

# Color Based Object Sorting System using Deep Learning



Pratik Roy, Satakshi Roy, Rahul Agrawal, Sonal Sharma

**Abstract:** Object sorting is a very common industrial application but at the same time it is a tiresome process as handling so many objects is a menial task which is not so promising in maintaining consistency and thereby arising quality issues. Object sorting, if done manually, is not only time consuming but also it seems to be an uphill task pragmatically. Nowadays amid various technological advancements, industries have become fully automated so an automated sorting system is essentially required to replace this conventional system of manual sorting knowing that this process can be made completely autonomous by properly channeling the use of technology. The main objective of this paper is to propose a smarter, intelligent and cost-effective object sorting system which categorizes the objects based on their respective color and will place them at their designated locations to minimize the cost and optimize the productivity. We have implemented the sorting system using Raspberry pi (an open-sourced Linux based board) interfaced with a camera module along with some side electronic circuitry such as servo motors and sensors. The color recognition is done using the IBM Watson visual recognition model where we have uploaded the dataset of captured images. For picking and sorting the objects, we have made use of a robotic arm that will rotate with the help of servo motor up to certain angles.

**Keywords:** IBM Watson Studio, Raspberry Pi, Robotic Arm, Transfer Learning.

## I. INTRODUCTION

Color is a very important feature based on which objects are distinguished, sorted and various industrial applications are performed. But if color sorting is done manually, it will be extremely tedious, time-consuming and monotonous job so it is very essential to build machines and automate them to ease the job of humans and make every work precise and optimized. Automation isn't the latest form of innovation but still, automation has arguably pinned to have created greatest influence as it is a positive step towards handling various types of machinery and processes to minimize the human involvement resulting in saving a sufficient amount of time. On the same note, this very automation can play a key role if we utilize it in sorting the objects based on the color on an industrial level where a large number of products are manufactured on a daily basis.

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\* Correspondence Author

**Pratik Roy\***, Junior, Department of Electronics and Communication Engineering, VIT University, Vellore, India. E-mail: roypratik63@gmail.com

**Satakshi Roy**, Student, Department of Electronics and Communication, Vellore Institute of Technology, Vellore, India. E-mail: satakshiroy1998@gmail.com

**Rahul Agrawal**, Student, Department of Electronics and Communication, Vellore Institute of Technology, Vellore, India. E-mail: agrawalrahuludr@gmail.com

**Sonal Sharma**, Student, Department of Electronics and Communication, Vellore Institute of Technology, Vellore, India. E-mail: sonal.sharma2017@vitstudent.ac.in

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There are some traditional methods already in existence for sorting the objects like placing the objects on the conveyor belt and sorting one at a time but these methods are expensive and time consuming. Instead, our motto is to sort the objects simultaneously based on color in a synchronized way making the entire system more flexible. The heart of the proposed system is Raspberry Pi which is an open-source Linux based operating system (OS). For visualizing the color of the object we will be using the IBM visual recognition model on IBM Watson Studio [1]. Upon color detection, a signal is sent to the raspberry pi which then directs that signal to the motor which will channel the object to get sorted to its respective section. A feeder will then pull the next object to get sorted. Thus, achieving an automated color based object sorting system.

## II. TECHNOLOGY

### A. Raspberry pi Model 3B

The Raspberry Pi is a low cost, credit-card sized computer that plugs into a computer monitor or TV, and uses a standard keyboard and mouse. It is a capable little device that enables people of all ages to explore computing, and to learn how to program in languages like Scratch and Python. We will be using this Linux based micro-controller to run our python script that will act as a gateway to the IBM cloud as well as taking input from the IR sensor, capturing the images and rotating the robotic arm all by one single micro-controller. It is a robust IoT edge device that can push its limit to run the deep learning models at the edge using frameworks like tensor flow-lite or tinyml [2].

### B. Noir Camera

The Raspberry pi Noir camera is the official night vision camera that was released by the Raspberry pi foundation. It can be attached to the Raspberry Pi by means of small sockets on the upper surface of the board and uses CSI interface that is meant for interfacing cameras with microcontrollers. The camera has no infrared filter on its lens making it ideal for infrared photography and taking pictures during night time.

