Inspection of Materials Dimensions Using Webcam in the Conveyor System

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Abstract: Measuring material dimensions in real time is a crucial component of the technological industry revolution. In industrial applications, the ability to discern material and its dimensions from pictures and videos may be highly valuable. Conveyor systems are used to transfer most materials in industries. In a conveyor system, material identification and dimensioning is a particularly challenging task. Every day, scientists and engineers put a lot of effort into developing machine learning and deep learning algorithms that will enable robots to comprehend and learn, outperforming humans at tasks. The machine learning model used to detection of material and its dimension from the pictures. The raspberry pi and pi camera used to capture the high-quality picture of the material on the conveyor system. The machine learning model build with help of python programming language. The material image taken from the conveyor system using webcam and processed through the image processing library like OpenCV and TensorFlow. The embedded system techniques and machine learning approaches are playing important role in this concept. The existing techniques for detecting materials and their dimensions in a variety of industrial applications are the main topic of this review article. The techniques and their achievements are compared.

1 INTRODUCTION

Conventional materials science research mostly relies on the expertise of lone specialists. Developing new scientific theories and expanding our understanding of the physical world are two areas in which expert knowledge is extremely valuable. But when it comes to forecast efficiency and accuracy, the conventional expert knowledge technique is obviously limited. Technological advancement frequently necessitates the development of new materials with certain qualities, yet it might take a long study cycle to learn enough about a single material system. Data volume, speed, and complexity are all rising as a result of improvements in experimental and computational techniques. Xiaoting Zhong, et al, 2022 However, a human expert can only analyse so much data at once. In order to create better materials more quickly, new research instruments are required.

As the title states itself the method is used to measure the real time dimension of a material in the conveyor system for industrial application. It is a very hot and trending topic in the field of computer science.the importance of object detection and tracking for material dimensions is increasing in various industrial and autonomous mobile system applications. The widespread applications of machine learning and computer vision have significantly impacted research. Currently, most standalone systems come equipped with vision sensors or cameras. As a result, mobile device localization and navigation depend on knowing the size and distance of objects in the immediate environment. Gokulnath Anand and Ashok Kumar Kumawat, 2021 Currently, machine vision applications find extensive utilization across various domains, including robotics, conveyor belt speed measurement, displacement systems, and fish length measuring.

Lan Fu, et al, 2022 Convolutional neural networks (CNNs)-based deep learning has recently greatly improved object-detection accuracy in photos saved in the.jpg, .jpeg, and.png formats. Many attempts have been made to apply this achievement to photos from the field of materials science by utilizing CNNs to identify the material's dimension in the image.

Thus, using machine learning approaches, this study examines material dimension inspection methods for industrial manufacturing. It goes over how to take a material picture using an embedded system application. The theoretical foundation of

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machine learning for material dimension identification is briefly described in section 2. The section 3 introduces a comprehensive examination of both machine learning and deep learning models used for the identification of materials and their dimensions. In Section 4, the outcomes of diverse both machine learning and deep learning models are juxtaposed, utilizing operational parameters. The study concludes in Section 5, followed by an exploration of prospects.

2 MATERIAL DIMENSION INSPECTION

2.1 Material Inspection and Detection Based on Raspberry Pi and Machine Learning Algorithm

Talha Bayrak et al., (2021) established TensorFlow, OpenCV, and Brachio Graph libraries in combination with a hardware-created drawing machine to recognize and draw objects. We accomplished this by using image processing to distinguish things and sketching them in the Raspberry Pi environment. Using the TensorFlow and OpenCV libraries, the software component recognized objects. The processed pictures were vectorized using the Brachio Graph library, and servo motor drawing experiments were carried out. The servo motor type and tuning changes were determined to be significant. The Brachio Graph library's calibration parameters can be fine-tuned for best results. During the test phase of this investigation, the objects were effectively identified, and drawings of the things were created using servos.

