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Trash Net based Waste Segregation Assistive System for Smart Cities

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Abstract: In addition to progressively unhealthy customer behavior, development, urbanization and eco- nomic growthhave led waste generation levels to in- crease dramatically over the last decades. This rapid development and use practiceshave bestowed waste production levels being the highest priority problem for humans and the natural environment. Since arange of industry practices are either specifically responsible for solid waste production indirectly. Sadly, only 5 percent ofthis colossal amount of waste is recycled. One poten- tially major response to this issue may be to segregate the waste at thepoint of production (homes, factories) itself. Since a range of industry practices are either specifically responsible for solidwaste production, or indirectly. In India an incredible 0.1 million tons of waste is generated every day. Unfortunately, only 5percent of this huge amount of waste is recycled. One potential response to this issuemaybetosegregatethewasteatthe point of processing itself. As well, pollution has been shown to reduce the average lifetime of manual segregation. Theadmirable goal of our project is to create a mechanized machine using machine learning models for the betterment of health,and to move towards a greener planet. We have therefore introduced an automated waste segregator, which helps to isolatethe waste at the point of disposal itself.This is planned to classify the waste using image processing into 3 major groups,includingFoodWaste,RecyclableandRejectWaste,therebyrenderingwastemanagementmoreefficient.

Keywords:WasteSegregation,InternetofThings,WasteManagement,WasteClassification,SolidandLiquidMaterials;

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1. Introduction and Related Work

The project aims to build a prototype for automated waste segregation using artificial intelli- gence. This prototype willdemonstrateawastesegregationandmanagementsystemforatypicalfastfoodoutletlikeMcDonald's.The idea is to leverage the powerful capabilities of Image Classification to completely automate the process of wastesegregationattheveryfundamentallevelofwastedisposalitself.Thedustbinanditsunderlyingtechnologyis designedtodetecttrash,visuallyanalyseit,classifyitandfinallydisposeofthe waste to its allocated bin. This process is fully automated and hence prevents all sorts of manual errors in disposing ofthewastewhichmaybearisingfromunawarenessoranunintendederror.

The basic conceptual model of the dustbin is, it has an image capturing unit where the disposed trash is first collected. Itsimage is captured via an embedded camera. The embedded hardware sends the image to the server which hosts the imageclassifier. The result obtained indicates one of the 3 categories the trash belongs to. The said indication is used by theembeddedhardwaretofacilitatethemovementofcertain mechanical components of the dustbin resulting in the trashgettinglodgedinitsappropriatebin [1-7].

The **segregation methodology** adopted is, classifying the waste into one of "Recyclable", "Food Waste" and "Reject". Wehave 3 bins that are placed within our main unit. Each bin corresponds to one of the above mentioned categories. Classes ofobjectslikepaper,plastics,glass,cardboard,metalaredisposedinto"Recyclable",fooditemsto"FoodWaste"andanything that cannot be identified or does not clearly belong to one of the above two categories is disposed of to "Reject"bin [8-12].

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2. Experiment Work

2.1. Introduction

TheprojectwasbroadlyphasedintoMechanicalDesign,HardwareandComponentDesignandSoftwareandAIComponents Development. This section elaborates on each of the tasks carried out in the entire development and integrationoftheproject [13-19].

2.2. Approach

2.2.1. Mechanical Model Design: The objective of this phase was to basically come up with a manufacturable design forthe dustbin. As illustrated, we had multiple sequentially dependent stages in this phase. The initial steps consisted of comingup with an outline for the basic model, deciding on its functionalities, and finalising a structural design. In the later stages,we designed the movables components and utilities for embedding hardware components and the chassis. Final steps werecreatingaCAD/CAMmodelandoutsourcingtheconstructionoftheprototype [20-23].

2.2.2. Image Classification Model Design: For the second phase, a thorough study was undertaken to understand whatwould be expected of design in real life. Based on this information, an appropriate data model and classification model wereadopted. Further on a unique machine learning program was developed in order to ensure optimal efficiency. This programwastrainedusingareallifedata-setinordertomimicthereallifescenarios [24].

