



“INTELLIGENT PART RECOGNITION, CLASSIFICATION AND SURFACE DEFECT DETECTION BY USING COMPUTER VISION (CV) & MACHINE LEARNING (ML)”

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Abstract: The defects in product detection are very much essential in manufacturing to maintain quality. We used Computer Vision (CV) and Machine Learning (ML) Algorithms to detect defects. By using Machine Learning (ML) Algorithm we set the highest standards to maintain quality control. First, we classify the object according to their shape and geometry which is already in the database. Second, find the defects in the object. Using a Machine Learning algorithm for defect detections. Third, we summarize and analyse the application of Computer Vision, Machine Learning and other technologies used for defect detection, by focusing on three aspects, namely method and experimental results. To in addition apprehending the problems withinside the area of defect detection, we inspect the capabilities and traits of the current device used for defect detection. The performance of general product production and inspection method can be elevated with commercial automation and it also minimizes resources and saves time. The core ideas and codes of studies related to high precision, high positioning, rapid detection, small item, complicated background, occluded item detection and item association, are summarized.

Index Terms - Computer Vision (CV); Machine Learning (ML); object detection; defect detection; quality control.

I. INTRODUCTION

Nowadays, the latest Industrial major change brought the latest and most powerful technologies in manufacturing. It is very much flexible in nature and customizable and very helpful for mass production technologies [1]. Therefore, the modern methods of production are displaced by new methods and smarter production is taking place as the machines are perceived to have qualities such as self-awareness, self-prediction, self-comparison, self-configuration, self-maintenance, self-organization and greater flexibility [2]. This means that machines will operate independently and will be able to make decisions and improve automatically through a continuous learning process [3].

Recently, the fall in the cost of sensors and connectivity has led to a constant increase in the number of industrial objects connected to the internet [4]. Therefore, object connectivity has become the key component of Industry 4.0, as this connectivity enables the collection of massive amounts of data that are never exploited because they are simply not understood or analyzed. Nevertheless, the optimal exploitation and real-time analysis of these data can increase productivity, improve machine health, enhance production line automation and lead to defect-free manufacturing [5].

In the manufacturing industry, the work of quality assurance is that customers receive defect-free products which meet their needs. However, when it is performed in a false way, it puts consumers at risk and affects the reputation of companies [6]. A tiny variance in manufacturing will stop the whole production, this is the problem in the manufacturing industry. Inspecting the product is very much necessary. However, there are several drawbacks related to manual inspection. The speed of inspection is slow and limits the throughput of the production line. Scalability is low and it takes a long time to train a qualified inspector.

Moreover, it isn't unusual for human overall performance to be risky after a protracted operating time. Today, system vision, which is an applicable subfield of synthetic intelligence [7], permits the management of 100% of the manufacturing in approaches with excessive cadences and particularly with the combination of system studying algorithms for photo identification [8]. Moreover, Machine-studying can move past fault detection and exactly understand the reasons for screw-ups by inspecting the information generated through the manufacturing chain in real-time [9].

Industry 4.0 incorporates various technologies such as “Internet of Things” (IoT) [22], cloud computing [23], automation (e.g., intelligent robots in product assembly lines) [24], big data and analytics [25] and artificial intelligence (AI) [26], amongst others. Most of these so-called Industry 4.0 technologies have been around much longer than the latest Industrial Revolution, so they are the technical prerequisites of Industry 4.0. However, the innovative character of Industry 4.0 lies in the fact that the various elements can communicate with each other and act autonomously, independently of the intervention of human operators. Therefore, the implementation of a computer vision-based automated system in the manufacturing chain for detecting defective products requires a judicious combination of the different technologies.

