PROGRESS REPORT

Final Year Project 1

Semester 2, 2018/2019

Bachelor of Computer Science

A. Project Information

Student(s)

1. Zian MD Afique Amin (1631005)
2. Khan Nasik Sami (1638153)

Project ID

533R

Project Title

Waste Management Using Machine Learning

Project Category

Research & Development

Supervisor

Dr Raini Binti Hassan

Table of Contents:

B. Introduction

Abstract

Waste Management is one of the essential issues that the world is currently facing does not matter if the country is developed or under developing. The key issue in this waste segregation is that the trash bin at open spots gets flooded well ahead of time before the beginning of the following cleaning process. The isolation of waste is totally done by unskilled workers which is less effective, time consuming and not totally plausible because of a lot of waste. So, we are proposing an automated waste classification problem utilizing Machine Learning algorithms. The goal of this task is to gather a dataset and arrange it into six classes consisting of glass, paper, and metal, plastic, cardboard, and waste. The model that we will use are classification models. For our project we will differentiate between four algorithms, those are CNN, SVM, Random Forest and Decision Tree. As our concern is a classification issue that is the reason, we have used a machine learning algorithm that is best for classifications. For our model, CNN accomplished high characterization on accuracy around 90.23%, while SVM additionally indicated an excellent transformation to various kinds of waste which was 85% and Random Forest and Decision Tree have accomplished 55% and 65% respectively.

Keywords: Image Classification, Trash Classification, Support Vector Machines, Convolutional Neural Networks, Random Forest, Precision, Recall, F1-support, Confusion Matrix

Problem Statement

The production of waste has increased dramatically in recent time. If waste is not managed properly, they can have a bad effect on the environment. So, the sorting of waste should be done at the initial stage possible, to maximize the number of recyclable items and reduce the possibility of contamination by other items.

Research Questions/ Hypothesis

1) What are the categories for segregation in this research?

Finding out whether a waste is paper, plastic, metal, glass materials or cardboard is the main target of this project. According to our training data provided in the dataset, we will try to determine the testing data to be detected by comparing the attributes of given examples.

2) What are the key features determining correct object:

At first the model will take an input picture at that point and separate the locale for that. At that point it will compare the features with the past trained data and toward the end it will order whether the provided data or object is matched with the trained model and how much is the accuracy. To show signs of improvement accuracy it is smarter to do some increase in the preparation information, so the object can be analyzed with different angles and views. It is additionally better to do reshaping in the pre-processing stage to keep all cases in a similar size.

3) Hypothesis:

By utilizing classification algorithms(CNN, SVM Decision Trees,), the model will help in seeing how the item can fluctuate from one another relying upon different factors, for example, comparing the grey scale images or RGB value that can range between 0 and 255. These qualities would then be able to be placed into a cluster. Another way is separating the pictures into little pieces and afterward placing them into neural layers and every one of the neural systems is placed into an exhibit. At that point we need to resize it while holding the subtleties of the picture. Then we must resize it while retaining the details of the image. After considering all the factors, the model will predict the accuracy of how likely an object will match with the trained sample.

Project Objective

1. To explore the dataset, which involves analyzing each feature variable to check if the variables are significant for building the model.
2. To visualize the dataset and find out incorrect images.
3. To build the model that will classify the images and sort them according to the classes.
4. To analysis the accuracy based on performance evaluation

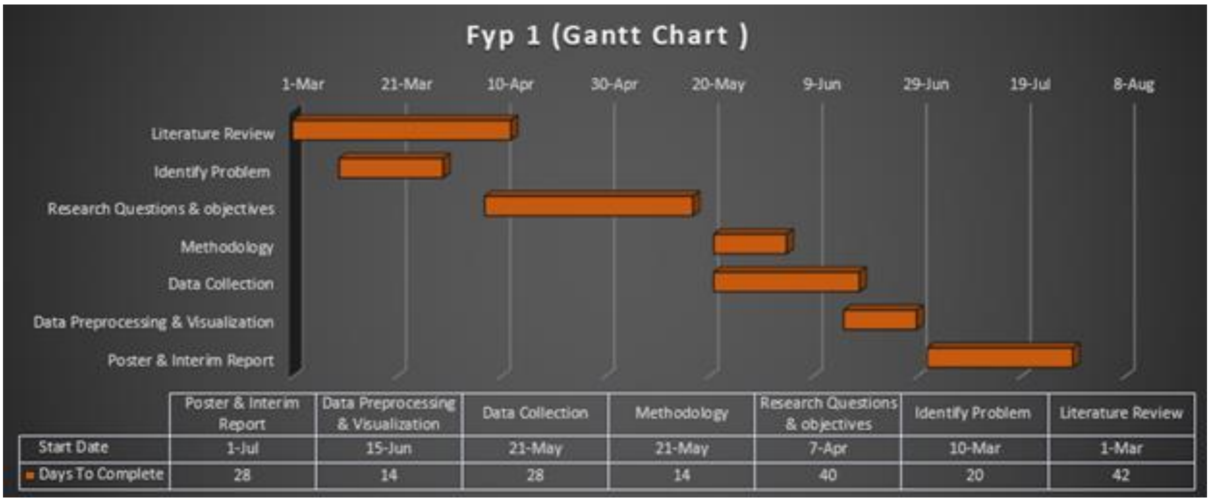
5. Finding out the best suitable algorithm for this process.

