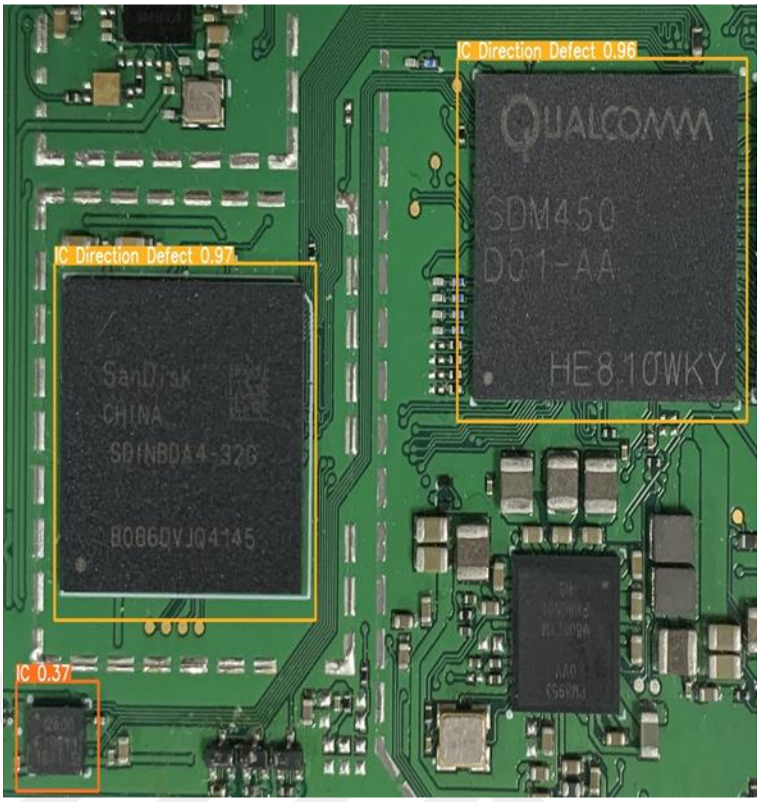

Figure 5.8 Performance of the Model on Sample_Image_2.

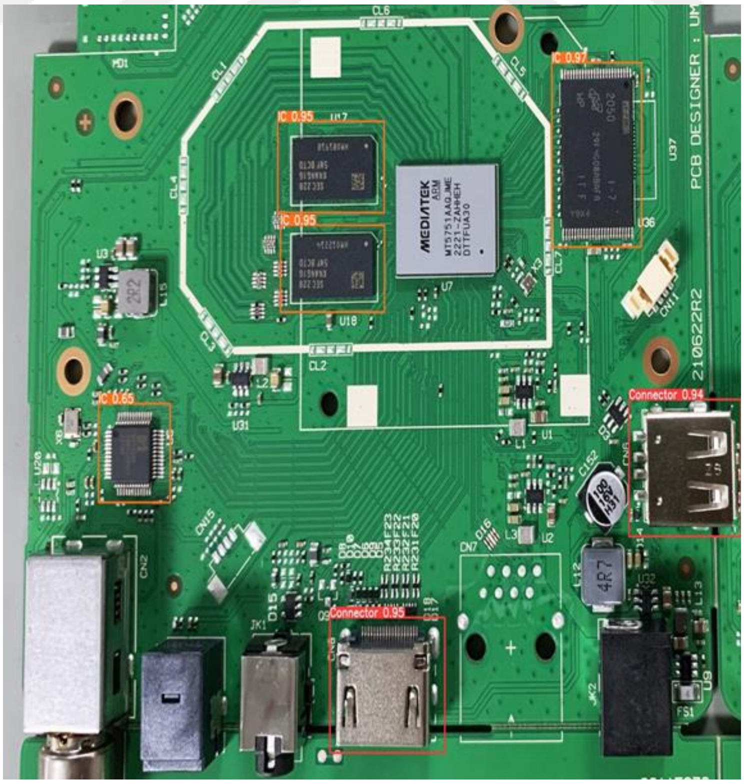

Figure 5.9 Performance of the Model on Sample_Image_3.