### C. Transfer Learning

Transfer learning through the use of synthetic images and pretrained convolutional neural networks offers a promising method to improve the object detection performance of deep neural networks [3]. Transfer learning uses fine-tuned pretrained models for individual datasets to get an inference with very high accuracy. These models have been trained using big datasets using multiple GPUs. These models mostly take weeks for training them to get some decent accuracy.

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We have tested out three different pretrained models for our dataset of self-captured images.

We tested on alexnet, resnet152 and inception-v3 models [4]-[5]-[6]. These models were trained using the COCO dataset and Imagenet dataset. Just by changing the final fully connected layers or the classification layers of these models and training them for few epochs, the models achieve good accuracy for testing out the validation dataset.

## D. IBM Watson Studio

The IBM Watson Visual Recognition service uses deep learning algorithms to analyze images and understand their content. It provides us the flexibility to analyze images for scenes, objects, faces, colors, food, and other subjects that can give us insights into our visual content. We can create and train our custom image classifiers using our own small collection of images. IBM Watson studio has use cases that include manufacturing, visual auditing, insurance, social listening, social commerce, retail and education. In our paper we are using the visual recognition model where we have uploaded the three different classes of image viz blue, red and green in the Watson studio. We trained the model and it makes API calls from the raspberry pi to get the inference from the cloud.

## E. Robotic Arm

Robotic arms are widely-used tools that are capable of lifting hazardous, heavy or other types of materials that human workers could not otherwise handle. They have been used for years in factories and laboratories to ease human task. Like other robots, robotic arms consist of a variety of different parts that contribute to making it function properly.

**1. Controllers-** Controllers are the main processors of the robotic arms and act as their brains. They can either operate automatically by being programmed or can be used for manual operation by giving output instructions directly from a technician.

**2. Arm-** The arm is the main section of the robotic arm and consists of three parts: the shoulder, the elbow and the wrist. These are all joints, with the shoulder resting at the base of the arm, typically connected to the controller, and it can move forward, backward or spin. The elbow is in the middle and allows the upper section of the arm to move forward or backward independently of the lower section. Finally, the wrist is at the very end of the upper arm and attaches to the end effector.

**3. End Effector-** It acts as the hand of the robotic arm. It is often composed of two claws, though sometimes three, that can open or close on command. It can also spin on the wrist, making manoeuvring material and equipment easy.

**4. Drives-** They are essentially the motors in between joints that control the movement.

## F. Pre-trained Transfer Learning Models

When building an intelligent machine, it becomes very critical to make it as accurate as possible. Accuracy not only depends on the network but also on the amount of data available for training. Therefore the networks are compared on a dataset called as Imagenet. A pre-trained model is trained previously and it contains the weights and biases representing the features of a particular dataset it is trained

on. They are extremely beneficial because we are actually saving the training time by using these models and making our task optimized.

**Alexnet Model:** This is one of the first deep learning network models that has pushed Imagenet accuracy by a significant amount as compared to the other traditional methodologies. It consists of 5 convolutional layers and uses Rectified Linear Unit for the non-linear part, making training process very easy as compared to traditional neural networks.

**Inception v3 Model:** It has a feature extraction part and a classification part with fully connected and softmax layers. This model achieves accuracy for identifying general objects with 1000 classes. It extracts the features from the input images and classifies them based on those features.

**Resnet Model:** The core idea of this model is “identify shortcut connection” that skips one or two layers. It is argued that stacking layers should not degrade the network performance, because we could simply stack identity mappings upon the current network, and the resulting architecture would perform the same. This indicates that the deeper model should not produce a training error higher than its shallower counterparts.

## III. EXISTING METHODS

The present scenario of industries use computer vision by processing the images to sort objects of various shapes and sizes. In the era of artificial intelligence this process becomes really fast and more efficient than the existing techniques. [7] There is a significant amount of delay when each and every frame is processed by softwares like OpenCV to come to a conclusion about the particular frame. Today, we are free to use cloud technologies and resources at our fingertips. One such example is the IBM cloud where many tie up to perform high end computational tasks in split seconds. The visual recognition model of IBM Watson studio runs on the concept of transfer learning as mentioned above. The small data set can give more than 90 percentage of accuracy which is enough for a task like object sorting in industries. Deep learning using neural networks has grown to be revolutionary. It has applications in almost every possible field. This research has designed and developed a sorting mechanism with the help of deep learning. The developed sorting mechanism would help incorporate objects with more than one color to be distinguished with high efficacy. [8]

## IV. PROPOSED METHOD

The solution is very simple when it comes to the technical aspect of it. The components used for this solution are cheap, robust and power consumption is very minimal. The Raspberry Pi acts as gateway to the IBM cloud. The camera module is attached to the micro-controller which captures the pictures of the objects present on the conveyor belt. As soon as the object arrives at the particular position on the conveyor belt, the sensor directs the raspberry pi to capture the image of the object. An API call is made to the IBM Watson studio where our trained model is kept.