Significance of Project

The world creates nearly one and half billion tons of civil strong waste every year, as per the World Bank, and that figure is relied upon to hit 2.2 billion tons by 2025. Diversion of plastics from landfill to reusing can conceivably spare what might be compared to 60 million barrels of oil every year and lessen landfill volume necessities by up to 20%. The U.S. Natural Protection Agency has suggested that source decrease, reusing, volume decrease, and landfilling be applied, in a specific order, in the treatment of city strong waste (MSW). Reusing has as of late become a significant segment of city squander the executive’s programs. Proficient computerized innovation exists for recuperation of steel, aluminum, compostable food waste and paper items from MSW. These things make up the heft of MSW. In any case, the main existing strategy to recuperate glass and plastic holders from MSW is to physically handpick them from the waste. So, the execution of AI and Machine learning can carry a decent answer for managing this extraordinary issue and to keep our condition a superior spot for all to live in.

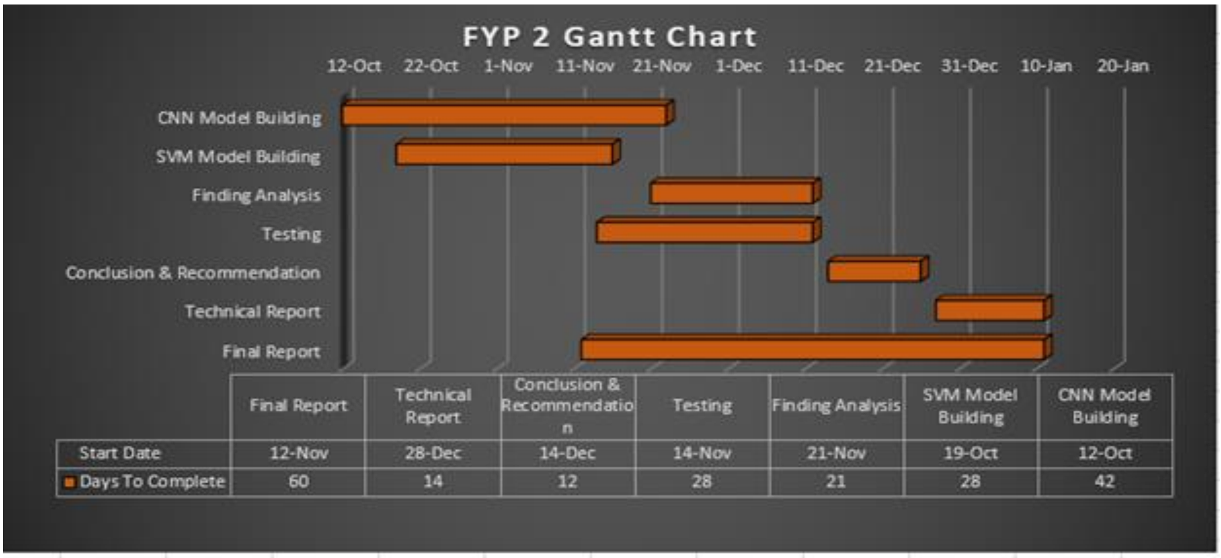
Project Schedule

Show the timeline (Gantt chart and milestone) of the execution of this project, including FYP1 and FYP2.



	Poster & Interim Report	Data Preprocessing & Visualization	Data Collection	Methodology	Research Questions & objectives	Identify Problem	Literature Review
Start Date	1-Jul	15-Jun	21-May	21-May	7-Apr	10-Mar	1-Mar
Days To Complete	28	14	28	14	40	20	42

Figure 1: FYP 1 Gantt Chart



	Final Report	Technical Report	Conclusion & Recommendation	Testing	Finding Analysis	SVM Model Building	CNN Model Building
Start Date	12-Nov	28-Dec	14-Dec	14-Nov	21-Nov	19-Oct	12-Oct
Days To Complete	60	14	12	28	21	28	42

Figure 2: FYP 2 Gantt Chart

C. Review of Previous Works

No	Year	Authors	Research Title	Main Technique Applied	Results	Future Works
1	2016	George E. Sakr, Maria Mokbel, Ahmad Darwich,Mia Nasr & Ali Hadi	Comparing Deep Learning And Support Vector Machines for Autonomous Waste Sorting	CNN, SVM,CNN AlexNet,Raspberry pi 3	SVM: 94.8% CNN: 84%	***1***.Increasing of images and varieties ***2***.By getting a dedicated machine learning server with 2 Tesla GPUs of 12GB memory each.

2	2018	Bernardo S. Costa, Aiko C. S. Bernardes, Julia V. A. Pereira, Vitoria H. Zampa, Vitoria A. Pereira, Guilherme F. Matos,Eduardo A. Soares, Claiton L. Soares, Alexandre F. Silva	Artificial Intelligence in Automated Sorting in Trash Recycling	Pre-trained VGG-16 , AlexNet, SVM, KNN,Random Forest	93%	
3.	2019	Olugboja Adedeji & Zenghui Wang	Intelligent Waste Classification System Using Deep Learning Convolutional Neural Network	Residual network(ResNet-50), CNN, SVM	87%	
4	2012	Alex Krizhevsky, Ilya Sutskever & Geoffrey E. Hinton	Image Net Classification with Deep Convolutional Neural Networks	Deep CNN,Dropout Method	Error rates of 37.5% and 17.0%	

