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Design of Artificial Intelligence Based Novel Device for Fault Diagnosis of Integrated Circuits †

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Abstract: Rapid advancement of integrated circuit (IC) technology has revolutionized various industries, but it has also introduced challenges in detecting faulty ICs. Traditional testing methods often rely on manual inspection or complex equipment, resulting in time-consuming and costly processes. In this work, a novel approach is proposed which uses a thermal camera and the Internet of Things (IoT) physical device namely Raspberry PI microcontroller for the detection of faulty and non-faulty ICs. Further, a deep learning algorithm namely You Only Look Once (YOLO) is coded inside the Raspberry PI controller using Python programming software to detect faulty ICs efficiently and accurately. Also, the various images of faulty and non-faulty IC are used to train the algorithm and once the algorithm is trained, the thermal camera along with the Raspberry PI microcontroller is used for real-time detection of faulty ICs and the YOLO algorithm analyzes the thermal images to identify regions with abnormal temperature patterns, indicating potential faults. The proposed approach offers several advantages over traditional methods, including increased efficiency and improved accuracy.

Keywords: deep learning; fault diagnosis; object detection; temperature variation; thermal camera; YOLO algorithm

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1. Introduction

Recent advancements in integrated circuit (IC) and system on chip (soc) technology has significantly transformed numerous industries, including electronics, telecommunications, and automotive sectors. However, this progress has also presented significant challenges in detecting and ensuring the reliability of integrated circuits (ICs). The system faults can lead to critical system failures, reduced performance, loss of production and substantial financial losses. However, it is essential to locate/identify the fault and to isolate it, in order to ensure recovery and safe mode operation [1].

Due to design or manufacturing defects, normal wear and tear, the faults are developed [2]. Traditional methods of detecting faulty ICs often rely on manual visual inspection or complex and expensive testing equipment. Contact methods are used to identify the discontinuity in connections to ICs. Furthermore, the non-contact methods such as X-ray, Ultrasound, Optical Comparators, Vision Systems, Computerized Tomography (CT) Scanning, Long Range, Laser Radar, thermal imaging etc. are used for fault detection [3]. These approaches are not only time-consuming but also prone to human error and subjective interpretations. Also, it is very essential to develop a module to diagnose a fault (Fault Detection) which may affect these system operations and to locate their root causes

(Fault Isolation) [4]. As a result, there is a growing need for automated techniques that can streamline the detection process, improve efficiency, and enhance accuracy.

Thermal imaging has been gaining focus for its efficiency and reliability [3,5–9]. All objects in nature, as far as their temperature is not higher than the absolute temperature (−273 °C) there is irregular movement of molecules and atoms, which causes the surface to continuously radiate infrared light. In common, the thermal imaging collects infrared light in the thermal infrared band between 8 μm–14 μm which lies in the electromagnetic spectrum between visible and microwave regions [9]. However, the humans are not capable to visualize these thermal radiations, the thermal cameras are utilized to visualize the thermal radiation emitted by the object. Once the thermal radiation emitted by the object is detected, the data is converted into gray value and the difference of gray value of each object is used to image. Furthermore, these thermal profiles of each objects can be assessed to detect various parameters such as hotspots, extent of heat spread and its location [3], [9–11]. Thermal infrared imaging has proven its significance across various industries including Medical, Building and Construction, Agriculture, Automotive etc. Furthermore, these industries showed improved efficiency, safety, and decision-making by making use of thermal imaging [12].

Non-Contact Thermal imaging combined with computer vision and machine learning are accurate, fast and non-destructive to detect faults as in recent years, computer vision and machine learning algorithms have emerged as powerful tools for automated defect detection in various domains, the fault diagnosis for integrated circuits with the help of automated defect detection can be generally classified into two stages namely Data acquisition and Image classification [3,5–9,12].

Data acquisition is the process of collecting data, while image classification involves categorizing images based on their content. Further, the data acquisition process includes data acquisition, data pre-processing, extraction of features, training of learning models, and inference output. Common approaches for model training in image classification are Support Vector Machine (SVMs), Random Forests, and deep learning namely Convolutional Neural Networks (CNNs) which can be time-consuming and resource-intensive [13,14]. These methods often require powerful hardware, such as Graphical Processing Units (GPUs) or Tensor Processing Units (TPUs), to train models effectively [14]. Also, real-time monitoring with these approaches can be challenging due to the computational demands involved in processing images in real-time. So, there is an increasing demand for a real-time approach that doesn't rely on high computational power, aiming to simplify the detection process.

