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The Raspbian Automatic Segregator of Household Waste

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Abstract:
Waste management or waste disposal are all the activities and actions required to manage waste from its inception to its final disposal. This includes amongst other things collection, transport, treatment and disposal of waste together with monitoring and regulation. It also encompasses the legal and regulatory framework that relates to waste management encompassing guidance on recycling. A large portion of waste management practices deal with municipal solid waste (MSW) which is the bulk of the waste that is created by household, industrial, and commercial activity. The life-cycle begins with design, then proceeds through manufacture, distribution, and primary use and then follows through the waste hierarchy's stages of reduce, reuse and recycle. Each stage in the life-cycle offers opportunities for policy intervention, to rethink the need for the product, to redesign to minimize waste potential, to extend its use. Product life-cycle analysis is a way to optimize the use of the world's limited resources by avoiding the unnecessary generation of waste. In the paper, the management of waste is done in a modern and efficient manner.

Index Terms: API, fill time, cleanup time, locations

I. INTRODUCTION

Ubiquitous objects are getting “smarter” and more “connected”, every day. With this ever-growing Internet of Things, every object can now be uniquely identified and made to communicate with each other. This approach has been applied to dustbins too, to monitor garbage collection, throwing light on numerous valuable insights. The paper too employs a similar approach, to not only monitor garbage collection but also optimize it, using machine learning. The method of unsupervised learning we utilize is K Means Clustering, widely used in data mining and analytics. The physical device uses an ultrasonic sensor to be aware of a dustbin's current content level. If the level reaches or exceeds a threshold percentage of the total capacity of the dustbin, it informs our servers, via an online API developed for this purpose. The API also stores related data - fill time, cleanup time, and location, to name a few. This dynamic dataset generated is analyzed by an algorithm, to determine the times of the day, when a regular cleanup should be performed, such that the dustbins are clean, for the maximum possible portion of the day. Data henceforth generated revealed that the installation has had a positive effect on the optimization. The most common consumer products recycled include aluminium such as beverage cans, copper such as wire, steel from food and aerosol cans, old steel which are used for furnishings or equipment, rubber tyres, polyethylene and PET bottles, glass bottles and jars, paperboard cartons, newspapers, magazines and light paper, and corrugated fiberboard boxes.

A): Today, waste management from its inception to its disposal is one of the important challenges for the municipal corporations in all over the world. Dust bins placed across cities set at open places are flooding because of increment in the waste each day and making unhygienic condition for the citizens, to maintain a strategic distance from such a circumstance we have proposed wireless solid waste management system for smart cities which allows municipal corporations to monitor status of dustbins remotely over web server and keep cities clean very efficiently by optimizing cost and time required for it. As soon as dustbin has reached its maximum level, waste management department gets alert via SMS via gsm module placed at dustbin so department can send waste collector vehicle to respective location to collect garbage. This paper improves practicality of IoT based solid waste collection and management system for smart city. The objective of the project is to enhance practicality of IoT based solid waste collection and management system for smart city.

B): A solution of the optimization garbage removal problem in the large cities is suggested. In this paper it described a system architecture to find time-optimal dynamic route for garbage trucks within “Smart Clean City” project. It proposed a formal mathematical model of the task of dynamic optimal route and formal the optimization criterion for time-optimal garbage collection of all waste from landfills. There are situations when the garbage collection truck (GCT) arrives but garbage containers are half-filled; at the same time the GCT does not arrive to the real full garbage container. This process helps to manage the process of sending a specialized GCT for the garbage collection only if the containers are filled. Infrared and ultraviolet rays help as a level sensor to transmit the information of filling of the container. The sensor will not remain active all the time so that the energy will be saved here. This way it will manage the optimal collection of Garbage from cities around the world.