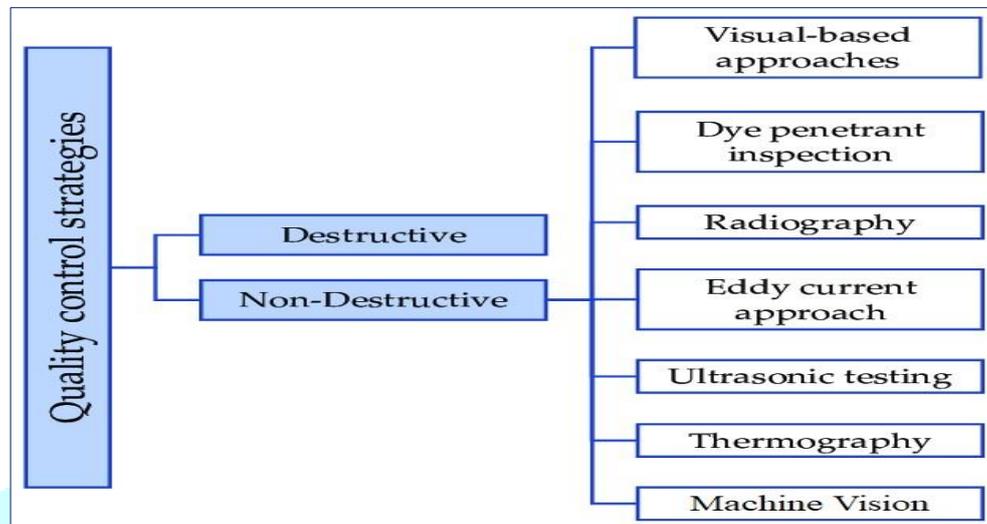


Figure 1: Categorization of the quality control strategies.

II. AIM AND OBJECTIVE

To Develop an automated intelligent inspection system using Computer Vision (CV) and Machine Learning (ML). So, it will be very useful to improve production efficiency and product quality.

- The objective is to detect mechanical parts or objects in real-time.
- My typical goals in defect detection include the recognition and detection of certain mechanical objects from training images. For that purpose, design a computer program, that automatically understands a defect or features in an image.
- And from that machine learning algorithms, discovers the various patterns in the detected user data and then make predictions based on these intricate data patterns for object detection, defect detection and its control.

III. DATASET

Make my training dataset and testing dataset for the customized object detection. I have prepared 1000 images dataset for customized object detection and 800 images for training and 200 images for testing dataset. So, in total, we are using a 1000 images dataset for model buildings.

IV. RELATED WORK

In the last few years, numerous exploration affairs had been accomplished to suggest smart and sensible system vision structures for defective product inspection, primarily based totally on the exploitation of generated information through one-of-a-kind incorporated technology into present-day production lines, the usage of quite a few gadget mastering techniques. What follows are a few great accomplishments in this field.

Wang et al. [12] proposed a machine vision model for product defect inspection based on deep learning and the Hough transform. The designed method detects defective products through three main steps: image pre-processing, region of interest (ROI) extraction and image identification.

Ireri et al. [13] proposed a tomato grading machine vision system based on RGB images. It is used for defected and healthy tomatoes. In this study, the L. Acolouror space was used because of its limited variance capability due to the sensitivity of the sensors [14], textural features were computer grey level from grey level co-occurrence matrices (GLCM) [15] and the tomato shape asymmetrical value was computed as a measure of shape regularity [16].

Jiang et al. [17] introduced the common computer vision techniques for textile quality control. Initially, the authors listed the difficulties encountered in implementing a computer vision techniques-based method for fabric defect detection in real-time.

Sahoo et al. [18] suggested a dynamic bottle inspection structure. To detect the defect in bottles.