2. Literature Survey

Over the last few years, there were many contact and non-contact methods which have been used for the detection of fault diagnosis of ICs. Nowadays, a non-contact method is widely used for better performance and detection of faults faster than the contact methods. Further, the non-contact methods are mainly carried out using X-ray, Ultrasound, Vision Systems, Computerized Tomography (CT) Scanning, Long Range Laser, Laser based Radar, Structured Light, thermal imaging etc. Out of these mentioned techniques, thermal imaging is meant to be best for the process.

Silva et al. (2013) have proposed a technique using Machine learning methods. Further, the proposed method comprised of three common steps such as extraction of features using Principal Component Analysis (PCA), Classification using the Nearest Neighbor (k-NN) and other methods; and evaluation of the classifier's performance using Cross-Validation (CV) technique [1]. Lo et al. (2019) have presented a review on the diagnosis of systems using Artificial Intelligence (AI) approach. Further, the authors have discussed the applications especially in the field of diagnosis of complex systems [5]. Al-Obaidy et al. (2017) have compared various soft computing methods which was utilized for fault detection of ICs. Also, the histogram thresholding is used to extract features which can be further reduced by principal component analysis. Furthermore, these minimized features can be given as input to the classifier which enables to classify defects in PCB at IC level [3].

Redon et al. (2020) have proposed a condition monitoring system by thermal image using denoising technique for reducing noise. Denoising methods have two methods namely continuous wavelet transform and stationary wavelet transform [15]. Huo et al. (2017) have proposed a Self-adaptive Fault Diagnosis of Roller Bearings using Infrared Thermal Images. In the stage one, the authors have decomposed the images using 2-Dimensional Discrete Wavelet Transform (2D-DWT) and Shannon entropy. Furthermore, the authors have utilized the histograms of selected coefficients as an input of the feature space selection method by using Genetic Algorithm (GA) and Nearest Neighbor (NN) for the purpose of selecting two salient features that exhibits highest classification accuracy [16].

The objective of this work is to combine thermal imaging with the YOLO algorithm and to develop an efficient and accurate system for real time monitoring of detecting faulty ICs based on their thermal characteristics and to overcome the limitations of existing methods.

3. Materials and Methods

The proposed device comprised of components such as Thermal Sensor, Raspberry PI 4 Model B controller and a battery. Figure 1 shows the overall block diagram of a proposed device. Further, the AMG8833 based thermal sensor is an 8 × 8 (64 pixels) two-dimensional non-contact type temperature detection module. Also, the thermal sensor is capable of transmitting the infrared temperature readings through Inter-integrated Circuits (I2C) protocol to the utilized Raspberry PI microcontroller.

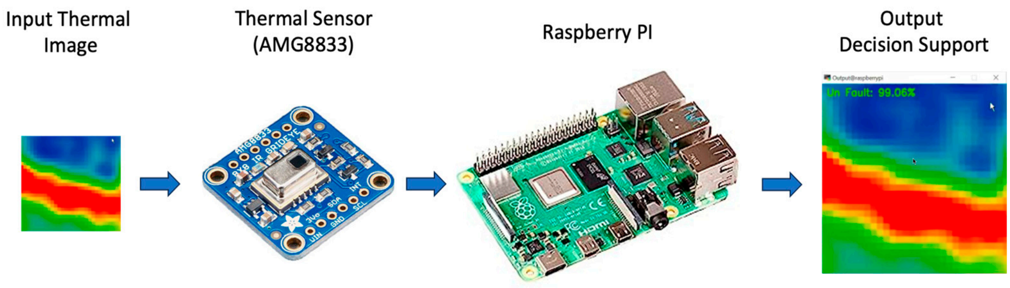

Figure 1. Overall diagram of a proposed device.

Figure 2 shows the connection diagram of AMG8833 thermal sensor module with Raspberry PI microcontroller. The I2C utilizes two different pins namely Serial Data (SDA) and Serial Clock (SCL). Further, the SDA and SCL of AMG8833 is connected to the SDA and SCL pin of the PI controller respectively which is shown in the Figure 2. Also, the AMG8833 thermal sensor requires 3.3 volts for its operation and it is fed by the Raspberry PI controller. In this work, a fast and compact module is proposed which can be used to identify the ICs fault conditions based on thermal profiles. Further, the short circuit faults based on electrical over stress is detected. Also, the electrical overstress can be caused because of high voltage.