2.2.3. Electronics: The primary objective here was to decide on reliable functional componentsso that they may be easilyimplemented in the proto- type. To this end, the appropriate components like sensors and MCU were identified. A tailormade firmware code was implemented in conjunction with the bread board. The hardware was to be tested to identify anyshortcomingsorpotentialreasonsforfailurebeforebeingapprovedforthefinalstep [25-28].

2.2.4. Application Design: In order to ensure that this project becomes useful to the majority of the populace, it has to befunctional but at the same time, convenient to use for the average user. To this end, a detailed analysis of the userrequirement is planned, which will be instrumental in creating a user journey document and a state chart diagram. It shall beimplementedintotheAPIdocumentcreationandUI/UXdesign.Takingintoaccounttheseresourcesafinalapplicationshallbedevel-opedwhichwillbetestedanddebuggedbeforebeingreleasedtotheclients [29].

2.2.5. Final Product Integration: Once all the indi- vidual components of the project have been built, they need to beintegrated together and their func- tioning and performance is to be assessed. There are multiple approaches to this phase.We have, what can be identified as, three evident interfaces of integration. One between the hardware and the software, theother between the mechanical model and the hardware components. This phase also covers the necessary testing that needstobedoneontheintegrationlevelaswellasthesystemasawhole [30-32].

2.3. MechanicalDesign

In this section we discuss the mechanical design of the dustbin. In order to arrive at the perfect design we had to do a lot ofcalculations and estimates. The design had to incorporate multiple functionalities and there were a lot of questions thatneededtobeansweredlike,

- Howwillthewasteenterthedustbin?
- Wherewillitsegregatethewaste?
- Howwillthesegregatedwastegoinsidetherightsection?
- Howwilltheuserremovethegarbagefromeachsectionandreplaceitwithanewgarbagebag?
- Wherewillallthesensorsbeplaced?

Thefollowingsubsectionsareanexplanationonhowwesolvedtheaboveproblems.

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2.3.1. Mechanical Model Design: *FIG1*isacross sectional diagram of the mechanical model. The scrap is thrownone-at-a-timethroughthecenteropeningatthetop.Thenthescraplandsonthesmallcubicalsection.Thecamerasin thewallsofthesectiontakemultiplepicturesofthescrapandthenthesegregationtakesplace.Afterwhich,thescrapi sthrowninsideit'srespectivesection(Recyclable/Drywaste,Food/Wetwaste,orRejectwaste)inthedustbin.