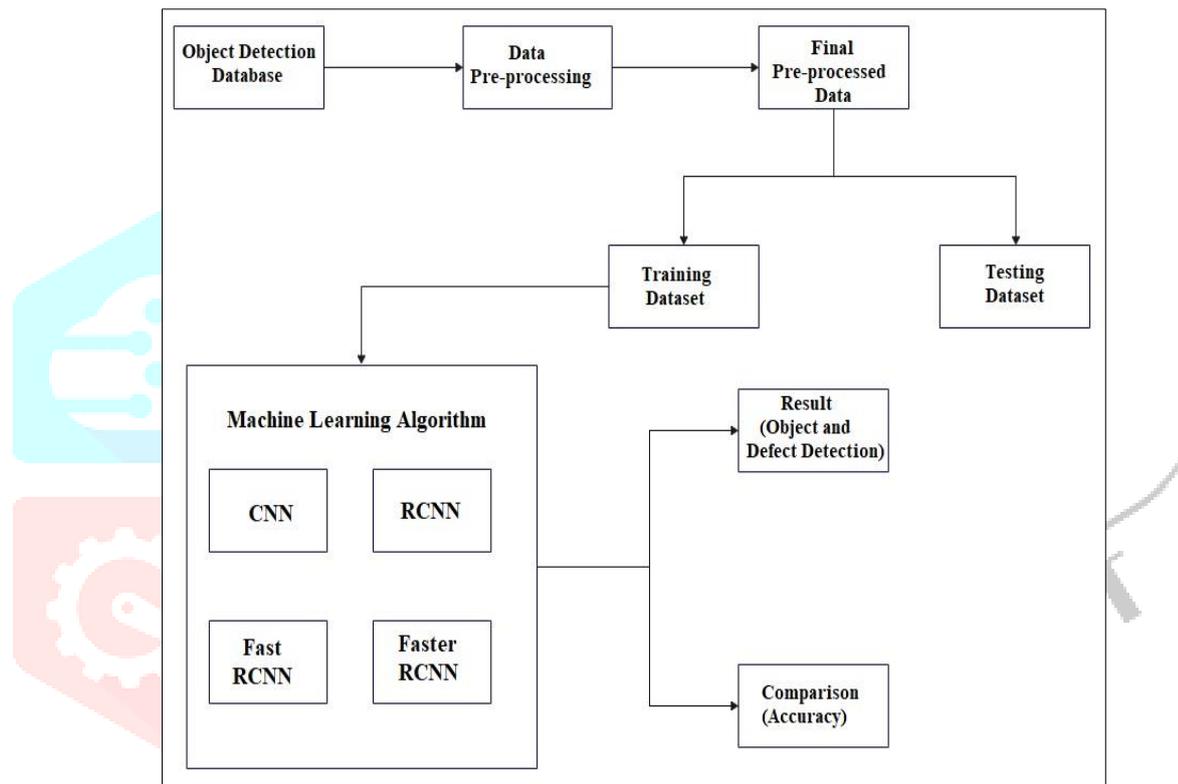
Liqun, W. et al. [19] designed an improved model based on VGG16 [20,21] and introduced the Inception v3 module for vehicle parts defect detection of the six most common categories of front axle left front and middle bolts, transmission shafts, parking locks and shift mechanisms, special steering tools, right headlight positioning bolts and shock absorbers.

V. METHODOLOGY

Data is a very important part of any machine learning system. To implement the system, we used Artificial Intelligence i.e., Machine Learning algorithms.

The below architecture clearly explains how the system's components communicate with one another, beginning with the user query for Part Identification. This model gives a clear picture of the huge data captured and then checks the dataset for mechanical component identification. If that data is present in it, it will further be processed and taking necessary action on it. During the pre-processing step, we split the dataset into training datasets and testing datasets.

Train the dataset using appropriately supervised learning algorithms for detection. Apply machine learning techniques to find any defect in the component or part for any new data that has appeared in the data set. After this data acquisition, a suitable algorithm of machine learning must be applied to compute the efficiency and capability of the model. Here we have applied various machine learning algorithms like CNN, RCNN, Fast RCNN and Faster RCNN etc. Metrics such as accuracy and precision will be calculated for the proposed model.

