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DETECTION AND CLASSIFICATION OF WASTE FOR SEGREGATION AND EFFICIENT RECYCLING BASED ON MACHINE LEARNING

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ABSTRACT: Waste management is a prevalent problem in the world today and is increasing with the rise of urbanization. For ecologically sustainable development, waste management is an important necessity in many countries. In developed countries such as India, improving management needs are generally recognised by officials. However, no attempt has been made to strengthen the condition and to make long-term improvements. We know that India's population is equal to 19.6 percent of the world's population. With the growth of intelligent cities in India, a smart waste management system is important. Since the volume of waste generated on a regular basis continues to increase. As the waste produced exceeds 2,5 billion tonnes, the best solution to dealing with this issue is important. The waste must be sorted in a basic manner so that it is possible for the landfill sites to ensure that waste is disposed of properly. Sorting waste necessitates the recruiting of new workers as well as additional time. Waste can be sorted and handled using a number of methods. The study and evaluation of waste using image processing may be a highly efficient tool in the waste management process. The conventional techniques of waste management are discussed in these articles. These often describe the pitfalls and means of solving the current structures. The paper also introduces a device specification for the removal of human work and advocates automated waste isolation.

KEY WORDS: Separation of waste, Waste Classification, Machine Learning, Image processing, Convolutional Neural Networks, Support Vector Machine

1. INTRODUCTION

As part of a recent study, the World Bank announced that there is an accumulation of waste across the world that has an average amount of $4 trillion each year, and this accumulation is also growing by 70% by 2025. The output of emissions from the least developed countries is projected to grow noticeably over the next 25 years. Solid waste, which includes paper, wood, chemicals, metals, glass, and other products, is becoming more stable on a global basis as a result of the development of manufacturing in metropolitan areas. Environmental contamination consists of garbage, which is a very expensive commodity that is toxic to the natural world. The health of the people living on the site would be impacted by the location of the facility, such as its proximity to a community and the quality of service. Incineration or burning is one means of dealing with garbage. Inside the combustion chamber, as one mixes fuel with waste, the released flame can not only burn off the waste, but can also pollute the environment. In order to protect the atmosphere and the wellbeing of customers, it is important to compost and separate waste into many different types of products that can be recycled using multiple processes, such as incineration.

Isolation and waste recovery should be facilitated in order to create a healthy environment. In the current separation and recycling process, the aim is to use a collection of large filters to extract and replace waste by hand with an automated waste sorting system, resulting in a reduction in energy use due to the reuse of energy. This ban will have a positive effect on the climate as well as economic opportunities. Any waste management solutions are not cost-effective. The management of waste The financial payments for long-term management of the environment, such as habitats, livestock and biodiversity, which are often far-flung and impossible to take into account, are environmental costs alone. When we press on with our everyday lives, the effect on the environment will become more pronounced.

In our landfills, there is a large amount of waste that can be stored. It is, however, necessary to eliminate all of the valuable recirculation products.

A division is typically classified into categories by naming each category after a law defined by an authority or person. Image segmentation has historically been incredibly difficult due to computing power limitations and a limited set of image images. While neural network software has advanced in recent years, it now has a much higher processing power and can accommodate much larger data sets. Two primary steps of proper identification and isolation include the proper treatment of the waste. In order to determine which form of material the waste is made of, sophisticated isolation techniques have been used. This requires the use of several processes to differentiate the various materials based on their mass or particle size. This is the most critical method before waste separation, so machine learning and image processing methods can or may not be used.

One of the various approaches used for analyzing vision data may be deep learning. This means that hardware processors can accommodate a larger range of software modules at once. In essence, CNN functions are similar to those of Neural Networks of equivalent capacity. To begin with, the Neural Networks technique is an achievable challenge. Between the neurons of the bio-. For the recognition of images, the neural network (CNN) seems to be more fitting. CNN helps you to automatically pick and discard forms in order to prevent those distracting final image attributes. In the field of image recognition, there is a lack of data available from deep learning research, but deep learning shows limited development. With multiple samples collected from a garbage bin, we selected a set of experimental data.

The Committee has made efforts to improve the classification of images and to increase the robustness of the networks of classification. According to this study, the Sage Bird data collection network's deeper network and short-circuit connections will be inadequate in this area of profound learning. In order to improve network reliability by analyzing and changing network configuration in the TrashNet data collection process, we are finding a suggested solution. Extending a network is achieved by utilizing additional layers that rely on the current network to link anything. Because of the amount of processing needed, this will take advantage of a minimum number of characteristics. The reliability of the enhanced network is significantly strengthened by using the isolation between the main network and the exception network to protect the security of the system. GPU (Graphics Processing Unit) is a major development in digital graphics over the past few decades, significantly increasing the computer's computing power and reducing the time it takes to process vast volumes of image data.

