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PCB Defect Detection Using Yolov5 on Raspberry-Pi

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Abstract: Conventional PCB fault detection are inefficient and error-prone, which tells us that automation is necessary. For this research, YOLOv5 is used onRaspberry Pi to detect sixcategories of PCB defects including MouseBites, Open Circuits,andShort Circuits in real-time. This system is offline capable and provides fast offline detection, accuracy, .and low power optimization. Its accuracyisconfirmedthroughprecision,recall,andmAPperformancemeasures.FindingsindicatethatAIdefectdetectionimproves defect detection significantly, and thus greatly increases PCB quality control while minimizing costs and reducing the ineffecient manual inspections.

Keywords: PCBdefectdetection,YOLOv5,real-timedetection,RaspberryPi,Embeddedsystem

I. INTRODUCTION

Electronic circuits can interface with a device to send or receive signals through a PCB's connectors. This means that quality controlisessentialduringtheproductionstagesincemistakesusuallyleadtoproblems.Theseproblemsincludemicrocracks, shorts,and other soldering imperfectionsthatarefound within thePCBand lowersthereliability ofthedevice, increasing the cost of servicing it. For as long as one can remember, manual inspections alongside electrical probes had been the primary techniques applied to screen circuit boards and check them for faults. The many approaches tend to be inefficient because precisely judging their quality is very sensitive to human error, especially in detecting small damages concealed within elaborate multi-layered structures that are packed closely. Tiny cracks within intricate high-density layouts, misaligned components after reflow, and small solder bridges are just some of the possible errors that increase the expenses of this operation. The increased complexity in designs has created an urgent need for effective automated fault detection systemsthatismoreefficientthancurrentalternatives.

Recently,automatedinspectiontechniquessuchasAutomatedOpticalInspectionhavegainedmomentumatagreatspeedand accuracy in faultdetection.ArtificialIntelligenceand MachineLearning technologies,particularly deep learning algorithms suchas Convolutional NeuralNetworks,havealsogainedgroundtospeedupthisprocess.Thelatestmajorbreakthroughinthis areaistheYOLO(You OnlyLook Once)algorithm,which hasgained tremendouspopularity, though foritsfastdetection of faultswithout sacrificing precision-this hasproven to work best when rooting out faultsin real time.

This study revolves around the application of YOLOv5, the most recent iteration in the YOLO framework, to develop a PCB defect detection equipment based on Raspberry Pi entrusted to real-time corrections. The general aim is to create a cheap and efficientmethodforthedetectionofsixclassesofPCBdefects:MouseBites,OpenCircuits,ShortCircuits,Spurs,Misaligned Components, andSolderingissues.Thispaperdescribesthedesignanddevelopmentofauser-friendlyreal-timefaultdetectionsystemwhichtakesin PCBimagesandhighlightsDefectBreaksbyplacingboundingboxesaroundthem.Theapproachutilizesspecificadaptationsofpre-trainedYOLOv5models,customizedwithweightsdesignedtodetectPCBrelateddefects,ensuringoperationalefficiencyonembeddedsystemslikethe RaspberryPiwithoutsacrificingaccuracy.Thearchitectureproposedhasimageuploadinterfaces,adefectdetectionpipeline,anda moduletodisplayoutputs,andtheoperationofthewholesystemontheRaspberryPiwouldbeseamless.UserscanuploadPCBimagesinJPGformatandinitiatedefectdetectionimmediately.A point of differentiation is that it is an offline solution and would thus work even in an environment with intermittent or zero internet following this approach. The application is designed to run on the Raspberry Pi as the local host to provide real-time feedback with loweroperational latencywhileavoidingthe security anddataprivacy concerns of cloudprocessing.Italsoallows processing of imageslocally while optimizingfor the low processing power that isemanating from the Raspberry Pi.

II. LITERATURE REVIEW

All The rapid advancement of deep learning and computer vision has led to significant improvements in object detection, pattern tracking, and defect detection across various domains. Systemsoperating independently, to industry specificuses, the YOLO(You OnlyLookOnce)algorithmhasprovenitsusefulnessfrombalancingaccuracyandspeedinrealtimetasks.Thisworksynthesizesinformationfromthesupplieddocumentstoevaluatetheirapproaches,methods,applications,andscopeinthe specialization critically.