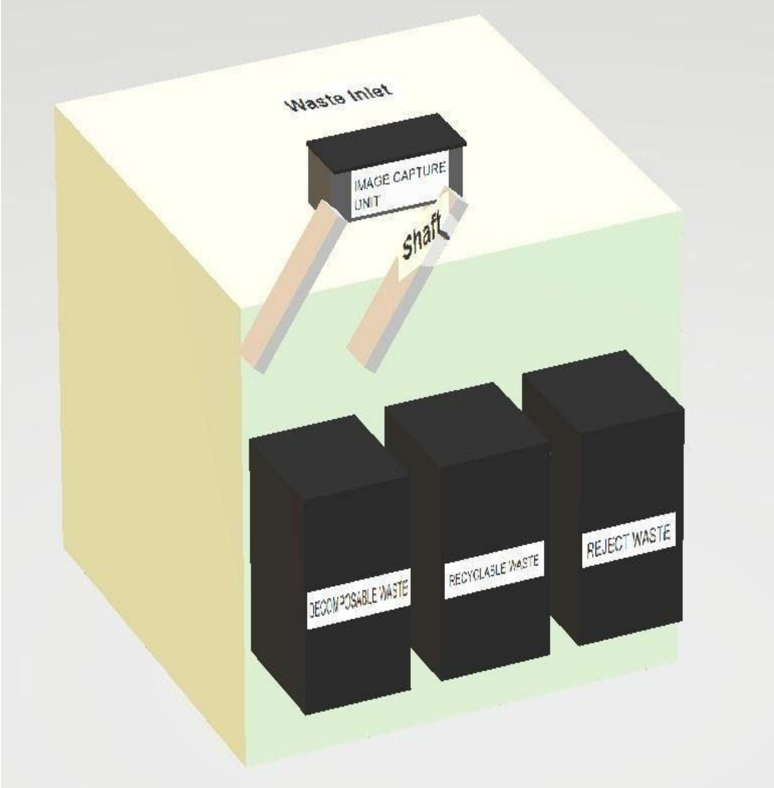

***FIG1**:3DCrossSectionoftheMechanicalModel*

2.3.2MechanicalModelSpecification: Therearefourmajormechanicalcomponentsinthemodel:

- **TheWasteInletUnit**isthetopopeningfromwherethescrapisputinsidethedustbin.
- **Image Capturing Unit** is where the main segregation takes place. After the scrap is thrown inside from the wasteinlet unit, the LEDs inside this unit are turned on and then the cameras in this unit take multiple pictures of the scrap andthenusingmachinelearningthecorrectsegregationtypeofthescrapisdefined [33].
- **SegregationDisc**isthebottomlayerof the Image capturing unit. As soon as the scrap's segregation type isdefineditopensandthescrapfallsdowninitsrespectivesection [34].
- **Waste Directing Shafts** are used to give direction for the scrap to goinsidetherightsectionofthe dustbin.Theseshaftsareattachedtoamotorwhichhelpstheshaftstorotateinparticularangles [35].

2.4. HardwareandComponentDesign

Asmentionedinmechanicaldescriptionthecompletesegregationsystemcontains4majorcomponents

2.4.1 Sensor Unit: A proximity sensor is placed on the top of the bin. When the waste enters the bin, the sensor sends asignal to the microcontroller, thereby enabling the rest of the circuits of the Waste Segregator. This distance is measured toreducethepowerconsumption [36].

2.4.2. ImageCapturingUnit: AsystemconsistingofapairofcamerasRaspberryPI5MPCamera,sochosenasithas

- 5-megapixelnativeresolutionsensor-capableof2592x1944pixelstaticimages
- Supports1080p30,720p60

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- Cost-effective
- Compatiblewithourmicrocontroller

forcapturingtheimagesoftheinputwaste.Duringthecapturetoovercometheproblemofdarknessinsidethedustbin,asetofLEDsareturnedON as soon as the waste is entered. Some buffer time for proper image capturing and fre- quency ofinletisaimedtobetakencarewhilewritingthecameradriversandLEDswitchingfunctionsinthefirmware.

2.4.3. Path Directing Control for Incoming Waste: After the image gets segregated using MLmodel, the output isprovided to the microcontrollertocontrolthemotorattachedtoone of the shafts. The controller commands to rotate intherequiredangleaspertheplacementofrespectivebins.theanglesdefinedaredefinedas-

S. No.	Target Dustbin	Angle of rotation of servo motor (in degree)
1.	Decomposable Waste Bin	60 degree clockwise
2.	Recyclable Waste Bin	No change (default position)
3.	Reject Waste Bin	60 degree anticlockwise

TABLE1:*WasteDirectingShaftAngles*

Note-Theanglesofrotationcanbedifferentforthedifferentsizedbins,theseareapproximateangles

Recyclable Waste Bin is kept at the centre position that is the default position of the shafts, as it is more likely to get filledfasterandreducepowerinmovingtheshaftsrepeatedly [37].

2.4.4. Bin Level Detector: To havea knowledgeof the fullness of respective bins so that there can be a closed-loopprocess for changing the bins that are filled till the threshold to avoid overspilling of the garbage as shown in figurebelow.To achieve this an ultrasonic sensor is required to be installed at the top of each of the dustbins. As soon as the wasteis filled until the threshold, the sensor will detect and send this information to the controller, and the controller thereby sendsthisinfototheserverusingWifimodule,whichcanbeseenontheandroidapp.