The issue of environmental pollution is getting more and more serious with the growth of human society [1], and environmental pollution is causing considerable harm to the earth and all its organisms[2]. Among them, household garbage is responsible for much of the waste. The decomposition of such household waste can result in a high concentration of chemical substances in the atmosphere [3], resulting in harm to the environment. Any domestic wastes that rarely biodegrade are also available. Plastics, for example, are a global pollutant that can be present in all aquatic ecosystems [4]. Consequently, the first step in addressing waste contamination is to identify the waste according to its nature. Many countries around the world need waste to be disposed of separately [5]. Jun Wang was the associate editor who organized the review of this manuscript and accepted it for publication.

Nevertheless, it is very difficult for anyone who lack technical experience to correctly classify all sorts of domestic trash. This topic can be solved by the intelligent garbage classification system. Applying it to intelligent garbage bins or smart phones will direct individuals to better dump domestic garbage. At present, the challenge is that the intelligent garbage classification system is unable to correctly categorize garbage images.

2. LITERATURE REVIEW

At present, waste is subdivided by many devices into various categories [6]. There aren't so many of them.

- Trommel separators / Drum Screen-A revolving drum perforated with troughs is found in the Drum Splitter. This sorting system sorts waste into various sizes. Smaller particles migrate into the troughs as waste flows through the battery, while larger particles linger in the battery.
- Eddy current separator—This device is used to isolate various metallic materials from waste. It works by separating waste into ferrous and non-ferrous metal groups using an electromagnetic process.

- Sorting induction- With a variety of sensors, this device transmits the waste material to a conveyor belt. The sensor helps to distinguish inside the waste the various kinds of metals. The metals that have been established are divided into a quick-air jet device that is attached to the sensors.
- Near-infrared sensors (NIR) – Since different materials have different reflective properties, the reflectance property used in this device is the parameter used to distinguish between different waste materials.
- X-ray technology- In order to differentiate them, this device uses the density properties of various materials.
- Finally, the most commonly used approach is the manual method for the isolation of waste. This is where the waste is manually sorted.

While the approaches mentioned above work well on a small scale, they are inefficient on a large scale. To a significant degree, these computers are difficult to maintain. With the amount of waste generated a day now in mind, it is important to buy several of these devices. But buying and repairing these computers would prove exceedingly expensive. These methods are often fundamentally unreliable, especially the manual method, which is vulnerable to multiple errors.

The aim of research in [7] is to automate this process by applying techniques of machine learning to the detection of waste in its images. Deep learning with CNNs and vector support machines are two common learning algorithms that have been used (SVMs). A different classifier is generated for each algorithm, which divides waste into three main categories: plastic, paper, and metal, using a 256 to 256 colored png waste file. The accuracy provided by both classifier models was compared in order to choose the best one, and the one chosen by the Raspberry Pi 3 was implemented. The pi was in charge of a mechanical device that directed the waste from its original location to the suitable waste container.

The author here uses the two techniques of machine learning just to test their speed of classification and apply the best models on the pi. The findings suggest that SVM achieved a high precision of 94.8 percent, while CNN achieved 83 percent of the same accuracy. SVM has displayed an excellent adaptation to diverse forms of waste. The CNN training NVIDIA DIGITS was used by George E Sakr et al., and the SVM training Matlab 2016a was used by George E Sakr et al. In the analysis of the author in the training sets, the drawback was the limited number of pictures. The images were shrunk down from their original resolution of 256 x 256 to 32 x 32 pixels. Overfitting became more of a concern as a result of this decline. The last model introduced in this study had a very low average time for execution of raspberry pi 3 (0.1s).

A team has developed the AutoTrash Project [8], an automated trash can sorting system that distinguishes the garbage from the compost and recycling properties. To identify the object, the team used Google's tensorflow program and created its own individual layer. The can is separated into various areas and the spinning top can position the object in its respective areas on the basis of its designation. Auto Trash will only divide items into recyclable or compostable categories, but classifying items into more than two categories will be more helpful for recycling.