C): Cities are becoming increasingly aware of the problems related to conventional methods of waste collection. In general, waste may be defined as unwanted materials that are not prime products which are of no further important to human in their actual form. In this growing era of technology we need to update everything which is around us. Even if it is as small as a dustbin. Recent enforcement of law by the Indian government for the welfare of sanitation workers has raised the need for an automated system in waste management. The existing waste management systems we have in our home are not up the mark according to the current technological era. We use all outdated techniques for segregation of waste which requires manual work to separate the waste into biodegradable, non biodegradable& hazardous waste. The existing garbage disposal system in India consists of unclassified waste collected from homes which are then segregated at a station manually. This segregation of solid waste done by manual labor can bring about many health hazards for the waste sorters in addition to being less efficient, time consuming and not completely feasible due to their large amount. To overcome these difficulties and made this process automatic we will use our deep learning libraries of machine learning which will help to detect the different kinds of waste and segregate it into various required categories. In our paper, we have proposed an automated recognition system using Biodegradable waste is used to generate power, enrich soil and act as food to animals.

III.MODULES

Module 1

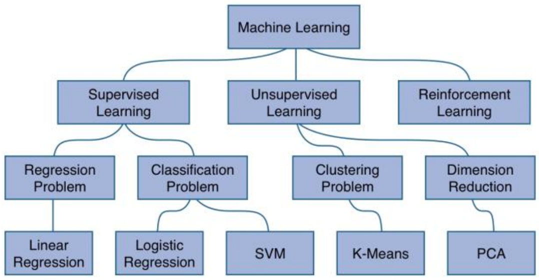
Machine Learning

Machine learning is the science of getting computers to act without being explicitly programmed. In the past decade, machine learning has given us self-driving cars, practical speech recognition, effective web search, and a vastly improved understanding of the human genome. Machine learning is so pervasive today that you probably use it dozens of times a day without knowing it. Many researchers also think it is the best way to make progress towards human-level AI. In this class, you will learn about the most effective machine learning techniques, and gain practice implementing them and getting them to work for you. More importantly, you'll learn about not only the theoretical underpinnings of learning, but also gain the practical know-how needed to quickly and powerfully apply these techniques to new problems. Finally, you'll learn about some of Silicon Valley's best practices in innovation as it pertains to machine learning and AI.

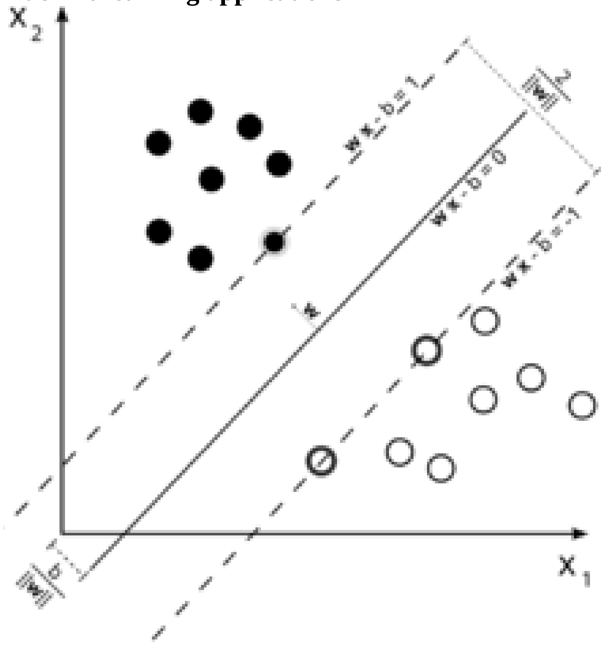
Machine learning tasks

Machine learning tasks are typically classified into several broad categories:

- Supervised learning: The computer is presented with example inputs and their desired outputs, given by a "teacher", and the goal is to learn a general rule that maps inputs to outputs. As special cases, the input signal can be only partially available, or restricted to special feedback.
- Semi-supervised learning: The computer is given only an incomplete training signal: a training set with some (often many) of the target outputs missing.
- Active learning: The computer can only obtain training labels for a limited set of instances (based on a budget), and also has to optimize its choice of objects to acquire labels for. When used interactively, these can be presented to the user for labeling.
- Unsupervised learning: No labels are given to the learning algorithm, leaving it on its own to find structure in its input. Unsupervised learning can be a goal in itself (discovering hidden patterns in data) or a means towards an end (featurelearning).
- Reinforcement learning: Data (in form of rewards and punishments) are given only as feedback to the program's actions in a dynamic environment, such as driving a vehicle or playing a game against an opponent.