Gokulnath Anand and Ashok Kumar Kumawat., (2021) designed an object detection and tracking system utilizing the Raspberry Pi camera for digital imagery in both computer and robot vision applications. The system comprises the Raspbian operating system, Python, and the OpenCV platform, all integrated to capture images through the Pi camera. This project addresses a burgeoning research area aiming to develop techniques assisting computers in acquiring and understanding information from digital images, encompassing movies and photographs. Specifically, the system employs object detection, a computer vision approach enabling the identification and pinpointing of objects in both images and videos. The implementation utilizes an efficient shape-based object detection method, achieving real-time displacement through the OpenCV programming library, Designed specifically for computer vision applications, the Raspberry Pi comes equipped with a camera module.

Varun Sai et al., (2023) Deep learning has dramatically improved the speed and accuracy of object identification algorithms. DL allowed for very accurate real-time object identification in current desktop PCs, as well as object detection utilizing the Raspberry Pi 3. Real-time object identification necessitates a significant amount of computing power, and reaching real-time speed is challenging in a system with restricted capability. Detecting things may be accomplished using a variety of techniques. Two methodologies were employed on the Raspberry Pi 3 B to assess their compatibility with limited hardware capabilities. The suitability of a deployed target detector hinges on achieving a sufficiently high resolution and frame rate for practical use in real-world applications. This approach involves evaluating parameters such as frame rate, accuracy, and response time.

Siddharth et al., (2018) Utilizing OpenCV, we amalgamated various components to formulate a program centered on Raspberry Pi for object recognition and tracking. The program encompasses two primary functionalities: Monitoring and identifying objects. The outcome of this endeavor is a Python software designed for Windows that is adept at identifying and tracking objects through the analysis of Values for Hue, Saturation, and Intensity (HSV) extracted from frames captured by the Raspberry Pi camera module.

Muhammad Sabih et al., (2023) optimal settings have been determined through the analysis of material flow rates on a conveyor belt, ensuring the automated preservation of the desired raw material ratio. A sight sensor strategically placed on the conveyor belt accurately gauges the rate at which raw materials flow. The identified area of interest is further refined through a voting-based segmentation method, isolating the region exhibiting the highest level of confidence. Machine learning algorithms, leveraging moment and contour information, are then employed to predict flow rates across multiple trials. A comprehensive evaluation of various techniques yields compelling results, with the Bagging regressor employed with optimal parameters on the final data split.

Mohd Shuhanaz et al., (2023) Suggested GPR data analysis using a machine learning system to reduce labor. In the process for identifying material dimensions, A structured approach is presented for categorizing the dimensions of subterranean metallic pipes. This methodology incorporates the utilization of Histogram of Oriented Gradient (HOG) as a feature extraction method. The investigation encompasses the examination and creation of a back propagation neural network and Support Vector Machine (SVM) for the purpose of classifying underground metallic pipes, yielding a notable accuracy rate of 98%. The figure 1 shows Directions of GPR scanning.

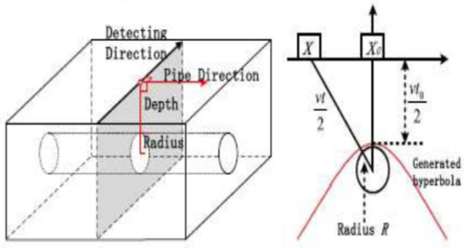

Figure 1: Directions of GPR scanning.

Xiaoting Zhong Et Al., (2021) Because of their high accuracy, machine learning models are rapidly being applied in materials research. The most precise machine learning models, on the other hand, are typically difficult to describe. Solutions to this difficulty can be found in explainable artificial intelligence (XAI). The interpretability of complex machine learning models, such as deep neural networks (DNNs), within the realm of materials science. The objective is to furnish materials scientists with a comprehensive introduction to Explainable Artificial Intelligence (XAI). The paper elucidates relevant concepts within the materials science context, aiming to clarify the nature of explanations in this field. Examples are used to show how XAI may help with materials science research.

Lan Fu et al., (2022) deep neural networks and deep learning have demonstrated significant success in a wide range of signal and image processing applications. This is particularly evident in situations where extensive annotated training data is needed, such as in supervised learning scenarios.While there is theoretical potential for leveraging deep-learning algorithms to enhance the processing of microscopic images capturing crucial microstructures in diverse material samples, Considering specific priors and requirements in materials science is crucial for maximizing performance improvements.It focuses on the critical issue of recognizing items of interest in microscopic materials-science photographs. To address this issue, we also provide several ways for incorporating multiple priors, such as object form, symmetry, and 3D consistency, with deep learning.