5	2019	Praveen Kumar Gupta, Vidhya Shree, Lingayya Hiremath and Sindhu Rajendran	The Use of Modern Technology in Smart Waste Management and Recycling: Artificial Intelligence and Machine Learning	ANN	Glass object-58% Metal object-67%	
6	2019	Miko Pamintuan, Shiela Mae Mantiquilla, Hillary Reyes, Mary Jane Samonte	An Intelligent Trash Bin for Automatic Waste Segregation and Monitoring System	IOT devices and Image classification ML model	75%	
7	2016	Yang Mindy & Thung Gary	Classification of Trash for Recyclability Status	SVM , CNN	The SVM performed better than the CNN	
8	2016	Gaurav Mittal,Kaushal B.Yagnik,Mohit Garg,& NarayananC.Krishnan	SpotGarbage: Smartphone App to Detect Garbage Using Deep Learning	Garbage Detection; Deep Learning; Computer Vision; Fully Convolutional Neural Networks;	Accuracyof 87.69%	

				Smartphone; Android		
9	2018	Yinghao Chu ,Chen Huang,Xiaodan Xie,Bohai Tan,Shyam Kamal and Xiaogang Xiong	Multilayer Hybrid Deep-Learning Method for Waste Classification and Recycling	CNN, Multilayer perceptrons , Multilayer hybrid deep learning	MHS-98.2% And 91.6% CNN-87.7%	
10	2019	Liu HuiYu, Owolabi Ganiyat O., Sung-Ho Kim	Automatic Classifications and Recognition for Recycled Garbage by Utilizing Deep Learning Technology	ACR, SpotGarbage, AMSS, MHS, DenseNet121	DenseNet121`scored highest 95%	In the future research, they will continue to optimize the CNN structure, and expand the collection of sample images, increase the number of train images to improve accuracy.

11	2019	Janusz Bobulski ,Mariusz Kubanek	Waste Classification System Using Image Processing and Convolutional Neural Networks	CNN	CNN with 10 epochs scored the max accuracy which is 99%	
12	2018	R.S.Sandhya Devi, Vijaykumar VR , M.Muthumeena	Waste Segregation using Deep Learning Algorithm	CNN	94%	Optimization of the results and prediction accuracies for various discrete inputs in real-time.
13	2019	J Sanjai, V Balaji, K k PranavB. Aravindan	AUTOMATED DOMESTIC WASTE SEGREGATOR USING IMAGE PROCESSING	SVM, Hardware components: Webcam,Raspberry pi , DC motor,1293d Motor Driver		

14	2016	Chesta Agarwal & Abhilasha Sharma	Image Understanding Using Decision Tree Based Machine Learning	Decision Tree	Successfully found the production rule required to generate the decision tree.	
15	2020	Xiujie Xu , Xuehai Qi ,Xingjian Diao	Reach On Waste Classification and Identification by Transfer Learning and Lightweight Neural Network	Lightweight neural networkMobileNetV2, SVM	98.4%	
16	2020	Ibrahim F. Hanbal, Jeffrey S. Ingosan, Neal Arden A. Oyam, Yafeng Hu	Classifying Wastes Using Random Forests, Gaussian Naïve Bayes, Support Vector Machine and Multilayer	Random Forest, Gaussian Naïve Bayes, SVM, Multi-layer perception	Random Forest: 97.49%, Gaussian Naïve Bayes: 81%, SVM:89%, Multi-layer perception:96%	

			Perceptron			
17	2019	Anna Bosch, Andrew Zissemen & Xavier Munoz	Image Classification using Random Forests and Ferns	Random Forest,	Random Forest: 45.3%	Future work will include more robust edge features and ROI detection using a more flexible region than a rectangle.

For the FYP 1, we have reviewed 17 articles in total, which are related to our research problem. Among the eight of them used CNN as the main or sub techniques for their research, and seven of them used Support Vector Machine Algorithm. We have seen in three cases the researchers have used IoT devices to classify their image data. We have witnessed researchers also have used ensemble methods like Random Forest and Decision Tree algorithms and even some hybrid models containing the mixture of two or more methods. We have explored the articles from the year 2015 until now so that we can evaluate or get an idea about the recent trends in solving an image classification problem. From the analysis, we can say that CNN and SVM have been the most consistent algorithms in the classification of image problems. Random forest performed well in a few cases but failed to achieve good accuracy in some cases. The same goes for the decision tree and ANN. Among the other methods which are used, Multi-Layer perceptron, Lightweight neural network, DenseNet, Pre-trained VGG-16, AlexNet, performed remarkably well. So, there is a good potential of using the deep learning methodology for getting a more successful and accurate result for the classification of waste objects.

D. Methodology

Data collection and splits

For the dataset, we have utilized the waste image dataset which was created by Gary Thung and Mindy Yang. Dataset was available in the internet sources and the owner of the dataset gave the permission to use for any kind of research purpose. The dataset contains more than 2000 pictures of different garbage which are cardboards, metal, plastic, paper, glass, metals. We have divided the dataset into training, testing, and validation pictures. The training set comprises half and the validation and test set are containing 25% each.

Tools

We will mainly use Google colab and python for our experimental setup and analysis process.

A. Google Colab: Google Colab is a free cloud administration where we can do the coding part. One of the major features of the colab is that we can easily change the runtime. For our project as the dataset is big, we use GPU runtime. One can improve your Python programming language coding aptitudes.

B. Python: Python is an interpreted, object-oriented, high-level programming language with dynamic semantics. Its high-level built in data structures, combined with dynamic typing and dynamic binding, make it very attractive for Rapid Application Development, as well as for use as a scripting or glue language to connect existing components together.