Spot Garbage [9] is a smartphone-based technology. It senses a waste pile and uses the mobile access location to locate the location of the waste. In order to classify image waste, the program uses neural convolution networks. This model is equipped to an absolute 87 percent precision using the GINI (Picture garbage) dataset. Person users can use this app to report trash in their immediate surroundings. The authors learned the model with the use of patches derived from the Bing Image Searches. This analysis shows case studies in which the amount of memory used is minimized, and the estimation time taken with zero accuracy errors decreases the amount of space used on the computer.

In [10], the division of waste into six groups was studied, such as metal, paper, cardboard, etc. A compilation of 400 plus pictures per category, using a dataset, was carried out by hand. The model used to divide the images into various groups were the Scale-Invariant Transforming Functions (SIFT) supporting vector machines and the Convolutionary Neural Networking. In this scenario, an eleven-layer CNN architecture was used to implement a network that was somewhat similar to AlexNet. The reliability of the SVM relative to CNN has been shown in experiments. 70% of the data was used to train the algorithm, with the remaining 30% being used for testing. With a training error of 30%, 63 percent of the accuracy was reached. No optimal hyper parameters were found and so those categories were omitted in order to detect optimum precision, suggesting that the use of CNN was not thoroughly qualified.

The Gray Level Co-Event Matrix (GLCM) approach for waste detection and classification is discussed by the author in paper [11]. Advanced contact mechanization and GLCM have been merged in order to improve the function of the waste assembly. In order to decide the finest parameter values in waste images, scrolling and quantification are GLAM parameters that have been tested. To fix the current problems and to simplify the control and efficiency of solid wastes, the proposed scheme incorporates a number of networking technologies such as geographic information systems (GIS), RFID, and general packet radio systems (GPRS). Functionality is derived from the GLCM and used as inputs to the multi-layer (MLP) panel and the nearest K K for waste segregation (KNN). The results backed up the conclusion that the KNN classification is used.

In [12], a groundbreaking approach is put forward by the author to quantify the similarity between different types and to classify the object using the result obtained. The authors assess similarities in their sense by evaluating competitiveness among points selected on the two considered shapes and then applying conformity to establish an alignment transformation. A descriptor is assigned to each point as the background of the shape to solve the symmetry problem. In relation to the type sense, which provides a distinctive feature of separation, the remaining points are captured at the reference point. The dimensional contexts of corresponding points on two identical forms would be the same, thus solving correspondence between them. According to the point rivals, the best transfiguration for coordinating the two modes is found.

Maps for the transition are given by regularized thin-plate splines. In a language that measures the weight of the alignment, the disparity between the types is calculated as the number of faults. In a closest-neighbour grouping system, the issue of identifying the template shape collected is assumed to be the description. The results are given for the contours, logos, numbers and the COIL dataset. One of the main characteristics of this approach is the estimation of shape similarities and rivalry according to the shape sense. This is a straightforward and straightforward procedure. It offers detailed descriptors for points, allowing for improved point recording, form recognition, and dimension matching. Many typical picture shifts, such as important 3D rotations of real-world objects, are seen to have variety in this experiment.

The author explains a technique [15] for classifying surfaces in real-world light that is unknown. The surfaces that are used are aluminum, plastic and paper. Their success illustrates the outcomes for surfaces of random geometry. The reflectance estimation algorithm reveals correlations between the surface reflectance and the data from the photograph. In real-world illumination, the spatial arrangement relies on statistical heterogeneity. Despite the fact that known geometry is used, this algorithm's statistic form is best suited to incorrect geometries. The reflective properties used in real-world surfaces of arbitrary geometry are used in this paper to distinguish objects from monochrome images.

To distinguish objects according to material identification, the author employs the Bayesian system [15]. By processing the surface of a single image, objects are recognized in different categories of material such as glass, metal, cloth, etc. Offer researchers a collection of low and mid-level features that are used to learn and accomplish various aspects of material presentation, as it is a challenging challenge to identify good, accurate, consistent features that can discern material from conventional object detection processes in different categories. In order to establish an optimal combination of characteristics, this paper proposes an LDA model that incorporates many features within a Bayesian framework.

A identification rate of 44.6 percent was reached by this method, effectively above the 23.8 percent state of the art. In consideration of the components, a Bayesian network and a large number of practical parameters are used. The identification rate for the suggested model has been improved by the ALDA system. In contrast with the state-of-the-art scheme, this enhanced efficacy and increased efficiency. The researchers have examined the contribution of each characteristic to the output benefit of the device. This was the first paradigm to use in order to see images in terms of their materialistic properties.