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An important part of computer vision and object detection is essential in applications such as self-driving cars and security systems.TensorFlowwhich wasusedbyPhadnisetal.(2018)[1]inthepublication "ObjectsTalk -ObjectDetection and Pattern Tracking Using TensorFlow," showcasing its efficiency in real-time cases for object detection and tracking of patterns. The abilityofTensorFlowtomanagesizableanddatasetswhilesavingcomputingefficiencywashighlightedbytheauthors.Theirstudydemonstratedthebenefitsofthesemodelsfortrackinganddetection,layingthebaseworkforcontemporaryframeworks like YOLO.

In"BlindNavigationSupportSystemusingRaspberryPi&YOLO,"Parvadhavardhnietal.(2023)[2]explainedtheseconceptsbycombiningYOLOandRaspberryPiinasystemintendedtohelptheblindandvisuallyimpaired.ThisapplicationofYOLO showshowadaptableitistoless-cost,resourcesettings.BecauseoftheRaspberryPi'sportabilityandYOLO,visuallyimpaired people can now see the real-world cases. This technique offered more precision in identifying obstructions than more conventional techniques like ultrasonic or infrared-based devices, particularly in modern environments.

ThedifficultnatureofPCBandtheneedofhighlevelprecision,defectdetectioninPCBproductionisasignificanttask.Machinevisionapproaches,likerule-basedandedge-detectionsystems,havefrequentlyfailedtohandlefaultsinavarietyofcases.Cai and Li (2022) [3] reviewed image-processing-based PCB defect detection techniques in detail in their paper "PCB Defect DetectionSystemBasedonImageProcessing,"pointsoutimportantdrawbackssuchasnoisesensitivityandlackofadaptability to changing conditions.

In"PCBDefectDetectionAlgorithmBasedonYOLOv5,"Chenetal.(2023)[4],anenhancedYOLOv5algorithmdesignedfor PCB fault identification in order to overcome these difficulties. The changes, which included using CSPDarknet53 as the backbonenetworkandaCIoUlossfunction,resultedinsignificantincreaseinspeedandmeanaverageprecision(mAP).Their research showed that YOLOv5 isreliable and can identify even the flaws, including misaligned tracks and missing parts, in a variety of scenarios.

Buildingonthiswork,Lietal.(2024)[13]createdaYOLOv5-basedmodelforPCBdefectdetectionin"AnImprovedYOLOv5-BasedModelforAutomaticPCBDefectDetection,"focusingonnoiseandreal-timeperformance.BothChenetal.(2023)[4] and Ling et al. (2023) [5] observed that YOLOv5 showed faster speeds than YOLOv4 while maintaining good accuracy in detecting faults.

AnanalysisofYOLOv5anditspredecessorsinPCBdefectdetectionshowstheimportanceofapplicationnecessities.YOLOv5 is adaptable for real-time, tasks owing to increased resilience and quick speed, while still maintaining better performance in defect detection accuracy. [4–8].

Anotherareawheremachinelearningalgorithmshaveshowngoodperformanceisfacialdetection.IntheworkbySinghetal.(2019)[6]usedthe RaspberryPitodofacialrecognitionusingmachinelearning-basedtechniquesincludingHaarCascadeand Histogram of Oriented Gradients(HOG). These techniquespoorly performance in low light and occlusion conditions, despite having a moderate level of precision and real-time results.

YOLO-basedmodelsarerenownedfortheirprecisioninhandlingcomplicatedsituations,eventhoughtheywerenotexamined in Singh etal.'swork.Theuseof hardware suchasthe Raspberry Pifor image processingwasfurthergiven intheresearchby Marot (2020) [9]. Marot showed the ability of single-board computers to access to advanced technologies by developing a framework for learning image processing basics.

Forautonomousdirectionsandnavigationtobesafeandeffective,objectdetectionshouldbeprecise.AccordingtoMohanapriyaetal.(2021)[10],intheirstudyofObjectandLaneDetectionforAutonomousVehicleUsingYOLOV3Algorithm,YOLOv3 is effective in detecting objects and lanes for autonomous vehicles. Their research showed how YOLOv3 can interpret high- resolution images quickly, which makes it appropriate for different driving situations.