C. Machine Learning algorithm(s) utilized, along with numerical equation(s).

Algorithms

To build our model on the trash image dataset, we will use 4 machine learning algorithms, which are Convolutional Neural Network (CNN), Support Vector Machine (SVM), and Random Forest and Decision trees. The possibility of Classification Algorithms is basic. You foresee the objective class by dissecting the preparation dataset.

Performance Measurement

To measure the performance of our algorithms we will take help from some of the performance measure features such as confusion matrix, precision, recall, F1-score, accuracy, and cross validation. We will define briefly next in the implementation part.

Data Preparation & preprocessing

As the information utilized in this test is an assortment of waste related pictures, there should be some pre-processing on them to change over the information in the configuration that can be taken care of to the AI models. Pictures in the preparation dataset had contrasting sizes, hence pictures must be resized before being utilized as a contribution to the model. Waste images were resized to the shape 256×256 pixels. Rectangular pictures were resized to 256 pixels on their most brief side, at that point the center 256×256 square was edited from the picture. During preparing, the contribution to our ConvNets is a fixed-size 224 × 224 RGB picture. The main preprocessing, we do is taking away the mean RGB esteem, processed on the preparation set, from every pixel.

Data Visualization

We have visualized the datasets and it looks like this:

Figure 3: Data Visualization

We have given the show_batch () and fixed the size and batch then the output looked like this image. So, the dataset is correctly visualized.

Modeling

I) Convolutional Neural Network:

The structure of the convolutional neural network developed is as follows.

1. **Convolution Layer**: This layer deals with convoluting the kernel grid the entire picture by applying the filters specified for it. This additionally goes about as an input layer where the information measurements of the picture are to be specified.

2. **Max-Pooling layer:** This layer deals with letting the sampling and processing time. Over fitting of the model is taken consideration at this layer by ensuring no additional parameters are added to the model.

3. **Dropout Layer:** This layer drops out the undesirable irregular arrangement of activations by setting them to 0. This process takes into consideration the preparation information and not the testing or validation information.

4. **Flattening Layer:** This layer is utilized to change over the components of the layer above it into a single dimension by taking a result of the considerable number of dimensions in it.

5. **Dense Layer:** This goes about as a output layer with the number of categories as the units provided to it with a specific activation function which respects a optimized outcome delivering model.

ii) **Support Vector Machine (SVM)**

The Support vector machine makes all the difference as it contains class of complex kernels like RBF (Radial Bias Function), Class Neural Network and polynomial classifiers and yet SVM is simpler to analyse, for SVM in a high dimensional element which is connected to input space nonlinearly, relates to a direct technique yet doesn't require any complex calculations in that high dimensional space. Every single significant figures and calculations occur in input space with the assistance of Kernels. It can be demonstrated that Optimal Hyperplane, which precisely is the maximum range of separation distance of two classes possesses the minimum function. This hyperplane is developed utilizing a quadratic function which makes it sufficiently streamlined to contain the most optimized patterns lying on its margin. These examples are named as support vectors that contain classification related data. Support Vector Machines are advantageous to utilize it as a result of its bits accessible for different kinds of information. With its default usage, it isolates two directly divisible classes based on a hyperplane. This sort of SVM is the LSVM (Linear SVM). All the accessible preparing vectors are part into two classes by considering the boundaries of a dataset and the hyperplane is chosen with the end goal that the support vectors are at the base good ways from the hyperplane. So, according to SVMs, only these support vectors are important to classify any class rather than the complete training examples. Thus, as indicated by SVM, just these support vectors are essential to group any class instead of the total preparing models. The separation between the support vectors and the hyperplanes is generally meant by D+ and D-though the margin of the isolating hyperplane is the whole of both these separations. In this circumstance, expectation of the data to be linearly separable was not there due to it being a multiclass classification problem. In such circumstances, we can utilize a function to change our information into a higher dimensional space. A simple polynomial function can be applied to the information accessible to change it into a parabola of information focuses. But this process can be computationally much expensive to follow and thus a kernel trick can be used in such cases. This includes utilizing a capacity that takes the vectors in the first space as its information and results into a spot result of the vectors in the component space. This in the long run changes the vectors in a nonlinear space into a linear space.

Iii) Random Forest

Random Forest is a well-known classifier utilized for multiclass classification, it includes n differed trees and randomization is at work at every growing or grown tree. Ballpark figure of each distribution over the class of pictures is named as leaf nodes of each tree.. Picture is classified when it is sent down at each node and tree and collected value is determined toward the finish of circulations of leaves. Randomization is a part of the calculation in two different ways; one is by subsampling the dataset in the training partition and by selection of node tests. Inspecting methodology assumes a significant job in the outcome classification. Millard and Richardson (2015) gave a contextual investigation of three angles which were test size, spatial autocorrelation and extents of classes inside the preparation test. Image Classification through Random Forest has shown sensitivity to factors like proportions ofclasses, size of sample and characteristics of training data. RF classifications ought to be reproduced for enhancing execution and precision in any event, it already is an ensemble approach to regression modelling and classification. Every algorithm has its own advantages and disadvantages.

Points of benefits of Random Forest include:

1. Can be compared to SVM and Boosting calculations with easy to use parameters and it is less sensitive to those parameters.
2. Lesser problem of overfitting compared to individual decision trees and hence pruning of trees can be avoided.
3. Automatic detection of outliers and important variables takes the precision higher and thus RF is nearly simpler to utilize. However, each advantage comes with its own set of limitations as well. Confinement of RF which have been investigated up 'til now is that, on account of regression trees, prediction is restrained till a particular range of response values in training dataset and consequently it turns out to be right around an essential that preparation information comprises of full scope of reaction factors and all examples ought to have all scope of reaction information esteems.

iv) Decision Trees

The decision of making strategic splits heavily affects a tree’s accuracy. The decision models are diverse for characterization and regression trees.