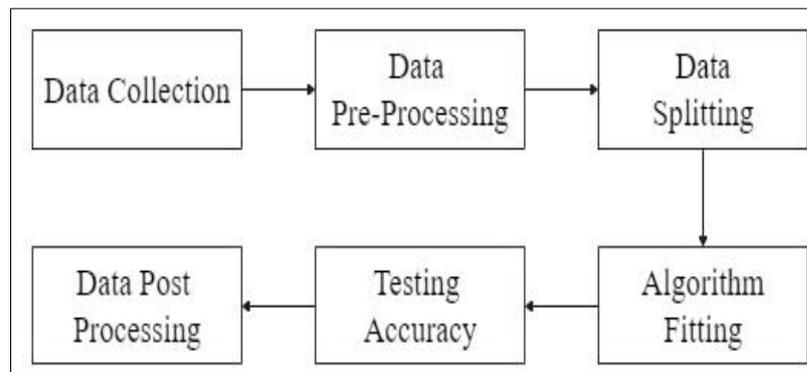


Flowchart 1: Architecture of Object Detection Model

To predict the best outcome, we initially wanted to use a couple of algorithms. However, some of them had to be vetted out because of their lower efficiency and accuracy. During our implementation, we guessed that CNN would perform well. However, our practical finding was slightly different. The efficiency and accuracy of CNN were well below the acceptable threshold of error. However, RCNN, Faster RCNN and Faster RCNN have performed well and had very good accuracy. We will compare all the algorithms and their outcomes in the latter part of the paper. Before even selecting the algorithm, we worked with, we had to collect the data. We had to collect the data electronically and reconstruct them using Computer Vision.

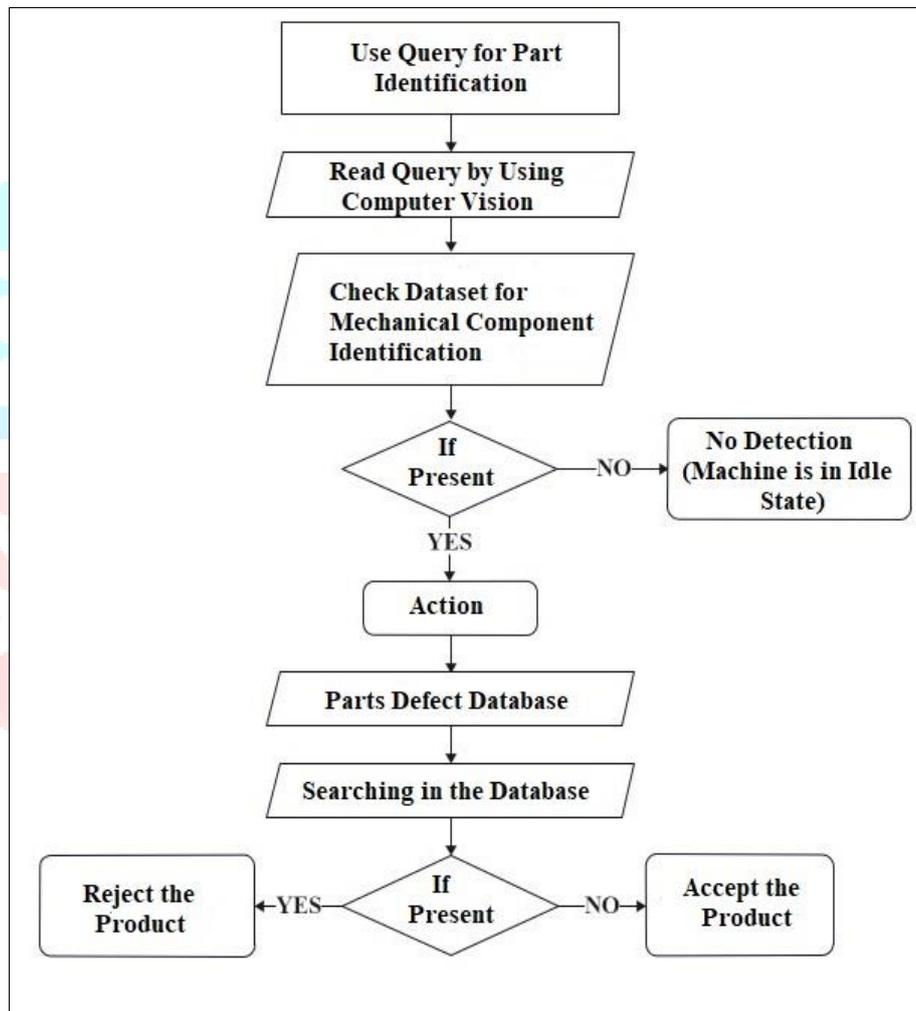
Our research work has been divided into a few major parts. All these parts together represent our research model. There are 6 steps that we have followed in our model:

- Dataset collection.
- Data pre-processing.
- Data splitting into train and test sets.
- Fitting the algorithm.
- Testing the accuracy of the model.
- Data post-processing in the form of performance metrics.



Flowchart 2: Workflow of data in Proposed Model

In below Figure, the project flowchart diagram shows how well these models perform the different steps to achieve the targeted result of the model.



Flowchart 3: Block Diagram of Proposed Model

❖ Algorithms for Proposed this Research Paper

Below are the algorithms used in this research paper, they are:

- Convolutional Neural Networks (CNN)
- Region-Based Convolutional Neural Networks (RCNN)
- Fast Region-Based Convolutional Neural Networks (Fast RCNN)
- Faster Region-Based Convolutional Neural Networks (Faster RCNN)

❖ **Summary of all Algorithms Used**

The below table is a summary of all the algorithms used in the project.

Table 1: Table of Summary of all the Algorithms used

Algorithm	Features	Prediction time / image	Limitations
CNN	Divides the image into multiple regions and then classifies each region into various classes.	–	Needs a lot of regions to predict accurately and hence high computation time.
RCNN	Uses selective search to generate regions. Extracts around 2000 regions from each image.	40-50 seconds	High computation time as each region is passed to the CNN separately also it uses three different models for making predictions.
Fast RCNN	Each image is passed only once to the CNN and feature maps are extracted. Selective search is used on these maps to generate predictions. Combines all the three models used in RCNN together.	2 seconds	Selective search is slow and hence computation time is still high.
Faster RCNN	Replaces the selective search method with the region proposal network which made the algorithm much faster.	0.2 seconds	Object proposal takes time and as different systems are working one after the other, the performance of systems depends on how the previous system has performed.

❖ **Implementation Tools and Methods**1. **Hardware Requirements**

Table 2: Hardware Specification

Sr. No.	Hardware	Specification
1	System Processor	64-bit Core i3 with 2.4 GHz
2	Hard Disk	50 GB
3	RAM	8 GB

2. **Software Requirements**

Table 3: Software Specification

Sr. No.	Software	Specification
1	Operating System	Windows 10
2	Front end Language	Python
3	Programming Language	R, Python, C++
4	Software Libraries (Framework)	TensorFlow, OpenCV
5	IDE Required	Jupyter Notebook / Jupyter Lab, Anaconda Navigator

VI. RESULT ANALYSIS

The core aim of our research was to establish a model that will efficiently and correctly detect. To do this, as mentioned above, we have implemented 4 different machine learning algorithms. This ensured us the ability to bring a comparison between varieties of different algorithms. Our target was to establish the best-performing algorithm for this field of work, based on our data.

We have applied multiple algorithms in our data set to determine and compare the performance level of the algorithm. Among the 4 algorithms that were applied, CNN had shown low accuracy and good performance and Faster RCNN had shown the high accuracy and the best performance. The algorithm would have worked well if the data had any pattern to them. Both RCNN, Fast RCNN and Faster RCNN performed well in our situation and among them, Faster RCNN had the most overall accuracy throughout the process. Table 4 represents the defect detection output.