AlexNet is definitely among the most common CNN templates for picture recognition. The ImageNet Large Scale Visual Recognition Challenge (ILSVRC), which took place in 2012, won recognition. AlexNet is commonly used because of its simple architecture, not as deep, and effectiveness. It is also noted for its outstanding success for very large datasets. Because of its high quality, it became a state-of-the-art in the classification of images, resulting in increased success.

The author has trained a large, deep-seated neural network in [15], which classifies approximately one million high-resolution images into thousands of different groups. The test data produced error rates of 37.5 percent and 17.0 percent on top 1 and top 5, respectively, as compared to previous versions. There were nearly 60,000,000 neurons with five layers of convolution in the neural network. Any of them were sponsored by max pooling layers and with a 1,000-way max of three layers. To minimize overfitting, researchers used a strategy known as "dropout." To speed up training, non-saturating neurons were used, as well as a very powerful GPU implementation. The findings indicate that a large and detailed CNN can deliver very good results on complex datasets with supervised learning techniques.

Notice that the output of the entire network reduces, even though a single convolutionary layer is omitted. As a consequence, the depth of the whole neural network is crucial in producing successful and efficient outcomes. When the machine was conditioned and expanded for a long time, but still a long way to equal that of the human visual system, the study shows a range of changes.

3. PROPOSED METHODOLOGY

This approach is based on the detection, processing and separation of waste materials. The waste in question is disposed of in the garbage, but it is a potential health threat. The device attempts to analyze and mark waste autonomously, which essentially requires only minimal human intervention. The final waste management process relies on this sorting, which is possible, based on the size and type of the item. The system is trained using computer training methods called CNN in order to understand, so that it learns more. The administration of the machine would eventually waste and discard some parts of the waste in order to reduce human labour. For the purposes of expanding waste disposal, this may be a potential business cast-off. Below, this map shows how to construct a hypothetical system.

A technique called noise reduction is used for image processing to increase the clarity of the frame. Ensure that the supervision protocol is in effect prior to the introduction of an image processing algorithm, so that the image's context can be taken into account and the output does not get blurred. The aim is not to base the image's final outcome on arbitrary attributes, but rather to leave the image somewhat random with omitted unused and excess sections. The method of feature extraction was carried out and implemented. The number of attributes that are reported is minimized by an extraction feature. The feature extraction converts the characteristics that have been used with the model (current attributes). Ses features affect the model's performance in a predictive way (predictions). Feature extraction is a method that can be used to enhance the speed and reliability of supervised learning algorithms. The GLCM (Gray Level Matrix) algorithm is used to extract the function elements from the ion micro-structure. Generate the extracted knowledge and train the predictive classifier and calculate the algorithm's accuracy. A hybrid classifier (a combination of a CNN and an MLP) is used in order to classify waste.

CNN is a common instrument for detailed digital image processing. CNN is a coalition of cells inside the brain. CDN images would usually be exchanged in groups, but it is necessary to take them as individual input for the sake of this analysis. The CNN neurons of UNM are unique in the sense that they are 3D (distance, height, and depth). The CNN architecture is made up of various convolutional layers, sparsely distributed polling layers, entirely linked layers, and a final normalization layer. A small number of the neurons in the first layer (the convolutionary layer) are connected by neurons in the layer above it (the completely connected layer). All of the layer activation neurons in the fully entangled layers are completely connected to one another, forming a mirror image of the previous layer.

Modeling and predestination also use Multi-Layer Perceptron's (MLP), one of the most advanced nonlinear classification into a deep learning and as well as regression models. To provide all of the processing power needed, responsive neurons are organized in layers. Layers are known as large, complex concepts, created by small building blocks (inputs) with subtle variations in their shape (outputs). As seen in the paper by [12], the MLP in this study is made up of one hidden strata of ten neurons. Any command that is constant will be run by this network. In order to add the weighted inputs to each sheet, neurons are used to add a predictor to the sum, and then apply an activation function to process the sum and compare it with the outputs.

To model a human psychic-neural system, a hybrid CNN and Hybrid CNN-MLP interface was developed and used. Your system is made up of many interdependent subsystems, including (1) the image system, (2) and (3) the language identification system to help you identify what the key back-end is.