Machine learning applications



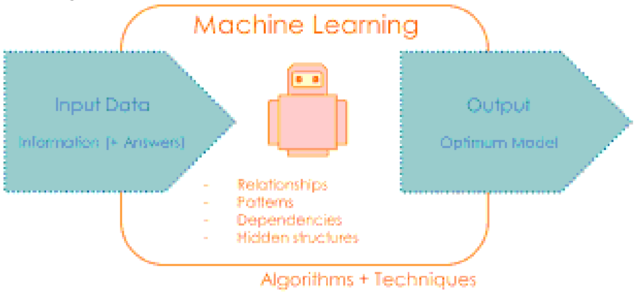
A support vector machine is a classifier that divides its input space into two regions, separated by a linear boundary. Here, it has learned to distinguish black and white circles.

Another categorization of machine learning tasks arises when one considers the desired *output* of a machine-learned system:

- In classification, inputs are divided into two or more classes, and the learner must produce a model that assigns unseen inputs to one or more (multi-label classification) of these classes. This is typically tackled in a supervised way. Spam filtering is an example of classification, where the inputs are email (or other) messages and the classes are "spam" and "not spam".
- In regression, also a supervised problem, the outputs are continuous rather than discrete.
- In clustering, a set of inputs is to be divided into groups. Unlike in classification, the groups are not known beforehand, making this typically an unsupervised task.
- Density estimation finds the distribution of inputs in some space.
- Dimensionality reduction simplifies inputs by mapping them into a lower-dimensional space. Topic modeling is a related problem, where a program is given a list of human language documents and is tasked to find out which documents cover similar topics.

Among other categories of machine learning problems, learning to learn learns its own inductive bias based on previous experience. Developmental learning, elaborated for robot learning, generates its own sequences (also called curriculum) of learning situations to cumulatively acquire repertoires of novel skills through autonomous self-exploration and social interaction with human teachers and using guidance mechanisms such as active learning, maturation, motor synergies, and imitation.

Theory



A core objective of a learner is to generalize from its experience. Generalization in this context is the ability of a learning machine to perform accurately on new, unseen examples/tasks after having experienced a learning data set. The training examples come from some generally unknown probability distribution (considered representative of the space of occurrences) and the learner has to build a general model about this space that enables it to produce sufficiently accurate predictions in new cases. The computational analysis of machine learning algorithms and their performance is a branch of theoretical computer science known as computational learning theory. Because training sets are finite and the future is uncertain, learning theory usually does not yield guarantees of the performance of algorithms. Instead, probabilistic bounds on the performance are quite common. The bias–variance decomposition is one way to quantify generalization error. For the best performance in the context of generalization, the complexity of the hypothesis should match the complexity of the function underlying the data. If the hypothesis is less complex than the function, then the model has under fit the data. If the complexity of the model is increased in response, then the training error decreases. But if the hypothesis is too complex, then the model is subject to over fitting and generalization will be poorer. In addition to performance bounds, computational learning theorists study the time complexity and feasibility of learning. In computational learning theory, a computation is considered feasible if it can be done in polynomial time. There are two kinds of time complexity results. Positive results show that a certain class of functions can be learned in polynomial time. Negative results show that certain classes cannot be learned in polynomial time.

Module 2

Internet of Things

The Internet of things (IoT) is the network of physical devices, vehicles, home appliances, and other items embedded with electronics, software, sensors, actuators, and connectivity which enables these things to connect, collect and exchange data, creating opportunities for more direct integration of the physical world into computer-based systems, resulting in efficiency improvements, economic benefits, and reduced human exertions.The number of IoT devices increased 31% year-over-year to 8.4 billion in the year 2017 and it is estimated that there will be 30 billion devices by 2020.[10]The global market value of IoT is projected to reach $7.1 trillion by 2020. IoT involves extending Internet connectivity beyond standard devices, such as desktops, laptops, smartphones and tablets, to any range of traditionally dumb or non-internet-enabled physical devices and everyday objects. Embedded with technology, these devices can communicate and interact over the Internet, and they can be remotely monitored and controlled. With the arrival of driverless vehicles, a branch of IoT, i.e. the Internet of Vehicle starts to gain more attention.

Consumer applications: A growing portion of IoT devices are created for consumer use, including connected vehicles, home automation/smart home, wearable technology, connected health, and appliances with remote monitoring capabilities.