FIG2:*UltrasonicFillLevelSensor*

Alltheabove-mentionedcomponentswere to be implemented but due to COVID-19 and thereby lack of hardwarecomponent accessibility, the projectnowhassomelimitationsinterms of the sensing and sending data to the androidapp.

New Plan of Action The components are simulated on Proteus IDE using an Arduino controller, servo motor and sensors.The components have also been modified accordingly and the new system consist of following components- Random ImagegenerationSimulationofWasteSegregator

Random Image generation- A function randomly generates the images and these images of the waste material are put as aparameter for the ML model to get it segregated in categories named as Recyclable, Decomposable and Reject. This script

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iswrittenonPythonShell,whichisconnectedtothesimulationmodelofamicrocontrollerunitviaserialcommunication.

Simulation of Waste Segregator- The Proteus IDE consists of simulation for various controllers including ARM, Arduinoetc.Wehaveintegratedthesimulatedsystemwithaservomotor.

2.5. SoftwareandAIComponents

2.5.1. ImageClassificationModelDesign:DataCollectionandCreationofDataset

Thedatasetofimageswascreatedbyfollowingthebelowenlistedapproach.

The initial step was to narrow down the categories to which the images of waste need to be put into. This would enable us toeventuallycategorizethewasteintooneofthe3typesofwastethatcorrespondstoeachofthedustbins.

The categories of trash were finalised to enable a smooth process of identification post classification performed by theNeuralNetwork.Plastic,Paper,Cardboard, Metal, Glass, Trash, Food Waste were the finalised categories at theendofthisstep. An image belonging to any one of the first five categories will be classified as “Recyclable”, Food Waste as“Biodegradable”andTrashas“Reject” [38].

The next step was to collect images for the dataset. The objective here was to create a collection of images that would verycloselyreflect the nature of the images captured of the actual waste from the camera embedded in the dustbin. Certainfactorswereidentifiedtoassesstheappropriatenessofanimagetoqualifyforthedataset.Theyareasfollows:

- Theimageshouldcompriseonlyasingleobjectwithamonochromebackground.
- Theobjectshouldpreferablybeoneofthethingsthatbelongstotheabovementionedcategories.
- The white balance of all the images need tobe uniform mimicking the lighting conditions of the image captureinsidethedustbin.

After extensive research, one such *Trashnet*dataset, which met all of the above mentioned criteria was found. *Trashnet*Trashnet dataset comprises six classes of waste materials which are paper, cardboard, plastic, glass, metal, and trash. Atpresent,thedatasetcontains2527imagesof 594 paper, 403 cardboard, 482 plastic, 501 glass , 410 metal, 137 trash classes. The pictures were captured by placing theobject on a white poster board and using sunlight and/or regular roomlighting.Theimagesareresizeddownto 512 x384whichisthestandardformostcommonlyusedclassificationmodels [39].The main drawback of *Trashnet*for our ap- plication was it did not contain images of food waste. This arose a newrequirement of collecting images of “fast food” since we are working on a prototype for a fast food chain. The images forfood waste also had to comply with the criteria defined for the rest of the dataset. Select images were handpicked andcuratedfromKaggle’s*FoodImages (Food-101) dataset*. The process involved selecting images of food taken on amonochromebackgroundandresizingthemtotheappropriateresolution.Python’sPILlibrarywasusedforthesame.The pre-processed images were then augmented with the existing data of the *Trashnet*dataset by adding the files to thefolderstructure [40].