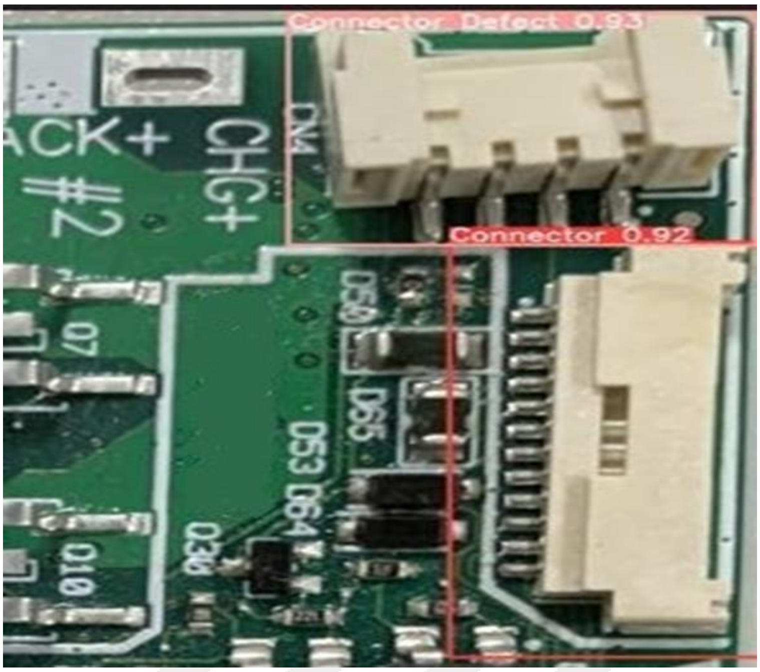

Figure 5.10 Performance of the Model on Sample_Image_4.

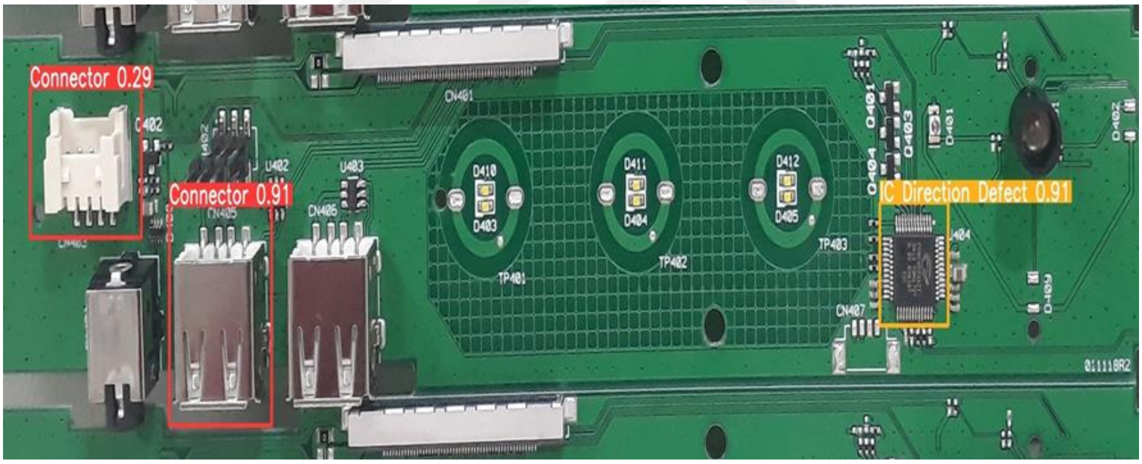

Figure 5.11 Performance of the Model on Sample_Image_5.