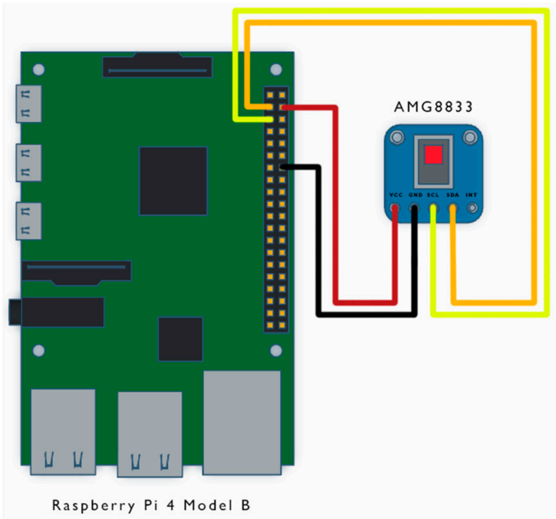

Figure 2. Connection diagram of thermal camera (AMG8833) with Raspberry PI microcontroller.

The proposed device is a simple handy device shown in the Figure 2 which can be moved over any integrated circuits through non-contact type.

3.1. Proposed Approach for Fault Diagnosis

Figure 3 shows the proposed approach for fault diagnosis and it is comprised of various stages such as preprocessing of input images, training and testing phase of YOLOV7 model.

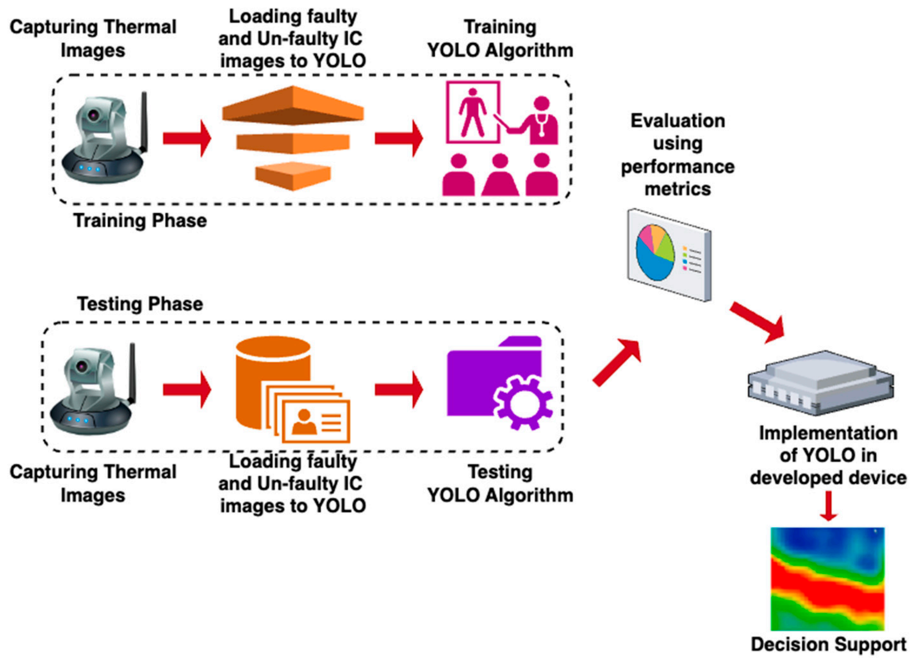

Figure 3. Procedure for fault diagnosis using proposed approach.

3.1.1. Preprocessing of Images

Data preprocessing is a crucial step before feeding data to a model. LabelImg is used to annotate faulty and unfaulty IC in images by drawing bounding boxes around them. These bounding boxes helps YOLO model to look for objects during training and testing. After Labelling Images this data is converted into .txt file format that YOLO understands. This format includes details like the position of the objects and their class labels.

3.1.2. YOLOV7 Algorithm

YOLO stands for "You Only Look Once", and it is one of the most effective object identification methods for partitioning images into a grid system. Each divided cell within the grid is in charge of detecting objects on its own. Because of its precision and quickness, YOLO (you only look once) is one of the most well-known object identification techniques. When comparing YOLOV5 and YOLOV6 in terms of accuracy, YOLOV7 has a 100% accuracy rate. As a result, the algorithm used in this proposed work is YOLOV7. The design and development of YOLOV7 involves two stages are involved namely training phase and testing phase.

In the training phase, the 80% of the total input preprocessed faulty and unfaulty thermal images are given to the proposed YOLOV7 algorithm for training purpose. Once the YOLOV7 model is trained, the testing process is carried out. In the testing phase, the 20% of the total input preprocessed faulty and unfaulty thermal images are given to the proposed YOLOV7 algorithm for testing purpose. Further, the performance metrics are evaluated to determine the efficacy of the proposed YOLOV7 model. The entire algorithm is coded using Python programming software and is executed in Raspberry PI controller. Furthermore, the Raspberry PI along with the thermal sensor module acts a handy device integrated with YOLOV7 provide decision support whether the IC is faulty or un-faulty.