Jan-Lucas Uslu et al., (2023) the devised detection method relies on a fusion of optical contrast between flakes and the substrate, along with their geometric characteristics. Our results showcase its capability to identify a significant portion of flakes with exfoliation across different materials, achieving an average recall (AR50) ranging from 67% to 89%. Moreover, with as little as five flakes, an algorithm of this kind may be taught efficiently. of a particular material, as exemplified in the case of few-layer graphene. WSe2, MoSe2, CrI3, 1T-TaS2, and hexagonal BN. Over the course of two years, our technique was assessed, and over 30 different researchers took over 106 photographs of diverse materials.

Sarvesh Sundaram and Abe Zeid., (2023) Quality inspection is one of the important stages that determines if a product is acceptable or not. Numerous factors influencethe examination of visual elements, leading to whole industry precision of the inspection approximately 80%. Achieving 100% inspection with cutting-edge production processes through Inspecting visuals manually is both time-consuming and costly. Despite the assistance of computer vision (CV) techniques in automating certain aspects of the visual inspection process, challenges persist. They are applying Artificial Intelligence (AI) based on Deep Learning (DL) to the visual evaluation process. On image data of casting goods, the recommended model boasts an inspection precision of 99.86%.

Xiaoquan Shi et al., (2023) five models for predicting filament dimensions were developed using decision trees, support vector regression, back propagation neural networks, random forests, and K-nearest neighbors. The back propagation neural network exhibited coefficients of determination of 0.9025 for line width and 0.9604 for line height. Notably, the parameters with the greatest influence on line width and height, in descending order, were nozzle diameter, height, printing speed, and extrusion pressure. The study revealed that stretched material resulted in a thinner filament, and the regularity of processing parameters on geometric size was found to be poor. Conversely, material compression had a significant impact on dimensions, with nozzle diameter playing a crucial role. Consequently, these research findings have the potential to be utilized for estimating Determining the dimensions of printing filament structures guides the selection of printing parameters and establishes the size of individual layers in 3D printing.

Nijdam et al., (2022) Various factors, such as Extrusion force, print velocity, nozzle size, nozzle elevation, and print temperature are key parameters in 3D printing. A crucial role in determining the success of the extrusion process and the dimensions of the extruded filament. Different viscosities demonstrate specific 'printability windows' during printing. Achieving uniform and consistent extrusion requires the precise adjustment of printing parameters. Furthermore, the dimensions of the extruded filament, both in terms of width and height, can vary significantly depending on the process conditions. Effectively predicting the geometric characteristics of the printed line arrangement is essential for optimizing 3D model slicing and enhancing the overall efficiency of 3D structure manufacturing.

Madhavi Karanam et al., (2023) The real-time application of the system in identifying objects and instantly providing their dimensions upon request. Object dimension measurement and detection represent crucial aspects of computer vision, playing a vital role in automating various human operations. Humans can recognize and locate items in photos and movies, but computers do not have that capacity without prior training. Machine learning, computer vision, and object identification methods must be used to educate the computer. This project demonstrates how to identify and measure the dimensions of an item in real time using a camera. We used the OpenCV and NumPy libraries to approximation the object's size in real time. Computer vision assists computers in seeing and comprehending. Computer vision assists computers in interpreting a 3D environment from a 2D picture and educates computers to do various activities. It also aids in Human Computer Interaction by distinguishing items from their surroundings and providing us with important information.

Chandan et al., (2018) various methodologies for object detection encompass Region-based Convolutional Neural Networks (RCNN), Faster RCNN, Single Shot Detectors (SSD), and You Only Look Once (YOLO) are all different approaches to object detection in computer vision. When prioritizing speed over accuracy, Faster-RCNN and SSD exhibit superior accuracy, with YOLO demonstrating even better performance. Achieving an optimal balance between identification accuracy and real-time processing, a combination of SSD and MobileNets in deep learning facilitates effective object recognition and tracking, ensuring both efficiency and speed.