TrainingtheImageClassificationModelwithSupervisedLearning

2.5.1.1. DecidingWhatLibrariestoUseforPreprocessingandTrainingtheModel

Since the requirement was of a model that would classify images into categories of waste, we needed a Transfer Learningapproach. This was to be achieved by using a pre-trained image classification model and then customising it for our datasetandresults [40].After extensive research and comparison, it was concluded that the FastAI library would provide the most efficient resultsandperformance.FastAI is a high level AI library built on PyTorch, which lets us build complex machine learning and deep learning modelsusing only a few lines of code. Furthermore, it implements some of the newest state-of-the-art techniques inspired fromsome of the latest research papers that allow youto get profound results on almost any kind of AI problem. This can bedemonstratedwiththeexampleofthedifferentiallearningratesfeature,which allows us to perform transfer learning with fewer lines of code andtime.Thisisachieved by allowing us to setdifferentlearningratesfordifferentpartsinthenetworkordifferentlayers [41].

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2.5.1.2. UsingTransferLearningtoTraintheModel

Transfer Learning: In today's practice of building deeplearningmodels,veryrarelyisan entire ConvolutionalNetwork, with random initialization, trained from scratch. Because it is highly rare to have a dataset of sufficient volume forevery kind of application. Instead, it is a common practice to pre-train a ConvNet on a very large dataset (e.g. The popularImageNetdataset, which contains about 1.2 million images which belong to 1000 categories). And then this trainedConvNetisusedeitherasaninitializationcomponentorafixedfeatureextractorforspecifictasksofinterest. There are several steps involved in this process. These steps are completely dependent on the li- brary being used, in thiscase FastAI. Splitting Data into Required Folder Structure: In this step, we split the data into Train, Test and Valid folders.Thisisdonetofacilitatecreating*databunches*,whichisexplainedinthefollowingpoint.Loading and viewing the data: FastAI uses data objects called *databunches*. Data needs to be passed to the model as a *databunch*sothatitcanbetrained.Finding the learning rate: FastAI provides meth- ods to find learning rates, these methods provide us with near perfectfigures. To find learning rates, we can use the *lr find* and *recorder.plot*methods which create a plot that associates thelearning rate with the loss. The optimal learning rate is basically the point with the steepest downward slope that still has ahighvalue.Creating a model and initial training: FastAI provides a method called *create cnn*, which isused to create a convolutionalneural network. *the create cnn*method requires two arguments, the data, and the architecture. The model that gets created onexecuting the method, uses the *resnet34* architecture, with weights pretrained on the pop- ularImagenet dataset. By default,onlythefullyconnectedlayersatthetopoftheconvolutionalneuralnetworkareunfrozen(tobetrained) [42].To train the layers we can use either the *fit*or*fit one cycle* methods. We have used *fit one cycle* which uses the concept of*1 cycle policy*, which basically changes the learning rate over time, learning from previous iterations to achieve betterresults.

2.5.1.3. Analysisofmis-ClassificationandImprovingAccuracyoftheModel

Themodelwehavesofarisnotthemostaccurateandneedsfurtherrefining.Thisrequiresthefollowingsteps:

- **Visualisingthemostincorrectimages:**FastAI's*ClassificationInterpretation*class is typically used to interpretthe results. An interpretation object can be created by calling the *from learner* method and passing it our learner. Then wecan use methods like*plot top losses*,*plot confusion matrix*or*most confused* to visualize the confusion matrix and exactdata points whichcausederrors.FastAI also provides a class for cleaning data using widgets. The *ImageCleaner*classdisplays images letting us to relabel or delete them. Using *ImageCleaner*needs to be preceded by the use of the method*DatasetFormatter().fromtoplosses*togetthesuggestedindicesformis-classifiedimages.
- **CleaningData:**Includesrelabelingand/ordeletionofmisclassifiedimagesandpruningofoverexposedim ages.
- **Final Training:** The output of the cleaning of the dataset is saved as a cleaned.csv file which can be used to reloadthe data. Now we apply the same training steps as in the initial training but using the new data. The saved weights were usedforefficiency.

2.5.2. AccessoryAPIsandLibraries:Savingandreloadingthemodel

This is one of the very crucial tasks. Saving the model helps us to reuse thetrainedweightsof the model and preventshaving to retrain it every time it needs to be used to make a prediction. We can simply reload the model and run the predictfunctiontomakeaprediction.