In the article "Detection of Missing Component in PCB Using YOLO," Chhetri et al. (2023) [11] used their YOLOv5-based model todetectmissingcomponents,whichimprovedPCBdefectdetection.Theirresultsshowedhowimportantdatasetsandstructuredtrainingproceduresaretoimprovingperformance.ByexperimentingwithvarioustargetdetectionnetworksforPCBdefects,Wuetal.(2023)[12]furthergaveYOLO's flexibilityintheirpublication.TheirresultsprovedYOLOv5istheleading algorithm for industrial use due to its accuracy and strength across various datasets.

Energy management and home automation have been completely transformed by machine learning into IoT devices. In their 2020 study, Raju et al. [14] explored how the integration of machine learning algorithms with Raspberry Pi would be able to maximize electricity consumption. They proved that significant energy efficiency can be achieved using demand-response mechanisms.

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III. METHODOLOGY

A. System Architecture

TheprocessoftheRaspberryPiandYOLOv5basedflawdetectionsystemisshowninFig.1.ThemethodstartswiththeuserprovidingtheRaspberryPisystemwithanimageofthePCB,thenitrunstheYOLOv5model,whichprocessestheimageand detects defects. The identified faults are passed to the Defect Detection Module, which analyzes the results. Finally, the Storage Module saves the detection data for further review or quality control purposes.

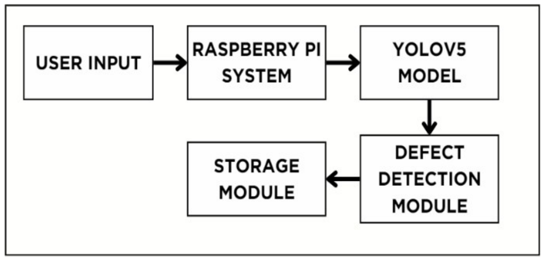

Fig.1Workflowofthesystem

B. YOLOv5Architecture

YOLOv5 uses the same head as YOLOv3 and YOLOv4. It consists of three convolution layers that predict the location of boundingboxes(x,y,width,height),objectnessscores,andobjectclasses.However,theequationsusedtocomputethetargetcoordinatesforboundingboxeshavechangedfrompreviousversions.Thedifferenceisshownbelow.
Equations(1)to(4)presentthepreviousversions
(YOLOv2,YOLOv3)tocomputethetargetboundingboxesandEquations(5)to(8)presentthemodelusedinYOLOv5forcomputingtheboundingboxes.

$$b_x=(t_x)+g_x. \quad (1)$$
$$b_y=(t_y)+g_y \quad (2)$$
$$b_w=f_w.\, e^{tw} \quad (3)$$
$$b_h=f_h.e^{th}. \quad (4)$$

where:
bx,by→Predictedboundingboxcentercoordinates bw,bh → Predicted bounding box width and height tx,ty,tw,th → Model’s predicted values
gx,gy→Gridcellcoordinateswheretheobjectisdetected fw,fh → Anchor box dimensions for the detectedobjectCentercoordinates (bx,by)areobtainedbyaddingthepredictedoffsets(tx,ty)tothegridcellcoordinates(cx,cy),ensuringthe bounding box stays within the grid but may cause localization instability.
Widthandheight(bw,bh)arecomputedusinganexponentialtransformationtokeepthempositive.However,thiscan sometimes result in oversized bounding boxes, leading to inaccurate predictions in edge cases.

$$b_x=(2.(t_x)-0.5)+c_x) \quad (5)$$
$$b_y=(2.(t_y)-0.5)+c_y) \quad (6)$$
$$b_w=p_w.(2.(t_w))^2) \quad (7)$$
$$b_h=p_h.(2.(t_h))^2) \quad (8)$$

Bydecreasingpositionalerrorsandensuringthatprojectedboundingboxesmorecloselymatchobjectsintheimage,theimprovedtransformations in YOLOv5 increase localization accuracy.
LossFunctioninYOLOv5
YOLOv5hasthreeoutputs,listedas following:
boundingboxes,objectnessscores,andrecognizedobjectclasses.TopredicttheoveralIloss,itusesCompoundIntersection over Union (CIoU) loss for location regression while adding Binary Cross Entropy (BCE) loss for class and objectness predictions all under a single framework. Equation 9 provides the total loss as

Loss=1Lcls+2Lobj+3Llo (9)

Where

Lobj-objectness loss (BCE loss).Lloc- localization loss (CIoU loss). Lcls-classificationloss(BCEloss).