Wang et al., (2020) the latest developments in object detection, this study explores advancements in the field, Incorporating Faster R-CNN, YOLO, SSD, and RetinaNet into the discussion. Additionally, it explores different datasets used in object detection and the evaluation metrics employed to gauge the effectiveness of object detection algorithms.

Manjula et al., (2016) investigated object detection and suggested a method for detecting and classifying things that used image processing methods with machine learning algorithms. Various ways are investigated in this, and the accuracy of the methods is calculated. On a bespoke dataset, the final recommended approach attained an accuracy of 87.5%.

Binay et al., (2017) The methods for object identification The research evaluated the precision, efficiency, and computational intricacy of different techniques, incorporating Haar cascades, Histogram of Oriented Gradients (HOG), as well as advanced deep learning models like YOLO, Faster R-CNN, and SSD.

Sredha Vinod et al., (2022) to locate missing bolts, an automated ESP32 camera is used to inspect the integrity of bolted steel components. Earlier study concentrated on improving bolt tightening quality. Insufficiently securing steel components through improper bolting can significantly compromise their mechanical strength, leading to potential structural failure. This investigation employed a methodology involving real-time photography of steel members using an ESP32 camera module. The captured video footage underwent processing in Visual Studio, employing the C++ language. Another aspect of the study incorporated a Faster Region-Based Convolutional Neural Network (Faster R-CNN), a swift and efficient approach. This neural network utilized an image dataset for training, facilitating the extraction of crucial elementssuch as bolts and holesin the steel components' areas of interest. The trained model demonstrated the ability to identify bolts and holes accurately. The study's findings indicated the reliability of the developed system, which is capable of promptly alerting users to any missing bolts. Leveraging TensorFlow for object identification, the Faster R-CNN algorithm achieved an impressive 95% accuracy, contributing to enhanced efficiency in quality monitoring processes.

Pranjal et al., (2020) For pothole identification, the Deep Learning-based algorithm YOLO is used. For pothole dimension estimate, an image processing-based triangle similarity measure is applied. The suggested approach gives relatively accurate pothole identification and dimension estimate results. The suggested approach also reduces the amount of time necessary for road maintenance. The approach utilizes a specially curated dataset comprising images depicting both waterlogged and dry potholes in diverse shapes and sizes.

2.2 Material Dimensions Inspection Based on PLC and Embedded

Nadin et al., (2023) In order to increase accuracy and efficiency, an integrated logic controller (PLC) was installed, which provided real-time monitoring and control of the material transfer plan of activities. Data and samples from industrial facilities were utilized to validate the success of this viewpoint. The observed outcomes reveal a significant advancement in material transfer operations, including a significant reduction in transfer amount times and a significant improvement in precision. The two large values reflect a 30% reduction in transfer time and a 15% drop-in mistake rate. The analysis of these data demonstrates the importance of PLCs in simplifying material transport as well as their future application possibilities. PLC-based solutions facilitate industrial material transfer and provide additional opportunities to increase productivity and effectiveness.

Manoj and Uday., (2017) A dissertation on conveyor systems is in progress to develop a tabletop model featuring a Configurable quantity of stations and an accompanying control board. The suggested conveyor has a length of 780mm and is capable of transferring items as large as 60 cubic mm. The configuration of stations, whether with or without interlocks, can be adjusted within the range of 2 to 5The conveyor system relies on PLC technology, smoothly integrating with the palletizer. The PLC exhibits robust programming features, including timers, counters, and customizable variable inputs, ensuring efficient operation serve as the fundamental operational elements that effectively minimize input and output requirements for the PLC.

Borkowski and Knop., (2016) The evaluation process involves inspection plans delineating the different production areas necessitating scrutiny. The initial phase typically involves the examination Incoming or receiving inspection was another term used for the assessment of raw materials. Subsequent inspections occur at regular intervals following various stages of production, with the specific nature of these assessments varying across industries. The inspection procedures for structural steel products vary considerably compared to those for microcontrollers. Upon reachingat the conclusion of the assembly line, a thorough inspection is carried out to determine whether the product meets the required standards for acceptance or if it should be rejected. Mirroring the concept of inbound inspection. In certain instances, the incoming inspection may also extend to the scrutiny of packaged products during the shipping process.