Smart home: IoT devices are a part of the larger concept of home automation, which can include lighting, heating and air conditioning, media and security systems. Long term benefits could include energy savings by automatically ensuring lights and electronics are turned off. A smart home or automated home could be based on a platform or hubs that control smart devices and appliances. For instance, using Apple's HomeKit, manufacturers can get their home products and accessories be controlled by an application in iOS devices such as the iPhone and the Apple Watch. This could be a dedicated app or iOS native applications such as Siri. This can be demonstrated in the case of Lenovo's Smart Home Essentials, which is a line of smart home devices that are controlled through Apple's Home app or Siri without the need for a Wi-Fi bridge. There are also dedicated smart home hubs that are offered as standalone platforms to connect different smart home products and these include the Amazon Echo, Apple's HomePod, and Samsung's SmartThings Hub.

Elder care

One key application of smart home is to provide assistance for those with disabilities and elderly individuals. These home systems utilize assistive technology to accommodate an owner's specific disabilities. Voice control can assist users with sight and mobility limitations while alert systems can be connected directly to Cochlear implants worn by hearing impaired users. They can also be equipped with additional safety features. These features can include sensors that monitor for medical emergencies such as falls or seizures. Smart home technology applied in this way can provide users with more freedom and a higher quality of life. The term "Enterprise IoT" refers to devices used in business and corporate settings. By 2019, it is estimated that EIoT will account for 9.1 billion devices.

Medical and healthcare

The futurologist's vision seems to be that soon you will share your exercise levels, heart rate, activity, and other essential data accumulated by your mobile device with your doctor. "More and more care will be delivered outside hospitals and clinics", "This means mobile devices – from smartphones to monitoring devices – will become increasingly important as the number of patients cared for at home or in sheltered accommodation or other community centers increases." IoT devices can be used to enable remote health monitoring and emergency notification systems. These health monitoring devices can range from blood pressure and heart rate monitors to advanced devices capable of monitoring specialized implants, such as pacemakers, Fitbit electronic wristbands, or advanced hearing aids. Some hospitals have begun implementing "smart beds" that can detect when they are occupied and when a patient is attempting to get up. It can also adjust itself to ensure appropriate pressure and support is applied to the patient without the manual interaction of nurses. A 2015 Goldman Sachs report indicated that healthcare IoT devices "can save the United States more than $300 billion in annual healthcare expenditures by increasing revenue and decreasing cost. Recent contributions even refer to IoT solutions for medicine as the Internet of Medical Things. Specialized sensors can also be equipped within living spaces to monitor the health and general well-being of senior citizens, while also ensuring that proper treatment is being administered and assisting people regain lost mobility via therapy as well. Other consumer devices to encourage healthy living, such as connected scales or wearable heart monitors, are also a possibility with the IoT. End-to-end health monitoring IoT platforms are also available for antenatal and chronic patients, helping one manage health vitals and recurring medication requirements. The Research & Development Corporation (DEKA), a company that creates prosthetic limbs, has created a battery-powered arm that uses myoelectricity, a device that converts muscle group sensations into motor control. The arm is nicknamed Luke Arm after Luke Skywalker (Star Wars).

Transportation

The IoT can assist in the integration of communications, control, and information processing across various transportation systems. Application of the IoT extends to all aspects of transportation systems (i.e. the vehicle, the infrastructure, and the driver or user). Dynamic interaction between these components of a transport system enables inter and intra vehicular communication, smart traffic control, smart parking, electronic toll collection systems, logistic and fleet management, vehicle control, and safety and road assistance. In Logistics and Fleet Management for example, The IoT platform can continuously monitor the location and conditions of cargo and assets via wireless sensors and send specific alerts when management exceptions occur (delays, damages, thefts, etc.). If combined with Machine Learning then it also helps in reducing traffic accidents by introducing drowsiness alerts to drivers and providing self driven cars too.