Decision trees use numerous calculations to choose to part a node into at least two sub-hubs. The creation of sub-nodes builds the homogeneity of resultant sub-nodes. As such, we can say that the virtue of the nodes increments as for the objective variable. The decision tree parts the nodes on every accessible variable and afterward chooses the split which brings about most homogeneous sub-nodes.

Implementation

Convolutional Neural Network:

For CNN implementation, we first extracted our images from the zip file and then divided the images into the classes. Then we have split the images into the train, test, and validation set. After that, we have visualized the dataset and create our CNN model. We have used Resnet34. It is known as a residual neural network which has a lot of layer inside it. And it is already pre-trained in ImageNet Database. A pre-trained CNN will perform better on new image datasets. Then we have selected the best parameter for our model using learn.lr_find and it gave us the perfect learning rate to reduce the error rate. With the learning rate, we then trained our model. After training, we have visualized the mostly incorrect images that my model did not able to perform well. It is because the photos received too much exposure or something, and this is not the fault of the model.
Then we have used the confusion matrix to find our accuracy of the model, and we have found that our model sometimes confused between glass and plastic, glass, and metal. Then we have predicted our model based on the actual images and observe that our model can successfully predict based on the actual images. I have ended up achieving an accuracy of 90%.

Support Vector Machine:
We have imported all the necessary libraries and specified the data categories. On the next step, we have joined all the subcategories of the data and resized the and converted them to the vector type using flatten function. Saved the preprocessed data in pickle format so that we can use the saved pickle afterword. We have shuffled the data which is an important part for getting unbiased result for the prediction. After splitting the data into training and testing data, we created the model for Support Vector Machine using SVC. For the first testing, we used the kernel to 'rbf', C=10 and kept the gamma to auto. Then for this configuration, the model was able to predict the waste with accuracy of 86%. Then we tried to optimize the model with hyperparameter tuning and for this we have used Grid Search method. It exhaustively generates candidates from a grid of parameter values . It goes to all the possible values provided. It took 22.4 minutes for our provided configurations to execute with 80 different possible outcome tests. Then they provided the accuracy of 86.2% which is the same as before. Then we tried again with it with 3 different kernel type, 4 different range of values for C. This time the accuracy was 85% but the score for the confusion matrix was better than before.

Random Forest :
Random forest classifier is a model combining of many decision trees. It samples random training data points while building the trees. It adds additional randomness in the model if the number of trees grows. It creates forest with many trees which are not correlated. Random Forest is a bagging algorithm for achieving low-prediction error.
Firstly, we imported the random forest classifier after all the preprocessing with n_estimatiors=10 which means with ten trees, criterion as entropy and with 50 random state. With this configuration, when we increased the number of estimators, the accuracy slightly increased. Then we tried to optimize it with random search optimizer as the hyperparameter tuning technique. It takes random configurations from the provided options. It can narrow down the possible outcomes which reduces the computation time. For the cross validation,

we used stratified K-fold validation technique where the randomness of the data is confirmed. It gave us the optimal configuration for testing. The cross-validation score increased to 70 which was previously 65. But the accuracy was unchanged which is 55% for our data set. Also, the other performance measurements scores were increased after the tuning with random search.

Decision Tree:

It provides the result as a graphical representation similar to flowchart where each nodes of the tree represents test cases. Each branch represents the outcomes from the test and the nodes represent the class labels.

After all the preprocessing, we have made the classifier for decision tree model. We used entropy as the criterion and the depth of the tree we gave the value as 10. Other parameters were chosen as the default ones. For this configuration, our model was able to predict the waste materials with 65% accuracy.

E. Preliminary Result Analysis

Accuracy

Accuracy is the most important part of the measurement feature. As we have done confusion matrix in our algorithms. That's why our accuracy measurement has been done by a confusion matrix.

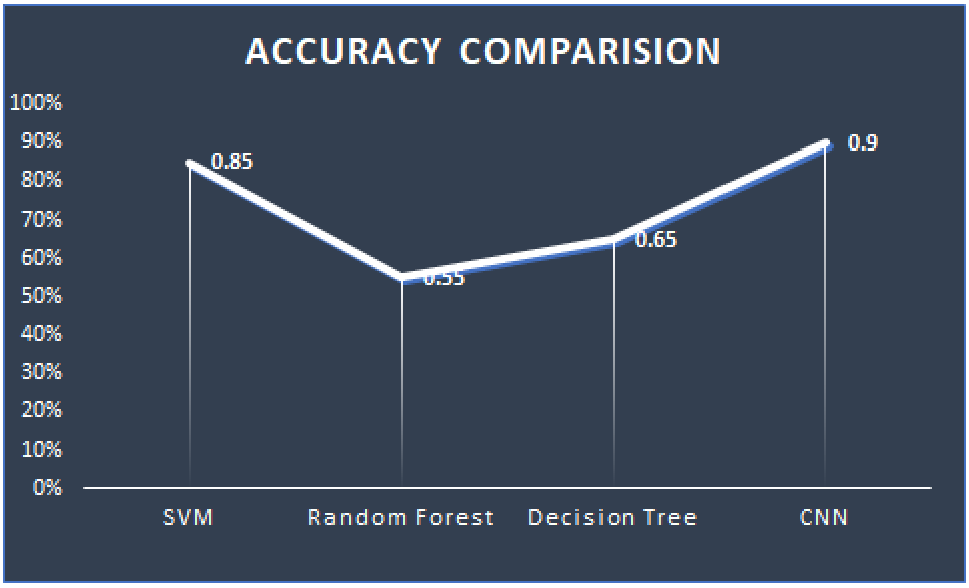


Figure 4: Accuracy Comparison

According to the value for different models plotted in the image above, it was discovered that CNN had the best among all with an accuracy of 90%. Again SVM calculation likewise demonstrated an exactness of 85% which is exceptionally near the precision of CNN. But, nearly the accuracy of Random Forest and Decision Tree are not sufficient. They have demonstrated an accuracy of 55% and 65% individually.