Xiaofei Zhang et al., (2019) when subjected to ultrasound activation, ultrasonic thermography (UT) emerges as an innovative non-destructive testing technique that captures damage through thermal imaging conducted by an infrared (IR) camera. However, noise and indistinct borders surrounding high-temperature locations in the UT test thermal pictures may confound and lead to inaccurate findings. As a result, the debate is built on extensive CFRP content learning. This UT employs low-power ultrasonic excitation. The high-dimensional nature of infrared image sequences is represented through data set modeling. Manifold learning is then employed to discern the intrinsic structure within the two-dimensional manifold of these data sets. The steady component detects VID and BVID (barely visible impact damage) by displaying the temperature increase caused by damage. The research configuration was constructed, and tests were conducted on CFRP plate samples exhibiting diverse degrees of impact damage. In a low-noise reconstructed static image, all impact damage may be identified and presented.

Sambathkumar et al., (2014) to measure the components, plug gauges are frequently employed. An automated system with pneumatic comparators is used instead of manual inspection. Because the manual examination could be more efficient, this measurement instrument requires improvement. The dimensions of this gadget are computed using a comparator setup. The Geneva conveyor transports the components from one location to another. It is vital to reduce the number of staff involved. We created a conveyor with a Geneva drive that may be used in industries. Consequently, a conveyor system is employed to transfer materials between different areas, with the specimen's size determined by its dimensions.

Dinesh et al., (2019) Sensors are employed to gauge the material dimensions, with the signal then transmitted to the control unit. Subsequently, the control device sends this is a suitable signal to engage the pneumatic cylinder. The pneumatic cylinder collects items that are the incorrect size. In today's engineering firms, the inspection conveyor is critical for material handling. Conveyors transport objects from one point to another. Sensors are used to measure the dimensions at the top of the conveyor. This procedure ensures that the belts are transported to their destinations on schedule. The figure 2 shows Material detection robot.

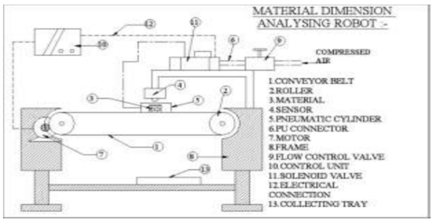

Figure 2: Material detection robot.

3 RESULT AND DISCUSSION

Inspecting material dimensions is achieved through the utilization of a Raspberry Pi and OpenCV platform. Object detection is implemented using either machine learning or deep learning algorithms to ensure accurate prediction and identification of detected objects, along with displaying their respective names, as illustrated in Figure 3.

We may check the casting goods using the SQI shop floor application. We inspect a faulty and an able product to illustrate the application's functionality. The goods are examined with the literal click of a button. The operator can record through the inspection procedure by going into relevant details pertaining items, equipment, etc., as depicted in Figure 4.

We measured several things and compared them to their real dimensions, then computed the percentage error to determine the measurement's accuracy which shown in table 1 and figure 5

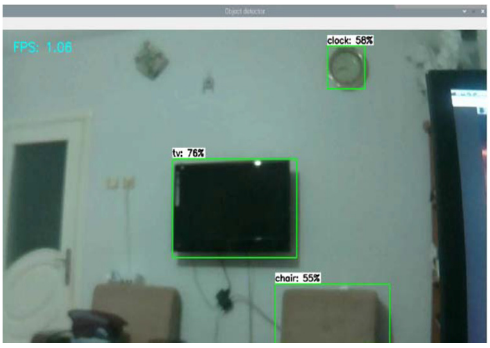

Figure 3: Object detection using the machine learning and OpenCV.