Table 4: Represents the defect detection output accuracy with approx. percentages

Algorithms	Object Detection Accuracy	Object Detection Accuracy with approx. Percentage (%)
CNN	Good	98.50
RCNN	Good	98.70
Fast RCNN	High	99.50
Faster RCNN	Highest	99.90

VII. CONCLUSION

In this modern world, almost every sector is being enlightened by different technological innovations and findings. India is also moving forward with these blessings although the most significant economic resource of our country. We believe this model can play a very essential part in today's world. Industrialization is a fundamental aspect of modern civilization. With increasing modernization and Industrialization, industrial growth and demand emerge as a massive factor in this. But this is lacking in using new technologies of machine learning. As a result, our industry should be familiar with all of the latest machine learning and other techniques.

These techniques help in getting the maximum output. Many algorithms of machine learning are applied to Industry to improve product quality and various factors. All the accuracy of the models was carefully obtained through various methods and compared with each other. Using multiple algorithms helped to understand which algorithm is more suitable for this system.

In this paper, we used various machine learning algorithms CNN, RCNN, Fast CNN and Faster CNN. This paper aims to enhance object detection methods. The primary output of this thesis is an in-depth description of the possible approach to tackling object detection without any human intervention. The secondary output is a standalone machine learning project that allows for future replications or modifications of the performed experiment.

VIII. SCOPE FOR FUTURE WORK

We hope that in the future, this model will be implemented with a much more efficient dataset for a specific piece of product or object that contains various information, and so on. So that no product or object is wasted by quality inspection and this system is more productive. We want this model to be used all over the world to help the growth of the Industrial sector. Both researchers and entrepreneurs may be interested in this field. In the future, we hope to create a cloud platform for all of the industries that will be using this model to share information all over the industries. This will let various industries in one country know about the prospect of product or object detection in another part of the world; down to a specific geographical unit.

REFERENCES

- [01] Cleverism. *Industry 4.0: Definition, Design Principles, Challenges, and the Future of Employment*. 2017. www.cleverism.com/industry-4-0/
- [02] Lee, J. Smart Factory Systems. *Inform. Spektrum* 2015, 38, 230–235.
- [03] Zhou, K.; Liu, T.; Liang, L. *From cyber-physical systems to Industry 4.0: Make future manufacturing possible*. *Int. J. Manuf. Res.* 2016, 11, 167.
- [04] C'olakovic', A.; Hadžialic', M. *Internet of Things (IoT): A review of enabling technologies, challenges, and open research issues*. 2018, 144, 17–39.
- [05] Cheng, F.-T.; Tieng, H.; Yang, H.-C.; Hung, M.-H.; Lin, Y.-C.; Wei, C.-F.; Shieh, Z.-Y. *Industry 4.1 for Wheel Machining Automation*. *IEEE Robot. Autom. Lett.* 2016, 1, 332–339.
- [06] Gunasekaran, A.; Subramanian, N.; Ngai, W.T.E. *Quality management in the 21st century enterprises: Research pathway towards Industry 4.0*. *Int. J. Prod. Econ.* 2019, 207, 125–129.