FastAIprovidesfunctionstoachievethesame,i)saveisusedtosavethemodelanditsoptimizerstate,

1. exportisusedwhenthemodelneedstobedeployedinproduction,itexportstheminimalstateoftheLearner,
2. loadisusedtoloadthemodelanditsoptimizerstate,
3. loadlearnerisusedtoloadaLearnerobjectsavedwithanexportstate.

ClassifierEndpointAPI

TheclassificationmodelneedstobeexposedasanAPIendpointtoenableitsusage.

This was achieved by building a Python API that accepts an image string in Base64 format and returns a Status Codeindicatingwhatcategorythetrashbelongsto.

Underthehood,theAPIloadsandrunstheclassifierontheimageinputtoit.Theclassifierreturnsaclasstheimagebel

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ongs to. The class is then mapped to one of the three categories of trash that it finally needs to be put into. The EndpointAPIwasscriptedinGoogleColabNotebook [43].

HostingtheClassifier

The Classifier Endpoint API needs to be hosted in order to make it accessible. Since the development environment for theClassifier API was Colab Notebook, the library flask-ngrok was usedto host the notebook for development, testing anddemonstration purposes. Flask-ngrok is a library that Makes Flask apps running on localhost available over the internet on astaticURLviathengroktool.

3. Commercial Feasibility

3.1. Introduction

Tounderstandthefeasibilityandbenefitofbuildingthewastesegregationdustbinweevalu-atedthecostofthedustbinversusthebenefit.

3.1.1. CostEstimation

The cost of building the dustbin includes multiple parameters like the manufacturing cost, one time RND cost, and theoperationaloverhead.Let'sdivedeeperintheparameters.

3.1.1.1. The Manufacturing cost of the dustbin is inclusive of the **(**material cost) and **(**the manufacturing + tooling cost). Thefollowing figure is the **BoM (Bill of Materials)** for the manufacturing of the dustbin. There's an extra column for 30%discount on the total cost, that column is added because material manufacturers give a 30-50% discount for bulk orders. So,formassmanufacturingthecostwillreducebyap-proximatelyRs.1000/-.

Component	Qty	Cost per Piece (In Rupees)	Total Cost (In Rupees)	Cost after discount (30%)
Camera	3	475	1425	997.5
Servo Motor	1	499	499	349.3
Proximity Sensor	4	250	1000	700
Microcontroller Board (nodemcu esp8266)	1	500	500	350
LED	4	50	200	140
Weight Sensor	3	280	840	588
Alluminium Sheet	2Kg	134/kg	268	187.6
Extra Hardware (Wiring, resistors, etc.)	-	-	100	100
Total Cost	-	-	Rs.4832/-	Rs.3412/-

TABLE2:*BillofMaterials(BoM)*

3.1.1.2. ManufacturingProcess+ToolingCost: ManufacturingProcess+ToolingCostforthedustbinmod elwillbeabout20%ofitstotalcostsowillbeequaltoRs.750/-approximately.

3.1.1.3. Final estimation: Inclusive of the other factors like operational cost, servicing cost, electricity bills, etc. the totalexpenditure per dustbin won't exceed Rs.10,000/- in the first installation year. The amount will reduce down to about Rs.5000/- peryearorlessintheconsecutiveyearsaftertheinstallation.Althoughthatstillseemslikeahugeamount,whenwew ent ahead and calculated the benefits and the revenue that could be generated from our model, we were

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truly surprised bytheresults.

3.1.2. ProfitEstimation

Toestimatetheprofitthatcanpotentiallybegeneratedfromourdustbinwestartedwithcal- culatingtheapproximateweight of waste it can hold. Following figure is a table of the important factors that come in place for calculating the ap-proximate weight of waste each dustbin can hold. As discussed earlier, the dustbin is divided into 3 sections - Recyclablewaste,FoodwasteandRejectwaste.The waste segregation will give us intangible environmental benefits that will lead to a more sustainable environmentwhich we can-not directly convert into cost but is a very important factor.As our dustbin helps inmainlysegregating thedrywastefromwetitgivesusnumerouspossibilitiestobebenefitedfurther.