Precision, Recall and F1-Score

True positive and true negatives are the perceptions that are accurately predicted. We need to limit false positives and false negatives so they appear in red shading. These terms are somewhat confusing. So let’s take each term one by one and understand it fully.

True Positives (TP) - These are the effectively predicted positive qualities which implies that the value of the actual class is yes and the value of the predicted class is also yes. For example if real class esteem shows that this traveler endured and predicted class discloses to you something very similar.

True Negatives (TN) - These are the effectively predicted negative qualities which implies that the value of actual class is no and estimation of predicted class is likewise no. For example if that true class says this traveler didn't endure and predict class discloses to you something very similar.

False positives and false negatives, these qualities happen when your real class contradicts with the anticipated class.

False Positives (FP) – When real class is no and predicted class is yes. For example if that real class says this traveler didn't endure however predicted class discloses to you that this traveler will endure.

False Negatives (FN) – When real class is yes yet predicted class in no. For example if that real class esteem demonstrates that this traveler endured and predicted class reveals to you that traveler will kick the bucket.

Precision:

If we divide the value of actual positives by the sum of true positives and false positives then we will find the precision.

Precision = actual positives / (true positives + false positives)

	Cardboard	Glass	Metal	Paper	Plastic	Trash
SVM	0.87	0.8	0.79	0.6	0.87	0.7
RandomForest	0.62	0.44	0.45	0.64	0.58	0.61
Decision Tree	0.63	0.65	0.54	0.81	0.6	0.58
CNN	0.98	0.8	0.86	0.9	0.91	0.63

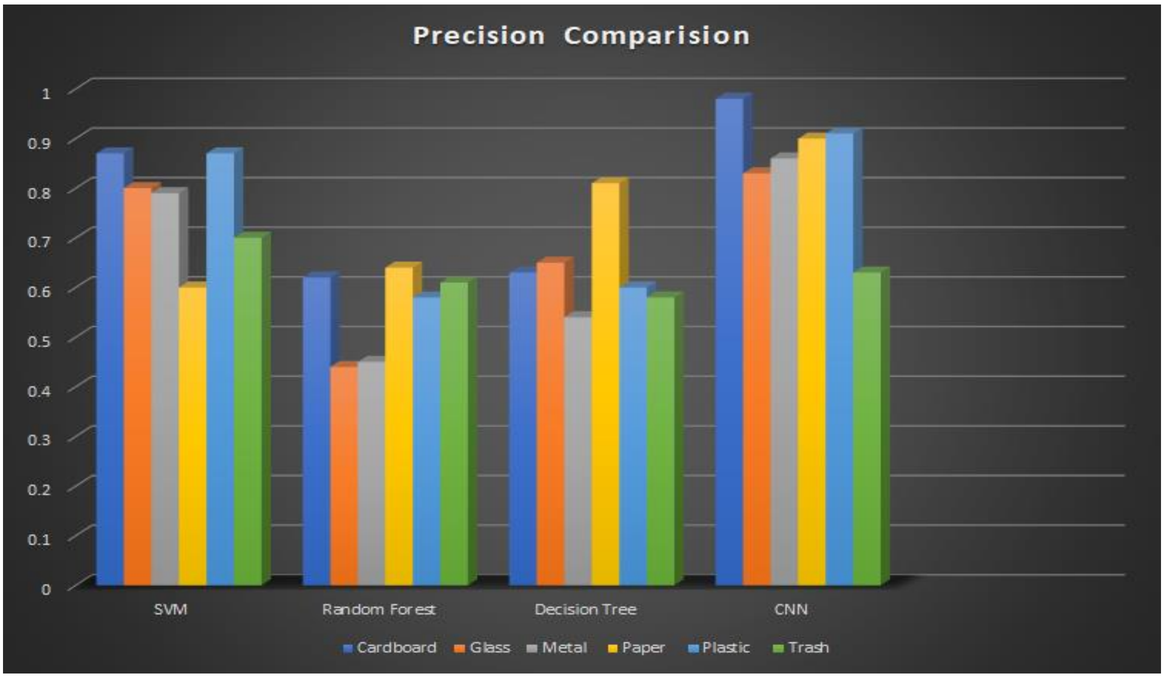


Figure 5: Precision comparison

Recall

Recall = true positive/ (true positives + false negatives)

	Cardboard	Glass	Metal	Paper	Plastic	Trash
SVM	0.81	0.8	0.85	0.6	0.82	0.83
RandomForest	0.54	0.38	0.67	0.64	0.54	0.46
Decision Tree	0.58	0.52	0.72	0.81	0.65	0.52
CNN	0.88	0.83	0.86	0.93	0.89	0.74

Figure 6: Recall Comparison

F1-Score:

F1 Score= i2*((precision*recall)/(precision+recall)).

