COMPUTER SCIENCE DEPARTMENT
2nd Floor, SV Building
900 San Marcelino St., Ermita, Manila 1000 Philippines
Trunkline: +63 2 524-2011 local 305

COMPUTER SCIENCE
RESEARCH 2022

Adrian Miguel D. Cortezano

Arniel Reyes

Christian P. Bautista

Denver Ryan L. Sebolino

Vince Yuan F. Gabinete

Detecting Biodegradable Materials in Waste Piles Using YOLOv4 Object Detection Model

In Partial Fulfillment of the Requirements for the Degree

Bachelor of Science in Computer Science

By:

Bautista, Christian P.
Cortezano, Adrian Miguel D.
Gabinete, Vince Yuan F.
Reyes, Arniel
Sebolino, Denver Ryan L.

January 2023

APPROVAL SHEET

In partial fulfillment of the requirement for the degree Bachelor of Science in Computer Science, this research project entitled: "**DETECTING BIODEGRADABLE MATERIALS IN WASTE PILES USING YOLOv4 OBJECT DETECTION MODEL**" has been prepared and submitted by **Adrian Miguel D. Cortezano, Arniel Reyes, Christian P. Bautista, Denver Ryan L. Sebolino, and Vince Yuan F. Gabinete** who are hereby recommended for oral examination.

EDWARD D. BUSTILLOS, MSCS
Technical Adviser

Approved by the Tribunal of Oral Defense with the grade of **PASSED**

CHRISTINA NAVARRO, MSCS
Chairman

WILLIAM BILL TURNBULL JR Member	**RICO T. TEODORO** Member

Recommended by:
EDWARD D. BUSTILLOS, MSCS
Class Adviser, CS Research Project 2

Accepted as partial fulfillment of the requirement for the degree of Bachelor of Science in Computer Science.

CHRISTINA NAVARRO, MSCS
Chairperson, Computer Science Department

AUTHOR'S DECLARATION OF ORIGINALITY

We, the members of the group whose names appear below hereby certify that we are the true and sole members of this thesis and that no part of this thesis has been published or submitted for publication.

We certify that, to the extent of our knowledge, our thesis does not infringe upon anyone's copyright nor violate propriety rights and that any ideas, techniques, quitations, or any other material of from the work of any other people included in our thesis, published or otherwise, are fully acknowledged in accordance with the standard referencing practices. Furthermore, in the extent that we have included copyrighted materials, we certify that we have obtained a written permission from the copyright owner(s) to include such material(s) in our thesis and have included copies of such clearances to our appendix. We declare that this is an authentic copy of our thesis, including any other final revisions, as approved by our Panel, and the Adamson University Computer Science Department, and that this thesis has not been submitted for other or higher degree to another university or institution.

Title: Detecting Biodegradable Materials in Waste Piles Using YOLOv4 Object Detection Model

Authors	**Signature**
Bautsita, Christian P.	
Cortezano, Adrian Miguel D.	
Gabinete, Vince Yuan F.	
Reyes, Arniel	
Sebolino, Denver Ryan L.	

Co-authors: Edward D. Bustillos

Date: January 2022
Place: Manila Philippines

ACKNOWLEDGEMENT

TURNITIN SIMILARITY REPORT

Detecting Biodegradable Materials in Waste Piles Using YOLOv4 Object Detection Model

ORIGINALITY REPORT

10%	7%	5%	5%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	www.v7labs.com	Internet Source	1%
2	Submitted to Üsküdar Üniversitesi	Student Paper	1%
3	Fathi Sei Pahangai Akbar, Steven Yanuar Prasetyo Ginting, Giovanna Cheryl Wu, Said Achmad, Rhio Sutoyo. "Object Detection on Bottles Using the YOLO Algorithm", 2022 4th International Conference on Cybernetics and Intelligent System (ICORIS), 2022	Publication	1%
4	www.mygreatlearning.com	Internet Source	1%
5	www.researchgate.net	Internet Source	<1%
6	scholar.sun.ac.za	Internet Source	<1%
7	www.ms.k.u-tokyo.ac.jp	Internet Source	<1%
8	Submitted to Abu Dhabi University	Student Paper	<1%
9	Irfan Kilic, Galip Aydin. "Traffic Lights Detection and Recognition with New Benchmark Datasets Using Deep Learning and TensorFlow Object Detection API", Traitement du Signal, 2022	Publication	<1%
10	mdpi-res.com	Internet Source	<1%
11	Nisha Maharjan, Hiroyuki Miyazaki, Bipun Man Pati, Matthew N. Dailey, Sangam Shrestha, Tai Nakamura. "Detection of River Plastic Using UAV Sensor Data and Deep Learning", Remote Sensing, 2022	Publication	<1%
12	nova.newcastle.edu.au	Internet Source	<1%
13	Submitted to Coventry University	Student Paper	<1%
14	Submitted to Indian Institute of Technology Guwahati	Student Paper	<1%
15	Submitted to University of Makati	Student Paper	<1%
16	Submitted to University of Wolverhampton	Student Paper	<1%
17	www.diva-portal.se	Internet Source	<1%
18	Fengkui Zhao, Lizhang Xu, Liya Lv, Yong Zhang. "Wheat Ear Detection Algorithm Based on Improved YOLOv4", Applied Sciences, 2022	Publication	<1%
19	repositorio.yachaytech.edu.ec	Internet Source	<1%
20	www.avidionshost.com	Internet Source	<1%
21	Submitted to Liverpool John Moores University	Student Paper	<1%
22	Zou, Zhengxia, and Zhenwei Shi. "Hierarchical Suppression Method for Hyperspectral Target Detection", IEEE Transactions on Geoscience and Remote Sensing, 2015.	Publication	<1%
23	digitalcommons.unl.edu	Internet Source	<1%
24	uia.brage.unit.no	Internet Source	<1%
25	www.ccacoalition.org	Internet Source	<1%
26	Submitted to Adamson University	Student Paper	<1%
27	nur.nu.edu.kz	Internet Source	<1%
28	opus4.kobv.de	Internet Source	<1%
29	towardsai.net	Internet Source	<1%
30	www.mdpi.com	Internet Source	<1%
31	G Sai Susanth, L M Jenila Livingston, L G X Agnel Livingston. "Garbage Waste Segregation Using Deep Learning Techniques", IOP Conference Series: Materials Science and Engineering, 2021	Publication	<1%
32	Haruna Abdu, Mohd Halim Mohd Noor. "A Survey on Waste Detection and Classification using Deep Learning", IEEE Access, 2022	Publication	<1%
33	Joseph Redmon, Santosh Divvala, Ross Girshick, Ali Farhadi. "You Only Look Once: Unified, Real-Time Object Detection", 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016	Publication	<1%
34	Scott A Becker. "Three factors underlying incorrect in silico predictions of essential metabolic genes", BMC Systems Biology, 2008	Publication	<1%