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The image is fed into the visual recognition model which gives the inference of the color of the object. IBM cloud sends back the results to the raspberry pi which in turn commands the robotic arm to pick and place the object on the particular box depending on its color [Fig. 1].

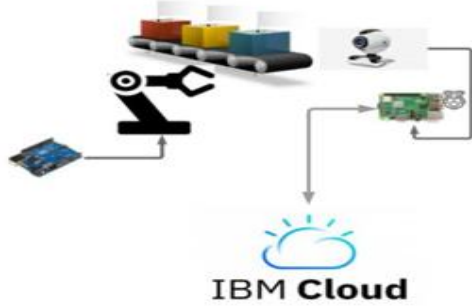


Fig. 1.Process

## V. DEMONSTRATION

We have built the prototype for our project using the Raspberry pi, noir Camera module, IR sensor, robotic arm and few colored boxes. We have taken around forty images of each class of the colored box for training dataset and around ten images for our test dataset. We kept it in three different bucket in the IBM cloud platform. We trained the visual recognition model which works on transfer learning to fine tune our model for high accuracy on unseen data [Fig. 2]. The IR sensor is interfaced with the micro-controller. When-ever the colored box is placed in front of the camera module, the sensor sends a high value which directs the board to capture the image and store it in a specific directory. IBM Watson studio API calls are made from the python script running on the raspberry pi. The image is transferred to the Visual Recognition model in IBM cloud. The Visual Recognition model process the image using transfer learning on pretrained model and gives an inference and IBM cloud sends back the information to the Raspberry pi. The inference received is in JSON format having the object class viz; blue-box, red-box or green-box and probability is extracted. The python script blinks the colored LED depending on the inference received and instructs the robotic arm to pick up the colored box [Fig. 3].