Eachlosscomponentisbalancedbytheweightsoftheparametersλ1,λ2,andλ3.

Withtheseenhancements,YOLOv5ismorepreciseandreliable,whichmakesitperfectforRaspberryPireal-timePCBfault identification.

C. YOLOv5forDetectingMultipleDefectsinPCBUsingRaspberryPi

1) EnvironmentSetup

Raspbian OS is installed on an SD card and configured on Raspberry Pi. Essential dependencies such as PyTorch, OpenCV, and TensorRT are installed to support deep learning-based image processing. Thisaligns with the step in the flowchart where dependenciesandlibrariesareinstalledbeforerunningthedetectionmodel.Fig.3presentstheflowchartoftheproposedwork.

2) ModelTrainingandOptimization

Since Raspberry Pi has limited computational capacity, model training is performed on a more powerful Windows system equippedwithahigh-performanceGPU.TheYOLOv5modelistrainedonadatasetcontainingimagesofPCBdefects, along withXMLannotationsspecifyingdefectlocations.Aftertraining,the model’sweights(best.pt)aresaved.Thiscorrespondsto the flowchart step where the model is trained and the optimized weights are stored.

To improve efficiency, the trained model is converted into alightweight format such as TensorFlow Lite (TFLite) or ONNX. These formats reduce computational overhead, making the model suitable for real-time execution on Raspberry Pi.

3) HardwareAccelerationandDeployment

Toenhanceinferencespeed,RaspberryPi’sGPUoranexternalCoralEdgeTPUisusedforhardwareacceleration.Thetrained and optimized model isthen importedinto Raspberry Pi. At thisstage, the system isreadyforreal-time defectdetection.This is represented in the flowchart where the model is imported and prepared for execution.

A camera module is attached to the Raspberry Pi to capture live images of PCBs. The camera provides real-time input to the defect detection system, allowing automated inspection of PCB quality.

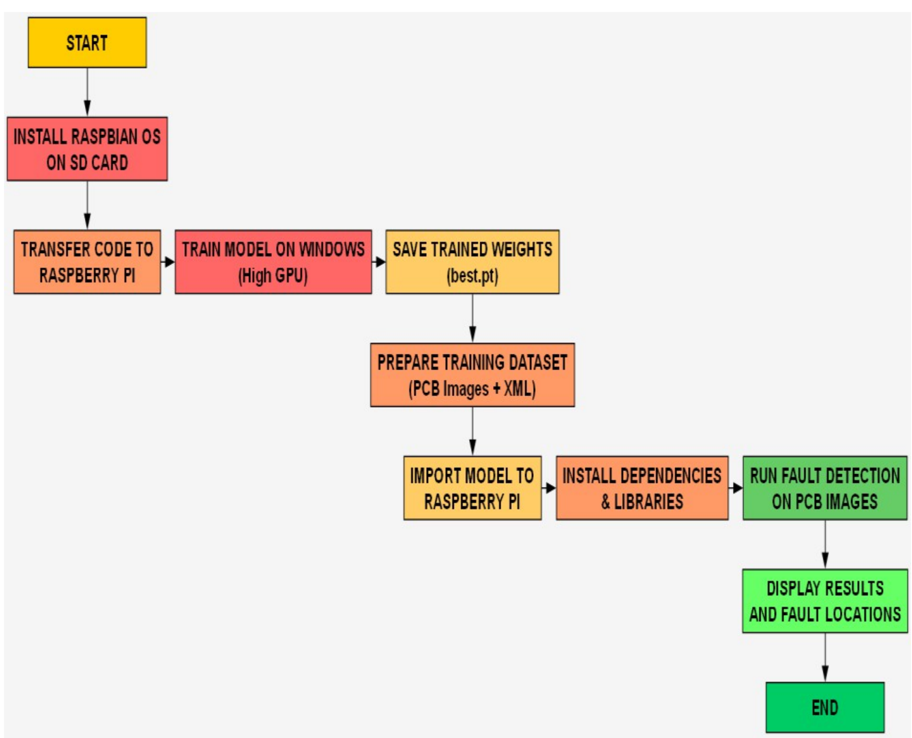

Fig.2.Flowchartofthesystem

4) FaultDetectionand Analysis

Oncethesetupiscomplete,theRaspberryPiprocessesincomingPCBimagesusingtheoptimizedYOLOv5model.Themodelusesboundingboxestoidentifyproblematicareasinordertodetectmultipleproblems.Theresultsareshowninstantly,giving users a sense of the PCB's status.