	Cardboard	Glass	Metal	Paper	Plastic	Trash
SVM	0.88	0.84	0.8	0.75	0.9	0.78
RandomForest	0.61	0.48	0.41	0.66	0.56	0.52
Decision Tree	0.71	0.61	0.53	0.76	0.62	0.55
CNN	0.92	0.86	0.84	0.91	0.9	0.68

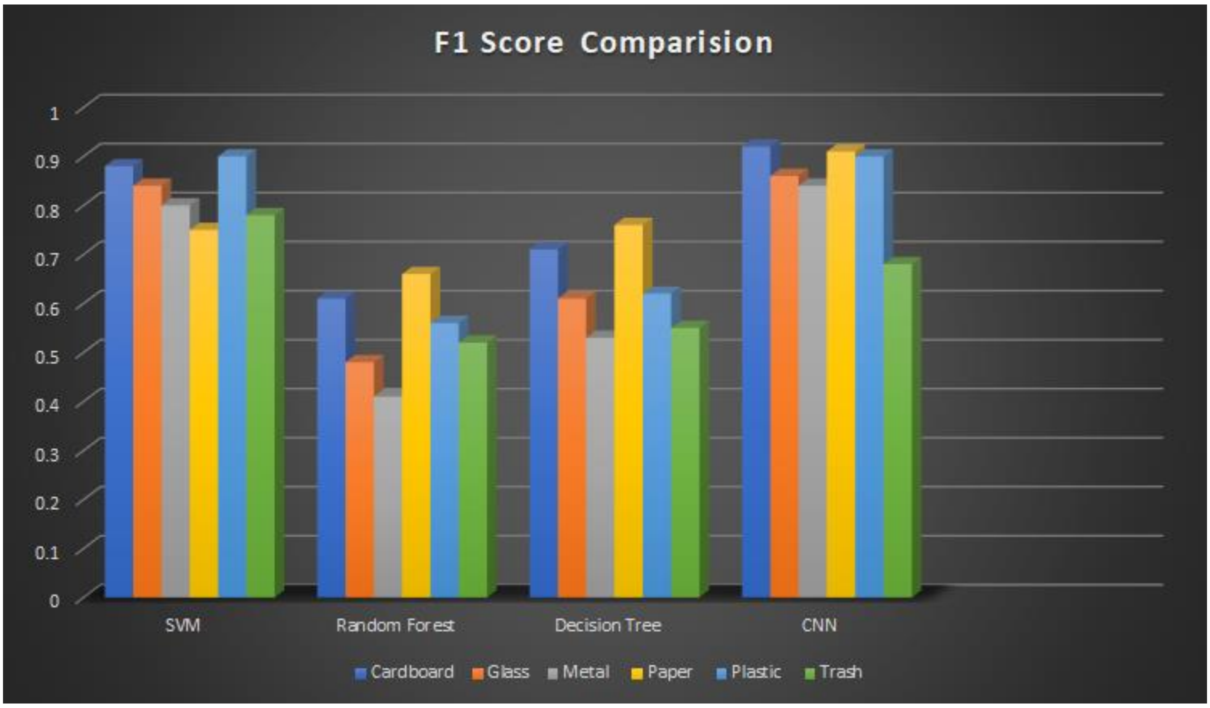


Figure 7: F1-Score Comparison

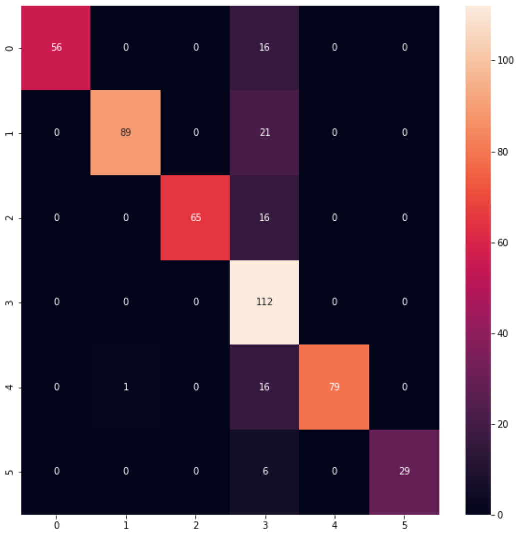


Figure 8: Confusion Matrix for SVM after tuning

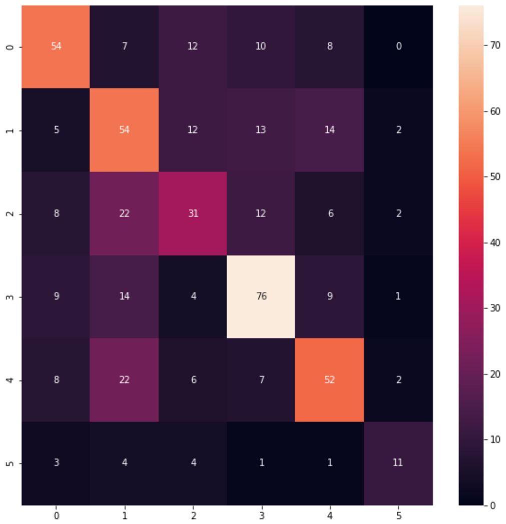


Figure 9: Confusion Matrix for Random Forest after tuning

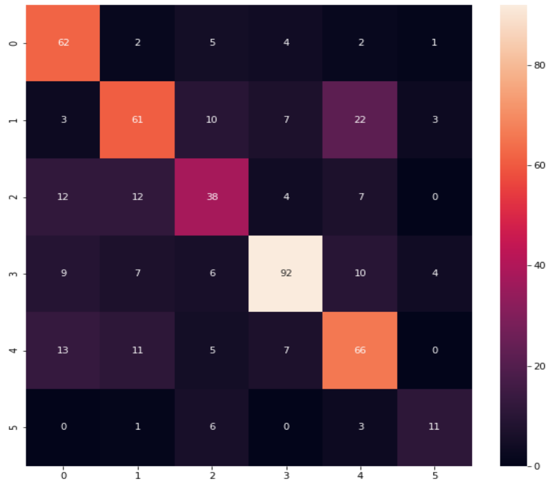


Figure 10: Confusion Matrix for Decision Tree

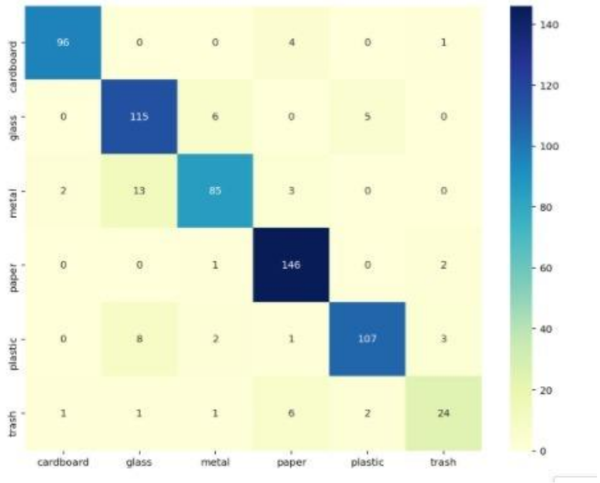


Figure 11: Confusion Matrix for CNN

Conclusion

As indicated by the survey directed and the outcomes assembled, it very well may be plainly observed that a Convolutional Neural system can beat the presentation of pretty much every model constructed up until this point. Boosting any calculation and approving it with Cross Validation plans with numerous folds, the presentation of any model can be raised. After building the best model for each algorithm using the hyper parameter tuning, CNN has come up with the best accuracy while SVM is slightly behind. But Random forest and decision tree have not performed well in classifying the waste images properly.

Future Work

For the future work, our plan is to work with the best algorithm, in our case which is CNN and we will try to emphasise on how to enhance the accuracy more by using other features. We will also try to work with a bigger dataset. Currently, our dataset has more than 2000 images of waste and in future we will increase this number and predict the accuracy. We are also planning to create a demo mobile app regarding the reusability of waste categories. It will help reduce the cost of buying new materials and also help to fulfil the sustainable goals also.

F. References

Ching Colli (2019). How to build an Image Classifier for Waste Sorting. 1-6

Chauhan, N (2019). Decision Tree Algorithm — Explained,1-6

Ciresan, D. C., Meier, U., Masci, J., Gambardella, L. M. and Schmidhuber, J. (2011). Flexible, High Performance Convolutional Neural Networks for Image Classification, p. 6.