No. of sections in the dustbin	Volume per section	Average density of waste	Weight of waste each section can collect	Total weight of waste the dustbin can collect	Weight of waste collected by each dustbin on a single day	Weight of waste collected by each dustbin in a single month	Weight of waste collected by each dustbin in a single year
3	216 ltr	0.3 kg/ltr	61 kg	189 kg	95 kg	2850 kg	34,675 kg

TABLE3:*BillofMaterials(BoM)*

3.1.2.1. Food/WetWasteCostBenefits: Thewetwastecanbeconvertedintomanureandsoldoutorusedforcommu nitybenefits.Approximately,41%ofthetotalwastecollectedonadailybasisisfood/wetwaste.Itaccumulate sabout14,261kgof food/wet waste in a year. It is estimated that 35-40% weight of wet waste collected is equal to the weight of compostgenerated by it. Therefore, about 5,704kg of compost can be generated in a year. Which is a lot. Current cost of compost inthe market is equal to Rs.150/kg. Even if we sell the compost for a minimum amount of Rs.50/kgit will lead toRs.2,85,200/- revenueinayear.

3.1.2.2. Recyclable/DryWasteCostBenefits: Ifweinvestalittleonmanuallysegregatingtherecy- clable/drywaste.Wecan further get more mon- etary benefits from it.Todigdeeperintothiswe found out thepercentageofdifferenttypesofrecyclablematerialsingarbage.Followingisatablerepresentationforthesame .

Simply segregating the recyclable waste into plastic, paper and metal can give us numerous ben- efits. To calculate theweight of different types of material we can collect in our dustbin in different time frames - we used the average percentageof different types of material in garbage from *FIG 3* and calculated the weight of each material our dustbin will collect in ayear. We have assumed that we will keep each dustbin in such proximity that in a day it will only fill about half its capacity,refer *TABLE 4*. So, as shown in *TABLE 4* everyday we will collect about 95kg of garbage. Therefore, the amount of plasticcollectedinadaywillbeequaltoabout3.8kg.Thefollowingtablein*TABLE4*showsthebreakdownindetail.

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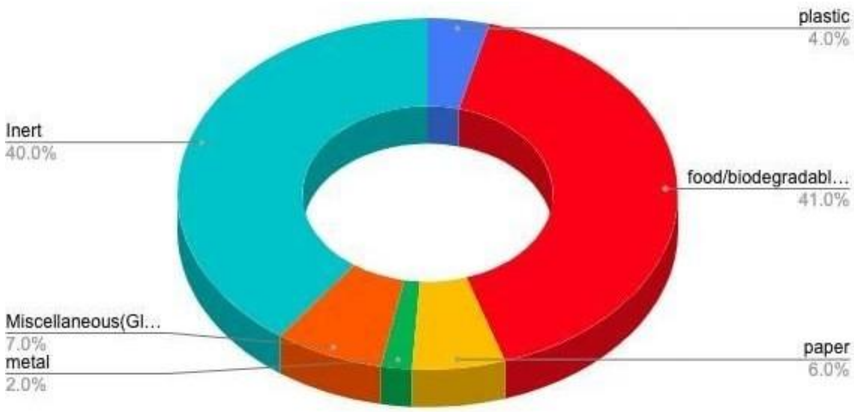

FIG3:*Percentageofdifferenttypesofscrapingarbage*

Even if we plan to do it manually and pay the person Rs.6,000 per year for segregating waste from one dustbin. It will leadto a total investment of about Rs.16,000/- per dustbin(Inclusive of the mfg cost). We went ahead and checked the currentmarketratesofdifferenttypesofscrapmaterials.