Defect data is also logged for additional examination. The Raspberry Pi either stores the identified errors and their locations locally or uploads them to a cloud-based platform for additional analysis. The flowchart's last steps, where detection findings are shown and saved for later examination, correspond to this.

5) EvaluationMetricsforPerformanceAssessment

Thefollowingevaluationmetricsaretakenintoconsiderationtoguaranteetheefficacyofthedefectdetectionsystem:

- Precisionandrecallquantifythemodel'sabilitytoidentifyflawswiththeleastamountoffalsepositivesandfalse negatives.
- Meanaverageprecision(mAP)evaluatesthemodel'sperformanceacrossdifferenttypesofPCBdefects.
- Latency&FPSdeterminethesystem'sabilitytoperformreal-timedetectionbymeasuringinferencespeedandframes per second (FPS).

Theseevaluationcriteriadeterminewhetherthesystemcaneffectivelyfunctioninareal-worldPCBqualitycontrolenvironment.

IV. RESULTS AND DISCUSSIONS

Someimportantconclusionsandillustrationsofoursysteminoperationareshownbelow.

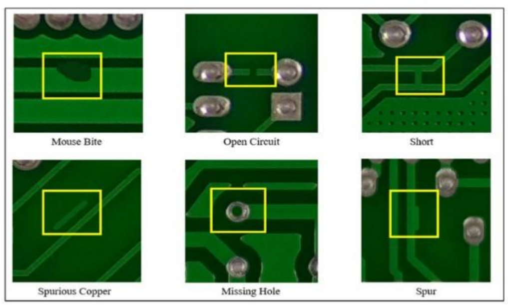

Fig.3.CommonPCBDefects

Some frequent PCB flaws are depicted in the above diagram. A "mouse bite," which resembles a nibble and is a tiny break in the copper trace, is what we have. A "open circuit" is a trace gap that interrupts the electrical flow. A "short circuit" occurs when traces accidentally connect to one another. "Spurious copper" refers to an overabundance of copper on the surface.

A"missinghole"revealsthatthereisnodrilledhole,whichaffectstheplacementofcomponents.Finally,a"spur"hasasmall unwanted protrusion of copper that might provide an unintended path for connections. These defects thus severely affect the functionality and reliability of electronic circuits.

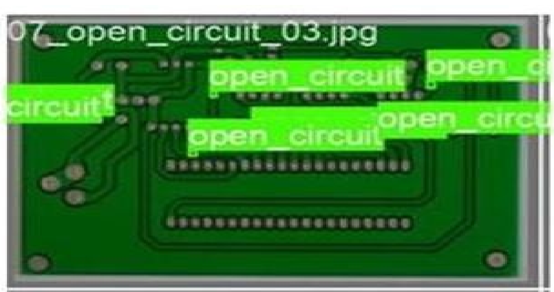

Fig.4.LabelledPCBDefects

Thenextfiguredepictsthepowerofourfaultdetectionsystem.AcloseupviewofaPCBshowsmultiple"opencircuit"defectswithdistinctlabelsmarkedoneach.Thebreaksinthecoppertracescanseverelyaffectelectricalflowasdeterminedbyouradvancedalgorithm.Thevisualrepresentationhereshowsthatthesystemaccuratelypinpointsandclassifiesthecriticaldefects that ensure the reliability and functionality of the manufactured PCBs.

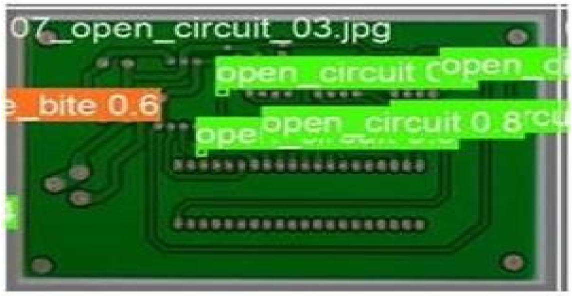

Fig.5.PredictedPCB Defects

This is the most exciting proof of the possibility of the concept of our system for the PCB defect detection mechanism. An imageclearlyshowswhatactuallyhappenstobeazoomviewofacircuitboardwithmanykindsofdefectsproperlyidentified and annotated. "open circuits," inside green boxes signify breaks in crucial electrical paths; a small irregular break in copper, thatappearsas"mousebite"wasmarkedinsidetheorangebox.Thisvisualevidenceunderlinesthesystem'simpressiveability to not only detect but also accurately categorize various types of defects, ensuring the highest quality standards in PCB manufacturing.