Building and home automation

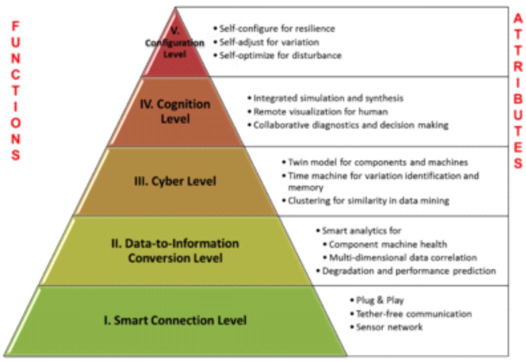
IoT devices can be used to monitor and control the mechanical, electrical and electronic systems used in various types of buildings (e.g., public and private, industrial, institutions, or residential) in home automation and building automation systems. In this context, three main areas are being covered in literature:

- The integration of the Internet with building energy management systems in order to create energy efficient and IOT driven "smart buildings".
- The possible means of real-time monitoring for reducing energy consumption[61] and monitoring occupant behaviors.
- The integration of smart devices in the built environment and how they might to know who to be used in future applications.

Industrial applications

Manufacturing

The IoT can realize the seamless integration of various manufacturing devices equipped with sensing, identification, processing, communication, actuation, and networking capabilities. Based on such a highly integrated smart cyberphysical space, it opens the door to create whole new business and market opportunities for manufacturing. Network control and management of manufacturing equipment, asset and situation management, or manufacturing process controlbring the IoT within the realm of industrial applications and smart manufacturing as well. The IoT intelligent systems enable rapid manufacturing of new products, dynamic response to product demands, and real-time optimization of manufacturing production and supply chain networks, by networking machinery, sensors and control systems together. Digital control systems to automate process controls, operator tools and service information systems to optimize plant safety and security are within the purview of the IoT. But it also extends itself to asset management via predictive maintenance, statistical evaluation, and measurements to maximize reliability. Smart industrial management systems can also be integrated with the Smart Grid, thereby enabling real-time energy optimization. Measurements, automated controls, plant optimization, health and safety management, and other functions are provided by a large number of networked sensors. The term industrial Internet of things (IIoT) is often encountered in the manufacturing industries, referring to the industrial subset of the IoT. IIoT in manufacturing could generate so much business value that it will eventually lead to the fourth industrial revolution, so the so-called Industry 4.0. It is estimated that in the future, successful companies will be able to increase their revenue through Internet of things by creating new business models and improve productivity, exploit analytics for innovation, and transform workforce. The potential of growth by implementing IIoT will generate $12 trillion of global GDP by 2030.



Design architecture of cyber-physical systems-enabled manufacturing system while connectivity and data acquisition are imperative for IIoT, they should not be the purpose, rather the foundation and path to something bigger. Among all the technologies, predictive maintenance is probably a relatively "easier win" since it is applicable to existing assets and management systems. The objective of intelligent maintenance systems is to reduce unexpected downtime and increase productivity. And to realize that alone would generate around up to 30% over the total maintenance costs. Industrial big data analytics will play a vital role in manufacturing asset predictive maintenance, although that is not the only capability of industrial big data. Cyber-physical systems (CPS) are the core technology of industrial big data and it will be an interface between human and the cyber world. Cyber-physical systems can be designed by following the 5C(connection, conversion, cyber, cognition, configuration) architecture, and it will transform the collected data into actionable information, and eventually interfere with the physical assets to optimize processes. An IoT-enabled intelligent system of such cases was proposed in 2001 and later demonstrated in 2014 by the National Science Foundation Industry/University Colla borative Research Center for Intelligent Maintenance Systems (IMS) at the University of Cincinnati on a band saw machine in IMTS 2014 in Chicago. Bandsaw machines are not necessarily expensive, but the bandsaw belt expenses are enormous since they degrade much faster. However, without sensing and intelligent analytics, it can be only determined by experience when the band saw belt will actually break. The developed prognostics system will be able to recognize and monitor the degradation of band saw belts even if the condition is changing, advising users when is the best time to replace the belt. This will significantly improve user experience and operator safety and ultimately save on costs.[72] Please see intelligent maintenance system for more reference.

Agriculture

There are numerous IoT applications in farming such as collecting data on temperature, rainfall, humidity, wind speed, pest infestation, and soil content. This data can be used to automate farming techniques, take informed decisions to improve quality and quantity, minimize risk and waste, and reduce effort required to manage crops. For example, farmers can now monitor soil temperature and moisture from afar, and even apply IoT-acquired data to precision fertilization programs. In August 2018, Toyota Tsusho began a partnership with Microsoft to create fish farming tools using the Microsoft Azure application suite for IoT technologies related to water management. Developed in part by researchers from Kindai University, the water pump mechanisms use artificial intelligence to count the number of fish on a conveyor belt, analyze the number of fish, and deduce the effectiveness of water flow from the data the fish provide. The specific computer programs used in the process fall under the Azure Machine Learning and the Azure IoT Hub platforms.