4. Results and Discussion

The normal circuit boards especially ICs and the boards having faulty ICs were considered for this study. For both faulty and unfaulty ICs, the required power supply was applied and the thermal images were obtained using AMG8833 thermal sensor module. Also, the total of 720 images including 360 faulty and 360 unfaulty thermal images were acquired and stored. Further, these 720 faulty and unfaulty thermal images were utilized in this work to train and test the proposed YOLOV7 model. Out of 720 images, the 576 images were used for training phase and the remaining 144 images were used for testing phase of YOLOV7 model. Further, the 576 faulty and unfaulty images were annotated using LabelImg software. Figure 4 shows the faulty and unfaulty image preprocessing using LabelImg software. Further, the faulty and unfaulty IC images were annotated by drawing bounding boxes around them and was given to YOLOV7 model as a train images.

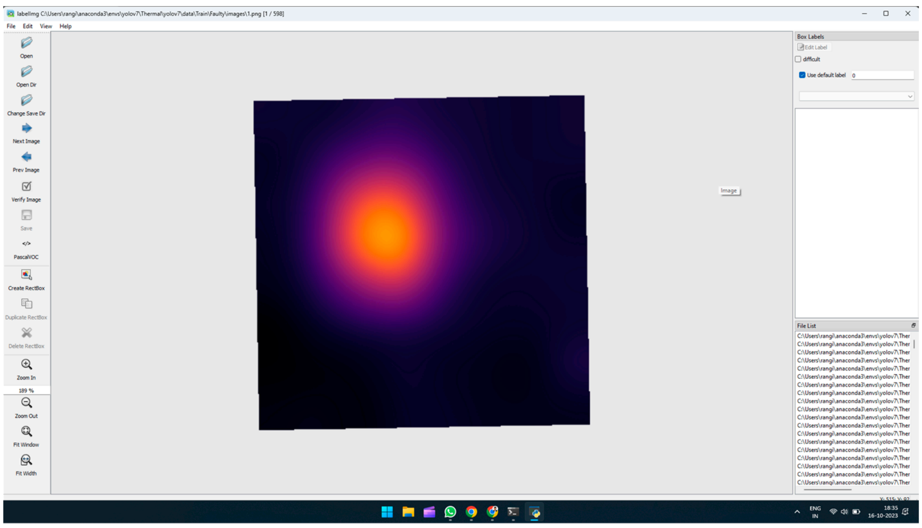

Figure 4. Data preprocessing using LabelImg software.

Once the faulty and unfaulty thermal images are acquired and processed, the fault diagnosis were carried out. Further, the 144 preprocessed faulty and unfaulty thermal images were utilized to carry out the performance of the proposed YOLOV7 model. Also, these 144 preprocessed faulty and unfaulty thermal images were fed to the proposed YOLOV7 model as the test images and the output prediction were obtained.

Figure 5 shows the fault diagnosis of ICs using YOLOV7 model. Further, it is seen that the prediction output of the YOLOV7 is given in terms of bounding box. Also, the faulty and unfaulty ICs are predicted and the prediction output is given as a caption at the top of the bounding box. Figure 6 shows the confusion matrix for faulty and unfaulty prediction using YOLOV7 model. Further, the confusion matrix given in the Figure 6 was generated after the testing process.