Material	Average amount of recyclable material in garbage	Weight of the material collected in our dustbin in a day	Weight of the material collected in our dustbin in a month	Weight of the material collected in our dustbin in a year
plastic	4%	3.8 kg	114 kg	1,387 kg
metal	2%	1.9 kg	57 kg	693.5 kg
paper	6%	5.7 kg	171 kg	2080.5 kg
Miscellaneous	7%	6.65 kg	199.5 kg	2427 kg

TABLE4:*WeightofDifferentMaterialsofScrapGenerated*

- TheaveragecostofscrapplasticisRs.20/kgwhichleadstoarevenueofRs.27,740/-peryear.
- TheaveragecostofscrappaperisRs.10/kgwhichleadstoarevenueofRs.20,800/-peryear.
- TheaveragecostofscrapmetalisRs.50/kgwhichleadstoarevenueofRs.34,680/-peryear.
- Theaveragecostofscrapglass,textiles,leatherisRs.20/kgwhichleadstoarevenueofRs.27,740/-peryear.

ThisaloneleadstoaboutRs.1,10,000/-ofrevenueperyearwhichequalsaboutRs.90,000/-profiteveryyear.Did anyone ever imagine sustaining the environment and earning profit while at it? The investment cost is also for the initialinstallmentyear.Ifthedustbinworksfor about 5 years without any major damages it can lead to about 5 lakhs of profitfromrecyclablewastealone. The numbers speak in the favour of our proposal. **Cost benefits are a lot greater than thecost of the dustbin**. Hence, even though the single product might be a lot costlier than a traditional plastic dustbin. The longtermcostbenefitsareimpeccable.

4. Result

The product is definitely commercially viableas proven in the above estimation. It’s also a need of the hour as every yearabout2.1billion tons of municipal waste is generated in the world and about 13 million tons of plastic is thrown in theocean every year. There are a lot of scary facts and numbers that prove that

the only solution to the waste haphazard is firstlevel of segregation.If the waste is segregated properly about 70% or more of the total waste that goes in the landfilloroceanscanberecycledorreused.Imaginetheamountofenvironmentalbenefitthatwilldo!
Another important metric to be considered is the accuracy of the Image Classification Model. Our model gives 92.76%accurate classifications on the Trashnet dataset which has been augmented with fast food images. (Given how the resultsobtainedbytheoriginalcuratorsofthedatasetwasaround63%accurate,ourConvNetModelhassignificantimprovements.)

5. Conclusion and Future Scope

5.1. Conclusion

Inthisprojectreportwepresentavisionofim-portanceofwastesegregation,itscorrectdisposalandrecyclingthrough-

- Puttingtechnologyinthefirstlevelofseg- regation is an amazing proposal and has numerous possibilities as abusinessaswellasforenvironmentalbenefits.
- Leveraging the power of contemporary AI technologies makes the product highly adapt- able, accurate and open toawidespectrumofpossibilitiestoinnovatefurther.

5.2. FutureScope

The experiment and results of our project solve a lot of difficult and important problems but, it still needs a lot of RND incertain areas. In the given time frame and with various constraints, we had to define our scope and edge cases in order toachieveaviablesolutionaroundit.
Furthermore, the Image Classification model was trained on an existing dataset of images of trash. This has to be trainedfurther to make it more accurate for our specific application i.e. train an- other layer of the ConvNet with images obtainedfrom the actual capturing unit of the dustbin's prototype. This whole proposal has a lot of future scope including the fewedgecasesthatwedidnotconsiderinthisproject.Followingisthelistforthesame.

- Segregationofcomplicatedwasteslikeburgerscoveredinsideapapernapkin,oraplasticcupwithcolddrinkinsideit.
- Buildingthemechanicalmodelandtestingthefunctionalitiespractically.
- Segregationofwastethrowninbulk.
- Percentagereductioninreject(unsorted)waste,inordertomaketheMLmodelmoreefficientandaccurateinachievingproductivesegregationbetweencompostableandrecyclablewaste

ConflictsofInterest: Theauthorsdeclarenoconflictsofinterest.

AuthorsContribution:M.Mistry,designedandconceptualizedthemanuscript. M. Mistry.,didtheproof-reading,editingandEnglishgrammarcheck**.**

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