Infrastructure applications

Monitoring and controlling operations of sustainable urban and rural infrastructures like bridges, railway tracks, on- and offshore- wind-farms is a key application of the IoT. The IoT infrastructure can be used for monitoring any events or changes in structural conditions that can compromise safety and increase risk. IoT can benefit the construction industry by cost saving, time reduction, better quality workday, paperless workflow and increase in productivity. It can help in taking faster decisions and save money with Real-Time Data Analytics. It can also be used for scheduling repair and maintenance activities in an efficient manner, by coordinating tasks between different service providers and users of these facilities. IoT devices can also be used to control critical infrastructure like bridges to provide access to ships. Usage of IoT devices for monitoring and operating infrastructure is likely to improve incident management and emergency response coordination, and quality of service, up-times and reduce costs of operation in all infrastructure related areas.[76] Even areas such as waste management can benefitfrom automation and optimization that could be brought in by the IoT.

Metropolitan scale deployments

There are several planned or ongoing large-scale deployments of the IoT, to enable better management of cities and systems. For example, Songdo, South Korea, the first of its kind fully equipped and wired smart city, is gradually being built, with approximately 70 percent of the business district completed as of June 2018. Much of the city is planned to be wired and automated, with little or no human intervention. Another application is a currently undergoing project in Santander, Spain. For this deployment, two approaches have been adopted. This city of 180,000 inhabitants has already seen 18,000 downloads of its city smartphone app. The app is connected to 10,000 sensors that enable services like parking search, environmental monitoring, digital city agenda, and more. City context information is used in this deployment so as to benefit merchants through a spark deals mechanism based on city behavior that aims at maximizing the impact of each notification. Other examples of large-scale deployments underway include the Sino-Singapore Guangzhou Knowledge City; work on improving air and water quality, reducing noise pollution, and increasing transportation efficiency in San Jose, California; and smart traffic management in western Singapore. French company, Sigfox, commenced building an ultra-narrowband wireless data network in the San Francisco Bay Area in 2014, the first business to achieve such a deployment in the U.S. It subsequently announced it would set up a total of 4000 base stations to cover a total of 30 cities in the U.S. by the end of 2016, making it the largest IoT network coverage provider in the country thus far. Another example of a large deployment is the one completed by New York Waterways in New York City to connect all the city's vessels and be able to monitor them live 24/7. The network was designed and engineered by Fluidmesh Networks, a Chicago-based company developing wireless networks for critical applications. The NYWW network is currently providing coverage on the Hudson River, East River, and Upper New York Bay. With the wireless network in place, NY Waterway is able to take control of its fleet and passengers in a way that was not previously possible. New applications can include security, energy and fleet management, digital signage, public Wi-Fi, paperless ticketing and others.

Energy management

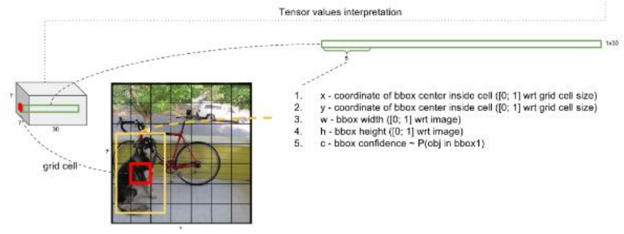
Significant numbers of energy-consuming devices (e.g. switches, power outlets, bulbs, televisions, etc.) already integrate Internet connectivity, which can allow them to communicate with utilities to balance power generation and energy usage and optimize energy consumption as a whole. These devices allow for remote control by users, or central management via a cloud-based interface, and enable functions like scheduling (e.g., remotely powering on or off heating systems, controlling ovens, changing lighting conditions etc.). The Smart grid is a utility-side IoT application; systems gather and act on energy and power-related information to improve the efficiency of the production and distribution of electricity. Using advanced metering infrastructure (AMI) Internet-connected devices, electric utilities not only collect data from end-users, but also manage distribution automation devices like transformers.