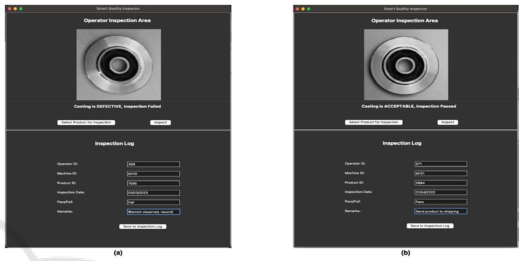

Figure 4: (a) Examination of a faulty product and (b) evaluation of an approved product.

Figure 5: Detection of Material Dimensions.

Table 1: Evaluation of Material Dimensions Across Different Objects.

Object	Original Length (mm)	Original Breadth (mm)	Original Area (mm²)	Predicted Length (mm)	Predicted Breadth (mm)	Predicted Area (mm²)	Accuracy (%)
Mobile	155	72	11,160	153.29	70.29	10,774.47	96.54
Pen	120	13	1,560	119.10	13.09	1,559.19	99.95
Book	275	164	45,100	276.01	163.50	45,127.63	99.94
Box	302	305	92,110	294.50	310.10	91,324.45	99.14
Wallet	91	73	6,643	92.74	74.69	6,926.50	99.72
Pencil box	140	45	6,300	141.10	45.00	6,349.50	99.21
Adapter	34	47	1,598	34.99	48.46	1,695.51	93.89

4 CONCLUSIONS

This work presents a real-time approach for item detection and dimension assessment. The various hardware parts and how they are put together are explained in detail. For material dimension inspection, a simple, low-cost approach utilizing machine learning and a deep learning model is described. The performance of many machine learning algorithms is examined and contrasted with their corresponding Python codes. The material was photographed using a Raspberry Pi and a Pi camera. Because it doesn't require a separate working platform like a personal computer, it is a complex approach. For the majority of computers and robot vision systems, the capacity to inspect material and its dimensions is crucial. In terms of open-world learning, human-level performance is still a long way off. It should be highlighted that although this material and its dimensions might be very helpful, they have not been employed extensively in many sectors. Since mobile robots and other autonomous machines are becoming increasingly often used.

REFERENCES

Borkowski, S.; Knop, K. “Challenges Faced in Modern Quality Inspection”, Management and Production Engineering Review, Vol. 7, No. 3, pp. 11–22 2016.

G. Chandan, Mohana and A. Jain, Real-Time Object Detection and Tracking by Using OpenCV and Deep Learning, ICIRCA, (2018).

Gokulnath Anand and Ashok Kumar Kumawat, “Object detection and position tracking in real time using Raspberry Pi”, Materials Today: Proceedings, 2021.

Jan-Lucas Uslu, TaoufiqOuaj, David Tebbe, Alexey Nekrasov, Jo Henri Bertram, Marc Schutte, Kenji Watanabe, Takashi Taniguchi,4 Bernd Beschoten, Lutz Waldecker and Christoph Stampfer, “An open-source robust machine learning platform for real-time detection and classification of 2D material flakes”, 2023.

Lan Fu, Hongkai Yu, Xiaoguang Li, Craig P. Przybyla, and Song Wang, “Deep Learning for Object Detection in Materials-Science Images”, Signal Processing for Advanced Materials, 2022.

Madhavi Karanam, Varun Kumar Kamani, Vikas Kuchana, Gopal Krishna Reddy, Koppula, and Gautham Gongada, “Object and it’s dimension detection in real time”, E3S Web of Conferences, Vol. 391, No. 01016, 2023.

Manoj M. Nehete and Uday C. Patil, “Design and Fabrication of PLC Based Conveyor System with programmable Station”, International Journal of Analytical, Experimental and Finite Element Analysis (IJAEFEA), Issue. 3, Vol. 4, pp 53-58, 2017.

Mohd ShuhanazZanar Azalan, Tang Esian, Hasimah Ali, Ahmad Firdaus Ahmad Zaidi and Tengku Sarah Tengku Amran, “Classification Size of Underground Object from Ground Penetrating Radar Image using Machine Learning Technique”, Journal of Physics, Vol. 2550, 2023.

Mr. N. Dinesh, Mr. D. Muthamilselvan, Mr. A. Sakthibalasundar, Mr. P. Sankaravignesh, “Fabrication of Material Inspection Robot”, International Journal of Engineering Research & Technology (IJERT), Vol. 7, Issue. 06, 2019.