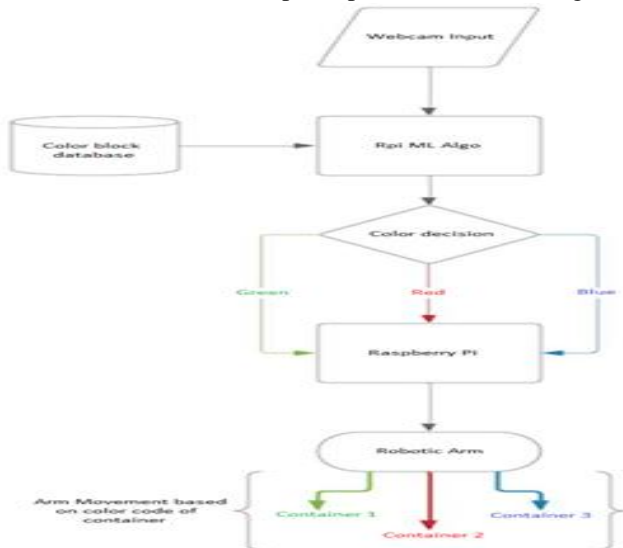


Fig. 2.Flow Diagram

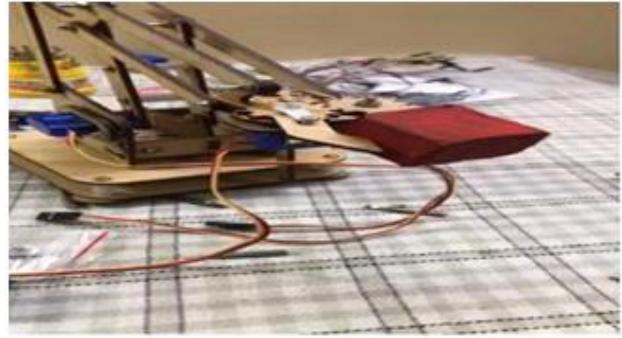


Fig. 3.Color Detection

ANGLES FOR DIFFERENT OBJECTS	
CATEGORY	ANGLE
BLUE BOX	30°
RED BOX	60°
GREEN BOX	90°

Fig. 4.Robotic Arm Rotation Angle

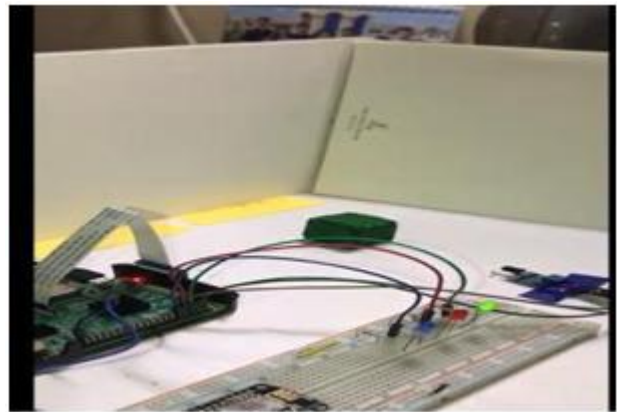


Fig. 5.Robotic Arm

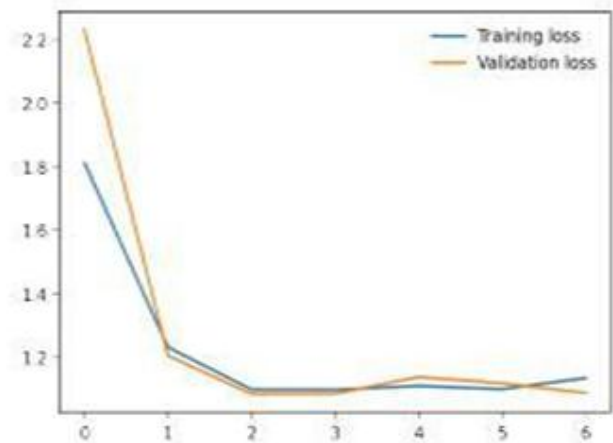
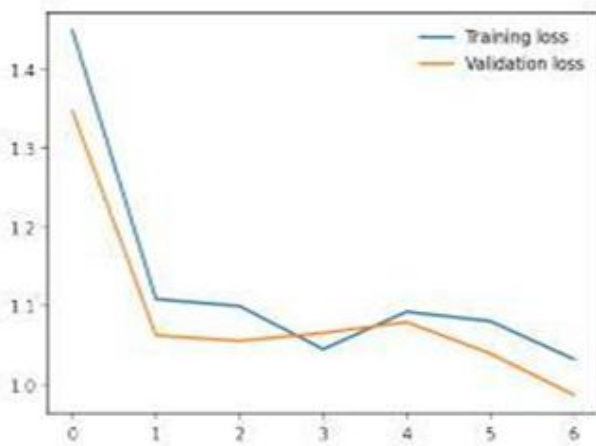
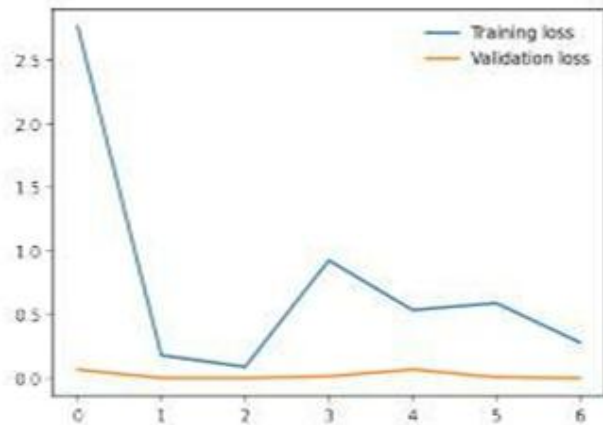