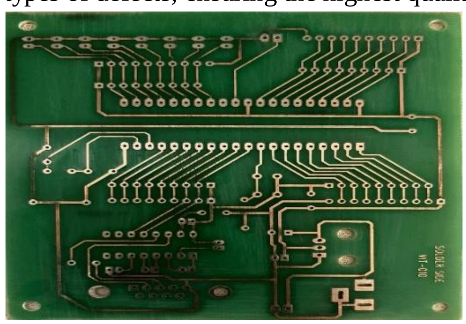

Fig.6.Real-timeinput

Our system has captured a live image of a double-sided PCB. The image shows the board's intricate design, with a dense network of copper traces etched meticulously onto its surface. This real-time input is currently being analyzed by the system toidentifyanypossibleflawsandguaranteethatthehighestqualitystandardsareupheldthroughoutthemanufacturingprocess. This live feed helps to proactively address issues as they arise and provides extremely important insights into the current production situation.

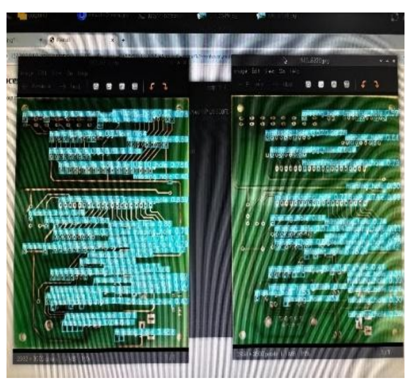

Fig.7.Realtimeoutput

Two PCB images are seen side by side in this picture fig.7. The potential flaws are shown in vivid blue in this figure on the left.Everyboardisthoroughlyexaminedbythesystem,whichhighlightsanyirregularitiesitdiscovers,includingopencircuits, short circuits, and other serious ones. Visual comparison of the PCB enables prompt and effective evaluation and prompt remedial action to ensure that only flawless boards go to the final assembly stage.

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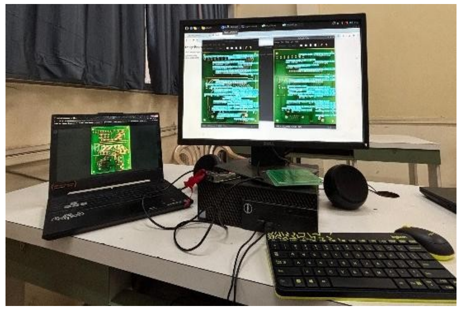

Fig.8.RealtimeSetupofthesystem

ThisisapictureofPCBfaultdetectionsysteminoperation.Thesystem'sreal-timecapabilitiesaredemonstratedonadedicated workstation. The system's output is shown on two computer monitors, one of which displays the original PCB image and the other, which uses vivid visual cues to show the errors that have been found. With this configuration, ongoing monitoring and analysis will be possible, guaranteeing that any possible problems are found and dealt with right away.

Withincreasingcomplexityinelectronicsmanufacturing,PCBdefectdetectionsystemiscrucial.Oursystemnotonlyidentifies faults but also provides real-time insights for proactive quality control. By integrating such technology, manufacturers can significantly reduce errors and improve product reliability, reinforcing high industry standards.

V. CONCLUSION

Insummary,theYOLOv5defectinspectionsystemisperfectionforPCBmanufacturingqualitycontrolthroughtheassureddetectionofmultipl edefectswithinasinglePCB.Identificationofdefectsofbothtypeandlocationbythesystemwillthusbeanenablingfactorformanufacturersinq ualitycontrol,particularlyprioritizingrepairattempts,hencekeepingcostslowwhile improving better product reliability.

Above all, predictive accuracy that captures the level of defect severity is the final piece of the puzzle missing, which ismost needed to direct the production and also set priorities in addressing those issues which are great trouble for the production. In making the system foolproof and scalable at will to address industry needs, more optimizations to the system in the sense of affixing measures of confidence and thorough testing from real-world cases are required.