Muhammad Sabih, Muhammad Shahid Farid, Mahnoor Ejaz, Muhammad Husam, Muhammad Hassan Khan and Umar Farooq, “Raw Material Flow Rate Measurement on Belt Conveyor System Using Visual Data”, Applied science innovation, Vol. 6, No. 88, 2023.

N. Sambathkumar, K. Sivakumar, D. Ganesan, M. Krishnakumar, H. Mohamad Ibrahim, “Design and Fabrication of Material Inspection Conveyer”, International Journal of Research in Aeronautical and Mechanical Engineering, Vol.2 Issue.3, pp. 129-134, 2014.

Nadin E S, Madhaneesh A, Sathiesh G V, and Arun Jayakar, “PLC Based Material Transfer Operation in Industrial Applications”, International Journal of Creative Research Thoughts (IJCRT), Vol. 11, Issue. 10, 2023.

Nijdam, J.J, Agarwal, D, Schon, B.S, “An experimental assessment of filament-extrusion models used in slicer software for 3D food-printing applications”, Journal of Food Engineering, Vol. 317, No. 110711, 2022.

Pranjal A. Chitale, Hrishikesh R. Shenai, Jay P. Gala, Kaustubh Y. Kekre and Ruhina Karani, “Pothole Detection and Dimension Estimation System using Deep Learning (YOLO) and Image Processing”, IEEE, 2020.

S. Manjula, Dr. K. Lakshmi, “A study on object detection”, IJPTFI, ISSN: 0975-766X, 2016.

Sarvesh Sundaram and Abe Zeid, “Artificial Intelligence-Based Smart Quality Inspection for Manufacturing”, Micromachines, Vol. 14, No. 570, 2023.

Siddharth Mandgi, Shubham Ghatge, Mangesh Khairnar, Kunal Gurnani and Prof. Amit Hatekar, “Object Detection and Tracking Using Image Processing”, Journal of Engineering Research and Application, Vol. 8, Issue 2, pp.39-41, 2018.

Sredha Vinod, Pshtiwan Shakor, Farid Sartipi and Moses Karakouzian, “Object Detection Using ESP32 Cameras for Quality Control of Steel Components in Manufacturing Structures”, Arabian Journal for Science and Engineering, 2022.

T. Varun Sai, B. Aditya, A. Mahendra Reddy and Dr. Y. Srinivasulu, “Real Time Object Detection Using Raspberry Pi”, International Journal for Research in Applied Science & Engineering Technology (IJRASET), Vol. 11, Issue. I, 2023.

Talha Bayrak, Vedat Marttin and Uğur Yüzgeç, “Raspberry Pi Based Object Detection and Drawing”, Global Conference on Engineering Research (GLOBCER’21), 2021.

U. Binay, N. Yadav, “Comparative Study of Object Detection Algorithms”, International Research Journal of Engineering and Technology (IRJET), Volume 4, Issue 7, 2017.

W. Wang, Z. Li, J. Deng, H. Yao, X. Xuan, Z. Wang, “A review of research on an object detection based on deep learning”, Journal of Physics, 2020.

Xiaofei Zhang, Yunze He, Tomasz Chady, Guiyun Tian, Jingwei Gao, Hongjin Wang and Sheng Chen, “CFRP Impact Damage Inspection Based on Manifold Learning Using Ultrasonic Induced Thermography”, IEEE Transactions on Industrial Informatics, Vol. 5, Issue. 5, pp. 2648- 2659, 2019.

Xiaoquan Shi, Yazhou Sun, Haiying Tian, Puthanveettil Madathil Abhilash, Xichun Luo and Haitao Liu, “Material Extrusion Filament Width and Height Prediction via Design of Experiment and Machine Learning”, Micromachines, Vol. 14, 2023.

Xiaoting Zhong, Brian Gallagher, Shusen Liu, Bhavya Kailkhura, Anna Hiszpanski and T. Yong-Jin Han, “Explainable machine learning in materials science”, Computational Materials, Vol. 8, No. 204, 2022.