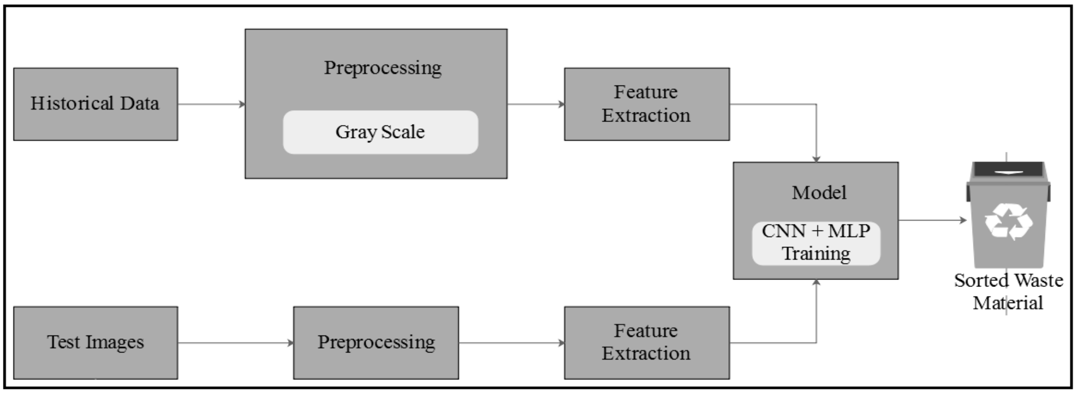

Fig.1. Proposed System Architecture

The next section will go through the three subsystems and relevant aspects of the interconnected architecture that has been illustrated. The direction of the arrows reflects the rhythm of work and interface contact. The computers will be able to keep track of what you have missed if you bring such waste materials into the Hybrid System. There is an included camera that CNN has tested that helps to capture the image. This user interface allows a person to enter numbers as part of a sensor system and capture them.

The machine gains maximum performance with a single CNN that supplies 22 outputs, and the entire numerical information from the sensor output. The location of top subject cells by a regression model is held in the MLP model in contrast to recent models that practice through a minimization of reasonable distances. And since CNN outputs are MLP inputs - and since CNN outputs are three-dimensional vectors - these models are capable of simultaneously generating binary classification effects.

4. DATA SET AND ITS SPECIFICITY

The data set used in this article is MobileNet and VGG16. There are 501 glass images, 594 paper images, 403 cardboard images, 482 plastic images, 410 metal images, and 137 garbage images in the 2527 RGB images. All of the photographs have a white backdrop and were shot in a well-lit setting. Both images have a file resolution of 512 X 384 pixels. Fig. 1 displays some of the MobileNet data set's garbage images.

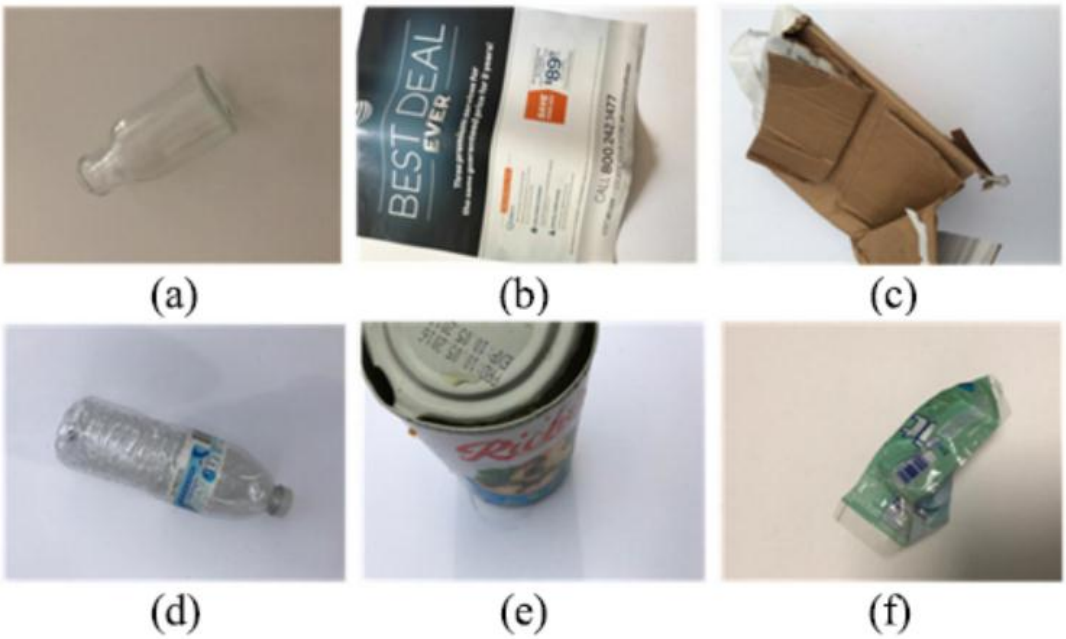

Fig. 2. Some garbage images of the MobileNet data set. (a) glass, (b) paper, (c) cardboard, (d) plastic, (e) metal, and (f) trash.