Sinceweintendtorefineandtestthesystem,weshallbeemphasizingincreasingitscapabilitytosupportmultipledesignsand manufacturing condition for PCB. It is intended to improve reliability elimination of spurious positives, ease PCB manufacturing, and facilitate effective error-free E-manufacturing. The benefit of technology to the entire is vastly enormous forconsumersand producersaliketowitnessimprovementsinproductqualityandthereductionoftheoverheadofproduction for the entire electronics sector.

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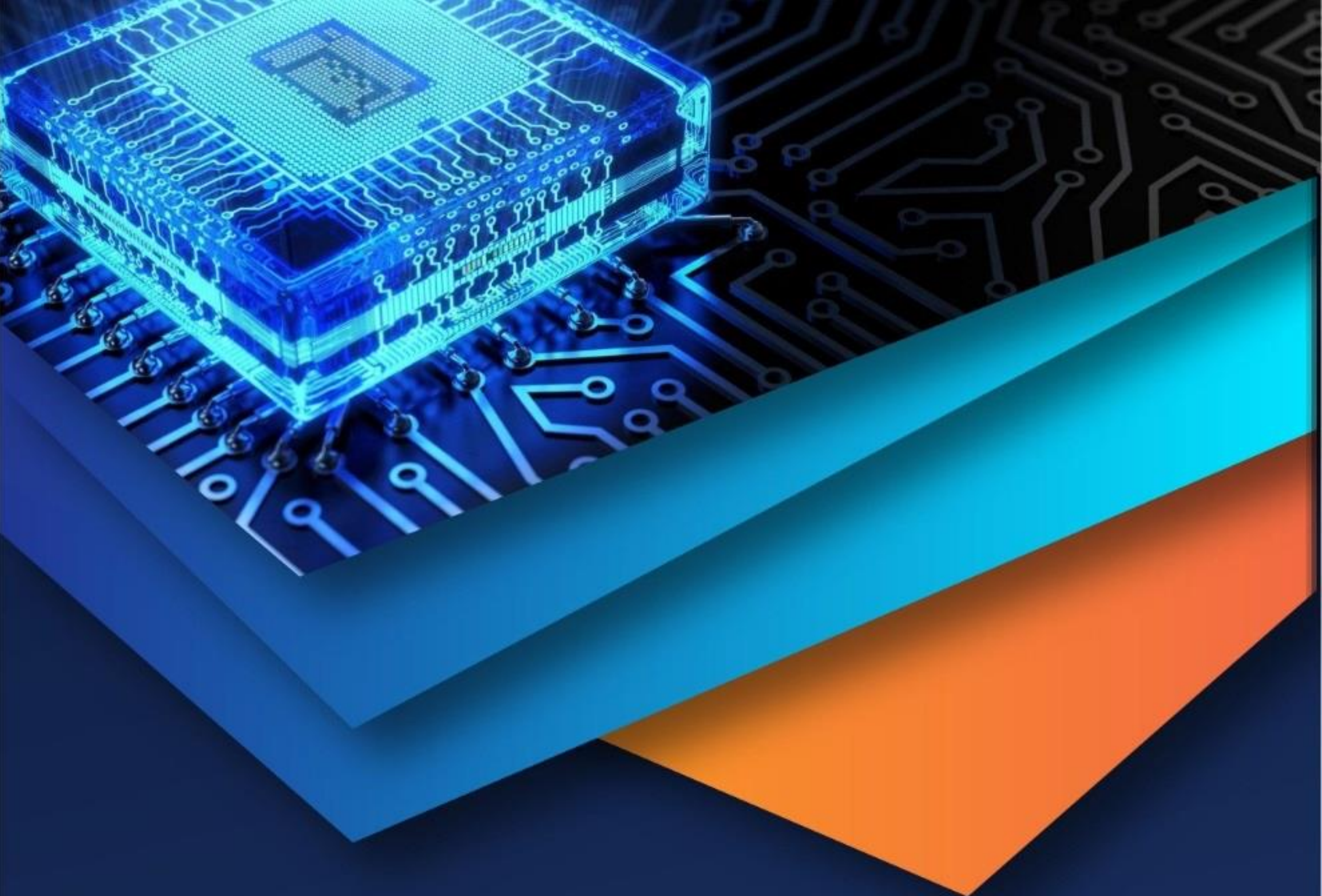

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