- [07] Intelligent Defect Inspection Powered by Computer Vision and Deep Learning. www.infopulse.com/blog/intelligent-defect-inspection-powered-by-computer-vision-and-deep-learning.
- [08] Semeniuta, O.; Dransfeld, S.; Martinsen, K.; Falkman, P. *Towards increased intelligence and automatic improvement in industrial vision systems*. Procedia CIRP 2018, 67, 256–261.
- [09] Chopra, V.; Priyadarshi, D. *Role of Machine Learning in Manufacturing Sector*. Int. J. Recent Technol. Eng. 2019, 8, 2320–2328.
- [10] Wang, J.; Fu, P.; Gao, R.X. *Machine vision intelligence for product defect inspection based on deep learning and Hough transform*. J. Manuf. Syst. 2019, 51, 52–60.
- [11] Ileri, D.; Belal, E.; Okinda, C.; Makange, N.; Ji, C. *A computer vision system for defect discrimination and grading in tomatoes using machine learning and image processing*. Artif. Intell. Agric. 2019, 2, 28–37.
- [12] Shafiee, S.; Minaei, S.; Moghaddam-Charkari, N.; Barzegar, M. *Honey characterization using a computer vision system and artificial neural networks*. Food Chem. 2014, 159, 143–150.
- [13] Moallem, P.; Serajoddin, A.; Pourghassem, H. *Computer vision-based apple grading for golden delicious apples based on surface features*. Inf. Process. Agric. 2017, 4, 33–40.
- [14] Otsu, N. *A Threshold Selection Method from Gray-Level Histograms*. IEEE Trans. Syst. Man Cybern. 1979, 9, 62–66.
- [15] Jiang, J.L.; Wong, W.K. *Fundamentals of common computer vision techniques for textile quality control*. In *Applications of computer Vision in Fashion and Textiles*; Wong, W.K., Ed.; Woodhead Publishing: Sawston, UK, 2018; pp. 3–15.
- [16] Sahoo, S.K.; Sharma, M.M.; Choudhury, B.B. *A Dynamic Bottle Inspection Structure*. In *Computational Intelligence in Data Mining*; Behera, H.S., Nayak, J., Naik, B., Abraham, A., Eds.; Springer: Singapore, 2019; Vol. 711, pp. 873–884.
- [17] Liquan, W.; Jiansheng, W.; Dingjin, W. *Research on Vehicle Parts Defect Detection Based on Deep Learning*. J. Phys. Conf. Ser. 2020, 1437, 012004.
- [18] Bayar, B.; Stamm, M.C. *A Deep Learning Approach to Universal Image Manipulation Detection Using a New Convolutional Layer*. In *Proceedings of the 4th ACM Workshop on Information Hiding and Multimedia Security IH&MMSec '16*, Vigo, Spain, 20–22 June 2016; pp. 5–10.
- [19] Qu, Z.; Shen, J.; Li, R.; Liu, J.; Guan, Q. *PartsNet: A Unified Deep Network for Automotive Engine Precision Parts Defect Detection*. In *Proceedings of the 2018 2nd International Conference on Computer Science and Artificial Intelligence CSAI '18*, Shenzhen, China, 8–10 December 2018; pp. 594–599.
- [20] Nord, J.H.; Koohang, A.; Paliszkievicz, J. *The Internet of Things: Review and theoretical framework*. Expert Syst. Appl. 2019, 133, 97–108.
- [21] Hashem, I.A.T.; Yaqoob, I.; Anuar, N.B.; Mokhtar, S.; Gani, A.; Khan, S.U. *The rise of “big data” on cloud computing: Review and open research issues*. Inf. Syst. 2015, 47, 98–115.
- [22] Pedersen, M.R.; Nalpantidis, L.; Andersen, R.S.; Schou, C.; Bøgh, S.; Krüger, V.; Madsen, O. *Robot skills for manufacturing: From concept to industrial deployment*. Robot. Comput. Integr. Manuf. 2016, 37, 282–291.
- [23] Ur Rehman, M.H.; Yaqoob, I.; Salah, K.; Imran, M.; Jayaraman, P.P.; Perera, C. *The role of big data analytics in industrial Internet of Things*. Future Gener. Comput. Syst. 2019, 99, 247–259.
- [24] Lee, J.; Davari, H.; Singh, J.; Pandhare, V. *Industrial Artificial Intelligence for industry 4.0-based manufacturing systems*. Manuf. Lett. 2018, 18, 20–23.
- [25] <https://www.analyticsvidhya.com/>
- [26] <https://www.towardsdatascience.com/>
- [27] <https://www.w3school.com/>
- [28] <https://www.kaggle.com/>
- [29] <https://www.stackoverflow.com/>
- [30] <https://www.geeksforgeeks.org/>