In Table 5.4, the Precision value ranges from 0 (undesired) to 1.0 (perfect). The class with the highest Precision is IC Direction Defect (approximately 0.912), while IC has the lowest precision (approximately 0.694). The Recall value also ranges from 0 (undesired) to 1.0 (perfect). The class with the best Recall value is Connector (about 0.877), while IC has the lowest Recall value (about 0.857). While the highest Accuracy results were obtained in Table 5.4, the lowest Accuracy results were seen in Table 5.1. When the performance result graphs of YOLOv5 training are compared, it is observed that the performance of the classifier will increase when the loss decreases. Confusion Matrix for multiple classification (Connector, Connector Defect, IC, IC Direction Defect) obtained for 150 epochs is shown in Figure 5.6. The TP (true positive) elements for each class are shown on the diagonal (top left to bottom right) as follows: 89% of all objects in the Connector class, 87% of all objects in the Connector Defect class 88% of all objects in the IC class and 86% of all objects in the IC Direction Defect class were categorized correctly. Additionally, 12% of objects of the Connector Defect class were incorrectly predicted as Connector class objects, while 2% of all objects belonging to the IC class were incorrectly predicted as unidentified/unclassifiable and 10% of objects were incorrectly predicted as objects of the IC Direction Defect class. 5% of all objects belonging to the IC Direction Defect class were misclassified as IC, while 9% were classified as unknown. After completing the evaluation of the YOLOv5 model on training, evaluation and test data, the model was tested on five additional images. In Figure 5.7, the Yolov5s model was successful in identifying and classifying IC Direction Defect at 150 epochs, with a sensitivity of approximately 0.89. In Figure 5.8, the Yolov5s model was successful in identifying and classifying IC Direction Defects at 150 epochs, with sensitivities of 0.97 and 0.96. In Figure 5.9, the Yolov5s model was successful in identifying and classifying mixed ICs and Connectors on the PCB, with sensitivity of 0.97 and 0.94, respectively, in 150 epochs. In Figure 5.10, the Yolov5s model was successful in identifying and classifying mixed Connector Defects and Connectors on the PCB, with sensitivity of 0.93 and 0.92, respectively, in 150 epochs. In Figure 5.11, the Yolov5s model was successful in identifying and classifying mixed Connector and IC Direction Defects on the PCB, with sensitivity of 0.91 and 0.91, respectively, at 150 epochs. When all these results were examined, it was observed that the performance values were generally better than the results in the literature. We expect that these performances will increase even more with the new images that will be collected. As a result, when the model started to be used in Vestel production lines, performance will increase with the large amount of images that will obtained from the production lines daily.

6. CONCLUSION

Manual inspections of printed circuit boards after assembly reveal that inspecting polarized components with the naked eye is costly in both labor and time. There are studies in the literature on using artificial intelligence methods to detect these defects. In this thesis, a YOLOv5 deep learning model is presented to detect missing components, reverse polarity and misalignment errors in printed circuit boards. The most important novel aspect of this thesis is based on the case of Vestel Beyaz Eşya Sanayi, it focuses on reverse polarity and misalignment errors, which have not been studied much in the literature.

The proposed YOLOv5 deep learning model was evaluated using real image data of printed circuit boards and achieved accurate detection results in under 0.102 seconds for each PCB image. The following mAP values were obtained in the evaluation: 0.931 for defect-free connectors, 0.929 for defective connectors, 0.865 for ICs and 0.903 for IC direction defects.

In the case of Vestel Beyaz Eşya Sanayi, the polarized components on the cards are checked manually by quality operators after assembly. With each PCB model change, a sample is chosen randomly for inspection. Approximately 10 different models of PCBs are produced on each production line every day. Checking each different PCB model takes at least 10 minutes. This time increases as the PCB becomes more complex. In other words, a quality operator spends 1.5-2 hours (10x10min) to perform post-typesetting inspections. Therefore, since it is not possible to examine all cards, lack of control in mass production can pose a high risk. In the case of mass production (e.g. 6000 units and above), the presence of one faulty PCB may result in re-inspection of all boards after the PCBs have been shipped to the customer. Returning the boards to the factory for rework requires additional labor, materials and transportation. Additionally, the likelihood of new defects appearing in PCBs may increase during rework operations.

The following observations were made regarding the problem solved in the thesis:

1) IC and connector components are included in approximately all PCB models,

2) Manual inspection of IC and connector components takes about 50% of the entire inspection,

3) The consequences of IC and connector failures carry a higher risk than other component failures.

In light of all these observations, it is predicted that the model will provide a minimum of 30% performance and efficiency in Vestel test processes.

We expect the performance to increase with the new images that will be obtained when the model is used in Vestel production lines. Therefore, as a future study, we plan to develop an embedded system that will be integrated into production lines. The embedded system will automatically collect images, runs the deep learning model and notifies operators in case of detect defection. In this context, our main focus will be to continuously expand the dataset, increase the algorithm reliability and minimize the time spent in the entire detection process.

Another possible future work is to train the model to detect defects such as "Capacitance Direction Error", "Diode Direction Error" and "Switch Direction Error".

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