Unlike other classification data sets, each image in the MobileNet data set includes only one object, which can make the job simpler for humans but not for computers. The convolutionary neural network has the power to remove characteristics far beyond human eyes. For computers, it is not difficult to use the trained model[16] to find the specifics of all the positions in the picture. However, the amount of features that can be retrieved is limited for MobileNet data set images that only include a single object, so the fault tolerance is low. There are no other artifacts in the picture that can provide additional details about the function. If there are substantial variations between the sample object and its class, the effect would be dramatic. One of the most complicated garbage classification tasks is this one. The small number of details in the MobileNet knowledge collection is another challenge. Because of the time-consuming gradient back-propagation optimization, deep learning relies on large-scale data for massive parameter training [17]. The training phase can be very complicated, and perhaps substantially overfitting[18], where the data is inadequate. We next checked it quantitatively, because of the two challenges of the MobileNet dataset.

5. IMPLEMENTATION

In section 3, fig.1 displays the proposed architecture of the system. The framework consists of several components, including an input dataset, pre-processing, image segmentation, feature extraction, preparation, and testing with the CNN algorithm. We used the CNN algorithm to distinguish melanoma and non-melanoma pictures in our study.

The measures used in the development of our proposed framework are below.

1. Input a dataset of photographs into the device.

2. Image pre-processing is used to increase image clarity and eliminate hairs from the image.

3. From the input image dataset, many attributes are extracted and a training file is produced.

4. The CNN classification algorithm is applied to the newly developed training file dataset and the current test input images.

5. Waste identification is the result of the CNN algorithm, i.e. whether the input test indicates the type of waste.

6. Graphical assessment is carried out at the end to check the performance of the system proposed.

5.1 Mathematical Formulation for Proposed System

System S is represented as

S = {ID, P, F, T, CNN, M}

1. Input Dataset

ID = {i1, i2, i3…in}

Where ID is the input image dataset and i1, i2…in are the number of images.

2. Preprocessing

PR = {pr1, pr2, pr3}

PR is preprocessing and pr1, pr2 and pr3 are the steps to be carried out during preprocessing.

pr1 be the reading of input dataset

pr2 be the enhancement of image input and

pr3 be the removal of hair from image.

3. Feature Extraction

F= {f1, f2, f3…fn}

Where F is the set of features extracted from the image and f1, f2, f3… fn are the extracted features such as border, thickness, color, etc.

4. Training and Testing file generation

T = {T1, T2}

Where T is the set of Training and Testing file and T1 is Training file and T2 is Testing file both the files contains various extracted features values while training file contains class of each image as 0 or 1.

5. Convolutional Neural Network (CNN).

CNN = {C, RL, PO, FC, LS}

Where CNN is algorithm consisting of various stages as

C is convolutional operation

RL be the ReLU activation layer

PO be the Pooling layer

FC be the Full Connection layer and

LS be the Loss function.

6. Waste Classification

W= {0, 1, 2, 3, 4, 5}

W is the set of Class having value 0 to 5

0 be the glass

1 be the paper

2 be the cardboard

3 be the plastic

4 be the metal

5 be the trash

6. EXPERIMENTAL ANALYSIS

6.1 Experimental Setup

All of the tests are written in Python and run in an environment with an Intel Core i5-6200U, 2.30 GHz Windows 10 (64 bit) computer with 8GB of RAM, as well as Anaconda (Jupiter) methods, algorithms, and techniques, and a competing classification method with feature extraction technique.

6.2 Result Analysis

In Figure 3, the system's success analysis is portrayed. The performance parameters and precision for both the MobileNet and VGG16 datasets was compared in terms of MSE Failure and Crossentropy.