Fig. 6.Resnet152



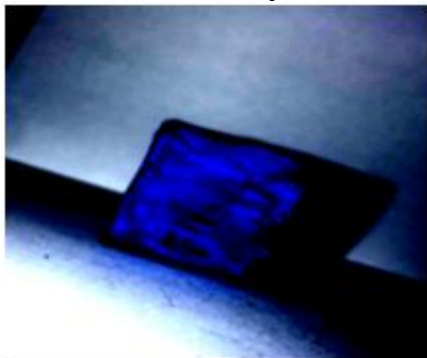


**Fig. 7. Inception-v3**

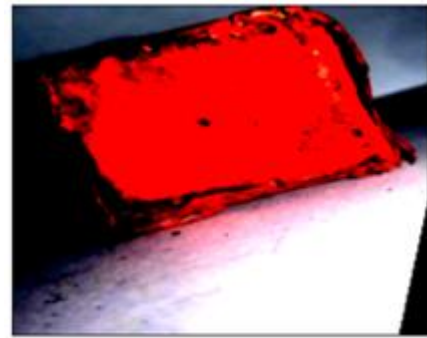


**Fig. 8. Alexnet**

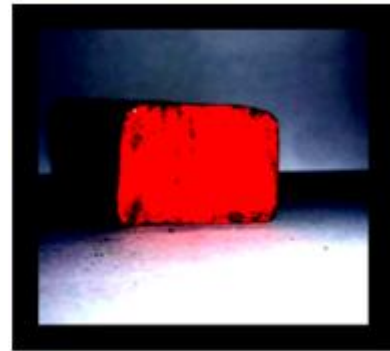
The robotic arm picks up the coloured box and has to rotate only till certain angle as given in the figure [Fig. 4]. The rotation of the arm is particular to the colour of the image of the image. The grip of the robotic arm releases the box and it is placed in the particular collecting container [Fig. 5]. We tested out our dataset on three different models: resnet152 [Fig. 6], inception-v3 [Fig. 7] and alexnet [Fig. 8]. Training loss refers to the error or loss that might have occurred on training the network with the given set of data and validation loss is the loss that can occur after running the validation data through the trained models. We compared the training loss and validation loss on these models and alexnet gave the maximum accuracy on test dataset.



**Fig. 9. Alexnet Tested**



**Fig. 10. Resnet152 Tested**



**Fig. 11. Inception-v3 Tested**

The figures, [Fig. 9], [Fig. 10] and [Fig. 11] show a few images of the colour detection done by the pre-trained models of transfer learning.

## VI. CONCLUSION

The desired objectives were successfully deployed in the prototype model of the project. Automating the whole process was the ultimate goal and has been done successfully. The future prospects of this project will be to distinguish the object not only on the basis of its color but also few other characteristics such as shape and size. Needless to say that automation is a necessity in industries because it not only improves the quality of life for humans at work but also it promises to give the world, an excellent quality of products and make services available at extremely faster rates, thus, reducing human error. Automation is taking over every sector of industries and the entire world. In this age of artificial intelligence and automation, humans can create exceptional solutions and structures which would otherwise have been impossible to think of before.

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## AUTHORS PROFILE



**Pratik Roy** - Junior at VIT University, Vellore, Bachelor of Technology in Electronics and Communication Engineering, high school at St. Francis Xavier, Kolkata, West Bengal, interned at Reliance Industries Limited and got experience in the domain of industrial automation, an enthusiast in embedded systems, solving real-world problems with the artificial intelligence of things. Email: roypratik63@gmail.com



**Satakshi Roy** - Student at Vellore Institute of Technology, Vellore, pursuing B. Tech in Electronics and Communication, high school at Holy Child English Academy, Malda, West Bengal. Interned at Reliance Industries Limited and gained knowledge about industrial control systems and automation. An enthusiast in the field of microcontrollers, VLSI system design and a graphic designer by passion. Email: satakshiroy1998@gmail.com



**Rahul Agrawal** – Student of VIT, Vellore pursuing B. Tech in ECE Department. High school at Alok Senior Secondary School, Udaipur, Rajasthan. Published a paper titled 'Automatic Vehicle Beam Controller' in IPACT2019 Conference held in VIT, Vellore. Done internship from Reliance Industries Limited (RIL), Gadimoga and gained knowledge regarding Industrial Automation and control systems. Email: agrawalrahuldr@gmail.com



**Sonal Sharma** - Undergraduate at VIT University, Vellore, Bachelor of Technology in Electronics and Communication Engineering, High School at Dr. D. Ram D.A.V public School, Patna, Bihar, Interned at Doordarshan and got the knowledge of media communication as well as satellite communications. Email: sonal.sharma2017@vitstudent.ac.in