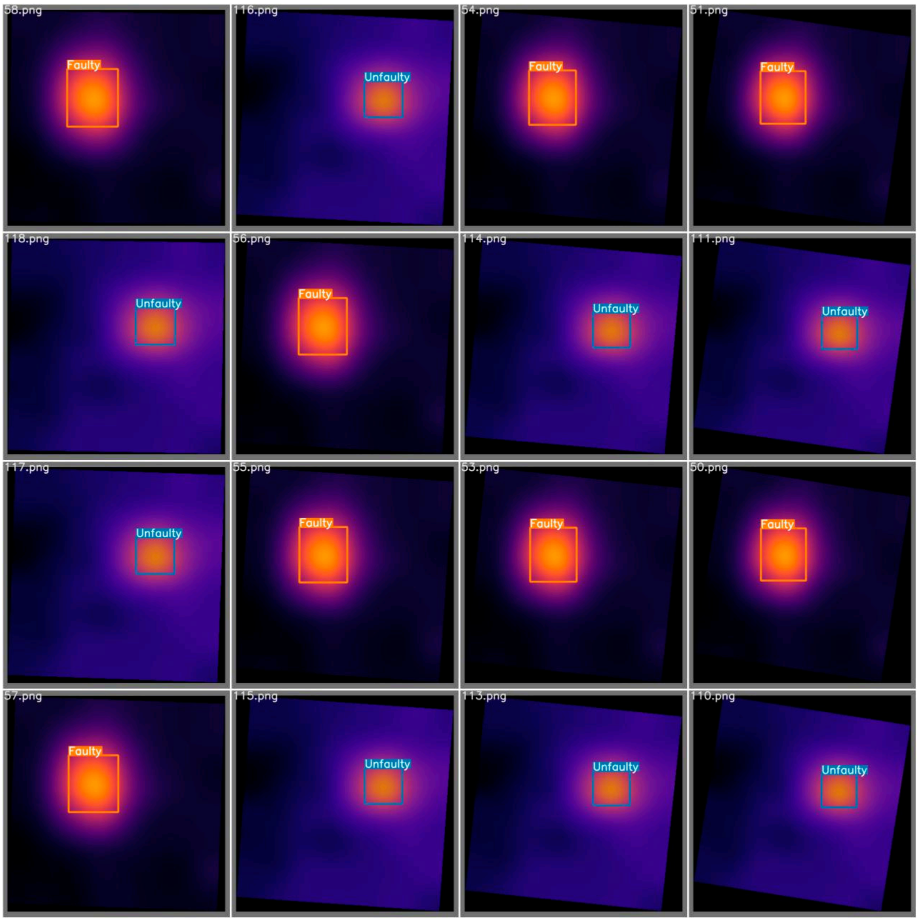

Figure 5. Fault diagnosis of Integrated Circuits using YOLOV7 Model.

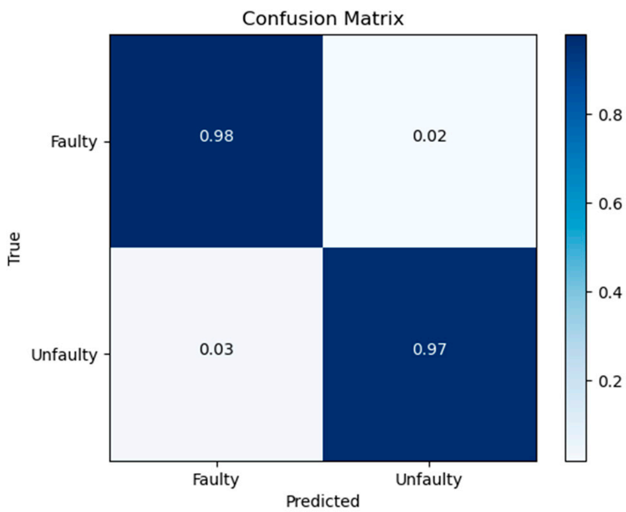

Figure 6. Confusion matrix for faulty and unfaulty prediction using YOLOV7 Model.

The four different performance metrics of YOLOV7 model were evaluated and presented in the Table 1. Also, the performance metrics are expressed in terms of %. Further, it is observed that the proposed YOLOV7 model has an accuracy of 97%. Also, the precision and recall of the proposed YOLOV7 model on faulty and unfaulty IC images are 97% and 98% respectively. Also, the F1_Score of the proposed YOLOV7 model is around 98%. From the performance measures, it is evident that the proposed device integrated with YOLOV7 model is highly efficient on classifying faulty and unfaulty IC's which gains more prominence in IC fault diagnosis applications.

Table 1. Performance metrics of YOLOV7 Model.

Performance Metrics	Percentage (%)
Accuracy	97
Precision	97
Recall	98
F1_Score	98

5. Conclusions

In this study, an efficient technique using thermal image processing was proposed to inspect faulty ICs located on PCB. Further, the thermal images were collected from AMG8833 thermal sensor module and the acquired images were preprocessed. These preprocessed images were given to YOLOV7 algorithm image classification. Results demonstrate that the proposed method provides 97 percent accuracy in detecting faulty and unfaulty images with less computational time. Further, by integrating the capabilities of thermal camera and YOLOV7 algorithm, the user can be alerted regarding the fault conditions of the circuit. In the near future, the proposed method can be automatized and the faults can be identified and monitored remotely using Internet-of-Things (IoT).

Author Contributions: P.S.K.R.P., V.S., and P.A. conceptualized the idea for this work. P.A. provided the required resources. P.S.K.R.P. designed and developed the hardware. N. and Y.S. carried out the investigation. P.S.K.R.P., N., and Y.S. acquired data and managed data curation. G.P. implemented the YOLO algorithm. N. designed visualization. P.A. validated the acquired results. V.S. prepared the original draft. N. and Y.S. reviewed and edited the original draft. V.S. supervised, and P.A. administered the work. All authors have read and agreed to the published version of the manuscript.

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