Foody, G. and Mathur, A. (2004). A relative evaluation of multiclass image classification by support vector machines, IEEE Transactions on Geoscience and Remote Sensing 42(6):1335–1343.

Karpathy, A., Toderici, G., Shetty, S., Leung, T., Sukthankar, R. and Fei-Fei, L. (2014). Large scale video classification with convolutional neural networks, Proceedings of the IEEEconference on Computer Vision and Pattern Recognition, pp. 1725–1732.

Li, Q., Cai, W., Wang, X., Zhou, Y., Feng, D. D. and Chen, M. (2014). Medical imageclassification with convolutional neural network, pp. 844–848.

Millard, K. and Richardson, M. (2015). On the Importance of Training Data Sample Selection in Random Forest Image Classification: A Case Study in Peatland Ecosystem Mapping,Remote Sensing 7(7): 8489–8515.

Ibrahim F. Hanbal et al (2020), Classifying Wastes Using Random Forests, Gaussian Naïve Bayes, Support Vector Machine and Multilayer Perceptron, 1-6.

Anna Bosch, Andrew Zisserman & Xavier Munoz (2019), Image Classification using RandomForests and Ferns, 1-4

Nurwauziyah, Iva & Sulistyah, Umroh & Gede, I & Putra, I Gede Brawiswa & Firdaus, Muhammad. (2018). Satellite Image Classification using Decision Tree, SVM and kNearest Neighbor.

Amari, S.-i. and Wu, S. (2016). Improving support vector machine classifiers by modifying kernel functions, Neural Networks 12(6): 783–789.

Adedeji, O., & Wang, Z. (2019). Intelligent Waste Classification System Using Dee Learning Convolutional Neural Network. Procedia Manufacturing, 35, 607-612. d doi:10.1016/j.promfg.2019.05.086

Meza, J. K. S., Yepes, D. O., Rodrigo-Ilarri, J., & Cassiraga, E. (2019). Predictive analysisof urban waste generation for the city of Bogotá, Colombia, through the implementation ofdecision trees-based machine learning, support vector machines and artificial neural networks. Heliyon, 5(11). https://doi.org/10.1016/j.heliyon.2019.e02810

Belgiu, M., Drgu, L.: Random forest in remote sensing: A review of applications an future directions. ISPRS Journal of Photogrammetry and Remote Sensing 114, 24– 31 (2016)

Breiman, L.: Random forests. Machine learning 45(1), 5–32 (2001)Zhao, Y., Zhang, Y.: Comparison of decision tree methods for finding active objects. dvances in Space Research 41(12), 1955-1959 (2008)