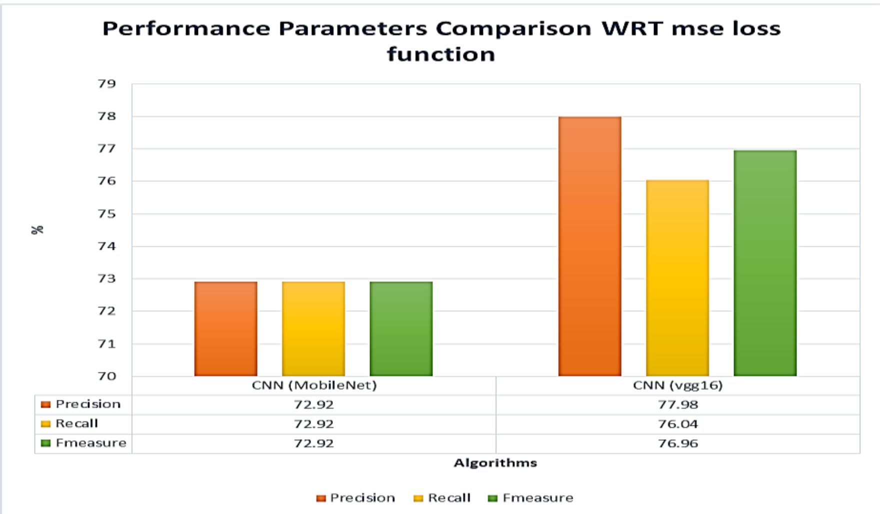

Fig. 3 Performance Analysis wrt Loss Function

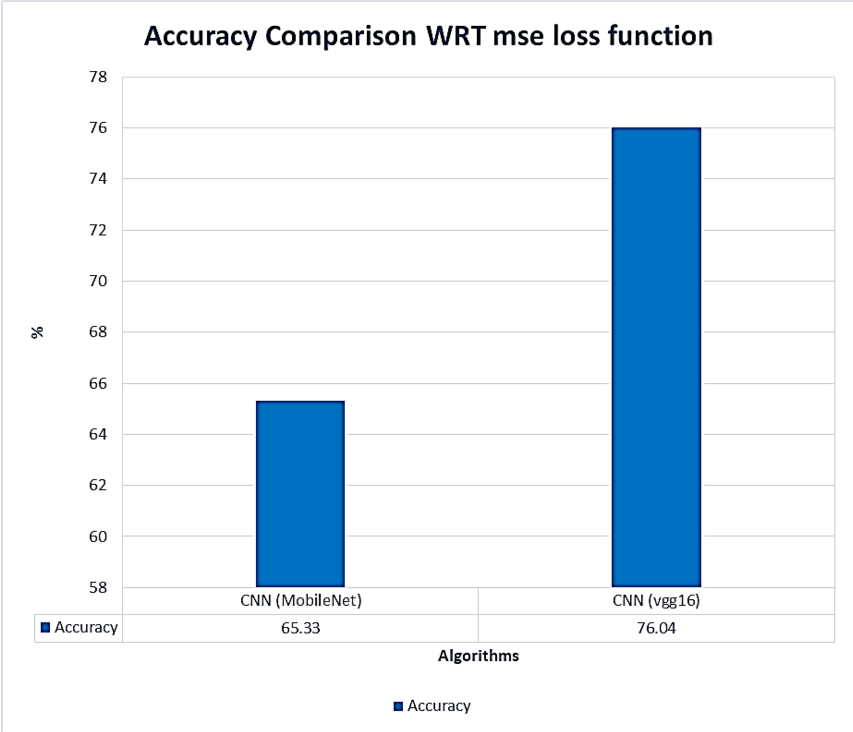

Fig. 4. Accuracy Comparision wrt Loss Function

The outcomes in Figures 4 demonstrate the importance and quality of the training and the accuracy of the validation. On each of the epochs, the training data is fed into the neural network and BackPropagation is performed for each epoch on every dataset. The average of the losses is deposited after each changing epoch and the mean is calculated. The damage is plotted against the age in which the procedure takes place and at which the brain is no longer able to cure or restore it. 4.