Environmental monitoring

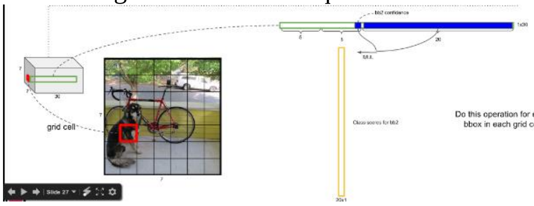
Environmental monitoring applications of the IoT typically use sensors to assist in environmental protection by monitoring air or water quality, atmospheric or soil conditions, and can even include areas like monitoring the movements of wildlife and their habitats. Development of resource-constrained devices connected to the Internet also means that other applications like earthquake or tsunami early-warning systems.

IV.WORKING

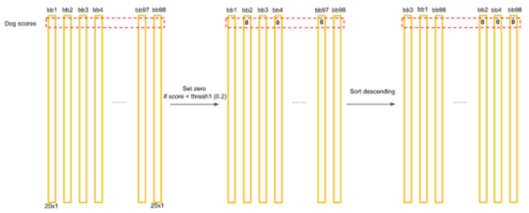
The working of this project is based on the YOLO Algorithm. Which states that You Only Look Once. With the help of this Algorithm, the system is able to detect any object which lies infront of it. It is able to detect the object with the help of the camera attached to the module. The camera is able to detect the objects which lie in the perimeter of it's range. It then compares the detected object with the one from it's existing library. To detect each object the object is divided into grid cells.



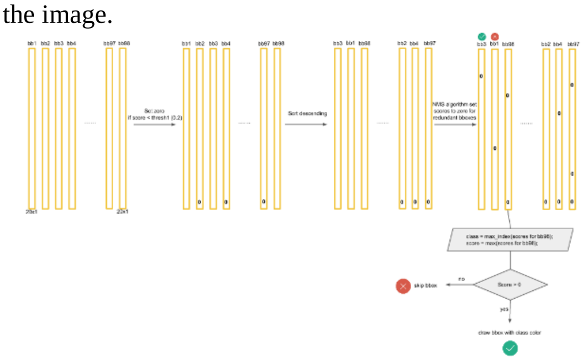
For every grid cell, you will get two bounding boxes, which will make up for the starting 10 values of the 1*30 tensor. The remaining 20 denote the number of classes. The values denote the class score, which is the conditional probability of object belongs to class i, if an object is present in the box.Next, we multiply all these class score with bounding box confidence and get class scores for different bounding boxes. We do this for all the grid cells. That is equal to 7*7*2 = 98.



Now we have class scores for each bounding box(Tensor dimension=20*1). Now let us focus on the dog in the image. The dog score for the bounding boxes will be present in (1,1) of the tensor in all the bounding box scores. We will now set a threshold value of scores and sort them descendingly.



Now we will use Non-max supression algorithm to set score to zero for redundant boxes. Consider you have dog score for boundingbox1 as 0.5 and let this be the highest score and for box47 as 0.3. We will take an Intersection over Union of these values and if the value is greater than 0.5, we will set the value for box2 as zero, otherwise, we will continue to the next box. We do this for all boxes. After all this has been done, we will be left with 2–3 boxes only. All others will be zero. Now, we select bbox to draw by class score value. This is explained in the image.



V.CONCLUSION

To conclude this project, the main algorithm required for the working is ready. Adding the Biodegradable dataset, the system will be able to detect and distinguish between both Biodegradable and Non-Biodegradable waste materials. With the help of this it will issue a flag=0 for Biodegradable and flag=1 for Non-Biodegradable. With these flags the Raspberry Pi will give the output to GPIO ports weather the trash will be going in Port A or Port B. Port A is for Biodegradable substances and Port B is for Non-Biodegradable substances.

VI.FUTURE ASPECT

In future we will be improving the image recognition speed of the whole mechanism by using the YOLT algorithm. It states You Only Look Twice.Also the whole mechanism will be made automatic in which more specification of waste will also be added like Toxic waste, Nuclear Waste and Radioactive Waste. To handle this kind of waste more and more expensive and sophisticated instruments will need to be added in the mechanical rig.

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