Fig. 5. Performance Analysis wrt to Crossentropy Loss

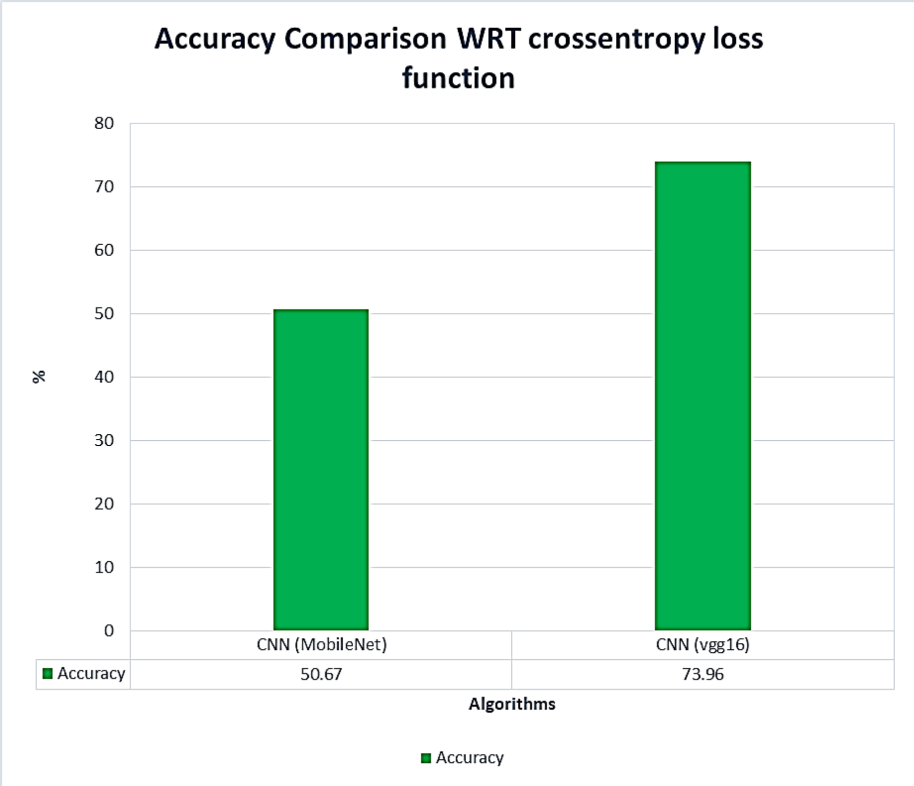

Fig. 6. Accuracy Comparison wrt Crossentropy Loss

7. CONCLUSION REMARKS

Many scientists and scholars have already carried out experiments and measurements in laboratories and other sites in order to find a way to cope with and prevent the pollution caused by refuse. In order to help with this method, different instruments have also been made, but they do not perform as well as others. Device modules such as raspberry pi have been used as a component to carry out the process in order to meet the target. Using the unit, the images of objects are scanned and then specifically marked without any errors. Although there are many solutions to these approaches, the systems are still under-protective, as all of these technologies can only be used on photographs of single objects that need to be identified and categorised with absolute accuracy. Convolution Neural Networks were considered to play a very important role in the process of goal identification and classification and can be shown to be the key step towards the advancement of such approaches. Methods and tests that can define the shape and dimension of objects have since been invented, but they are usually only used on objects that can fit under a certain category or size, which often makes it more difficult to distinguish such objects. For eg, how can you know that it is a certain shape after finding a scrap of metal on the side of a parking lot? Smaller than that, or bigger? Previously, features of different objects, such as the object's physical reflectance and even a classification dependent on the material used in the object, were often used to differentiate pictures. A variety of experiments of this type have concentrated on the detection and classification of single objects in recent years. Therefore, combined with the variety of datasets used by the algorithms to measure the precision and accuracy of the algorithms already used, the form of datasets that are reliable and hit the lower part of the merit number should be experimented with. This current scheme is meant to only classify a single entity in a digital image as an alternative to the human being in a single cell in a digital image. We had previously written to you that isolating individual objects from a pile of garbage in a real-life environment and then sorting them out would be incredibly complicated because the volume of trash present would be millions of tons, and it would take an extremely long time. As a result, several distinct and isolated objects must be used in a single image. While the updated varieties have fewer waste forms, they are also delightful in more ways than one. The residue from this is otherwise referred to as manure and recyclable waste. Items that are not recycled are split into recyclable and non-recyclable goods and all are separately subject to individual forms of recycling methods. Toss both of these recyclables into a single tub following the "Golden Law." It would make sorting recyclable products from garbage and waste into separate groups quicker and quicker throughout the recycling process.

There has been a significant rise in the usage of mobile devices over the past decade, according to the statistics, which can be attributed because of the exponential development of electronics and technology. Two years have passed and are significantly limited at the moment where the battery of a mobile fails. Our need to recover such a significant amount of electronic waste will rise as our use of electronic devices grows. Since of part is made of various materials (such as steel, aluminum, and gold), and each of these materials can be treated in different ways (for example, steel can be melted down, but not paper), recycling these parts becomes incredibly challenging. It is advantageous to provide a systematic mechanism for the disposal of electrical equipment and their replacement components.

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