Exclude quotes On
Exclude bibliography On
Exclude matches Off

TABLE OF CONTENTS

LIST OF FIGURES

Detecting Biodegradable Materials in Waste Piles Using YOLOv4 Object Detection Model

Bautista, Christian P.
BS in Computer Science
Department of Computer Science
chistian.bautista@adamson.edu.ph

Cortezano, Adrian Miguel D.
BS in Computer Science
Department of Computer Science
adrian.miguel.cortezano@adamson.edu.ph

Gabinete, Vince Yuan F.
BS in Computer Science
Department of Computer Science
vince.yuan.gabinete@adamson.edu.ph

Reyes, Arniel
BS in Computer Science
Department of Computer Science
arniel.reyes@adamson.edu.ph

Sebolino, Denver Ryan L.
BS in Computer Science
Department of Computer Science
denver.ryan.sebolino@adamson.edu.ph

Abstract—Methane is a very potent component of what makes up greenhouse gasses and plays a huge role in global warming. Though the Earth releases methane through natural factors, industries have increased its methane emissions to dangerous levels. One such cause of methane emissions is because of landfills and the anaerobic biodegradation buried organic matter undergoes. This makes waste segregation a very important task for the community. The study uses object detection for waste segregation to identify biodegradable materials in waste piles and in cluttered environments to increase segregation efficiency and determine the feasibility of this approach. The study uses the YOLOv4 detection model, a state-of-the-art model that performs exceptionally well in real-time, in both speed and accuracy. The network is trained on 3 classes of biodegradable materials images (food, paper, and cardboard), which were taken from the internet or captured by the researchers themselves. The research also uses transfer learning to make up for its small dataset of 4,374 images. The results of the study shows that an object detection approach in segregation using YOLOv4 is feasible, producing satisfactory detection results for each class in image, video, and real-time tests.

I. INTRODUCTION

Biodegradation is a natural process wherein organic matter is broken down by microorganisms. This process is enhanced by the addition of oxygen, which helps decompose the organic matter faster.[1] When matter underneath piles of garbage decompose, they do so anaerobically, without the help of oxygen; a process that produces methane which, in an uncontrolled environment, can be harmful.[2]

Too much build-up of methane in the atmosphere causes significant global warming due to methane being a powerful greenhouse gas.[3] In the past 100 years, despite the amount of methane being lower than carbon dioxide, its role in warming the planet has been more significant.[4] With large uncontrolled landfill sites present throughout the world, methane production from human waste has become the third largest source of human-caused methane emissions in 2020.[5]

To reduce waste delivered into landfills, methods such as recycling and segregation have been implemented by communities. This study aims to add to the effort in segregation by using object detection to assist in detection of biodegradable materials in waste piles and landfills.

The YOLOv4 model will be used as the basis for the created model. YOLOv4 is a single shot object detector based on the Convolutional Neural Network (CNN) [6], known for its good performance in real-time object detection, in both AP and FPS.[7]

A. Background of the Study

Computer vision is a subset of machine learning that focuses on training machines in understanding both real and virtual imagery. A prominent part of this field is object detection, an image processing technique which uses recognition and localization on images to locate objects. Unlike image classification and segmentation, object detection detects these objects by applying bounding boxes around them.

The recent boom in object detection has been studied in [8], which shows that a huge number of publications were made during 2017 to 2020, with 2019 being the year with the most publications for One-Stage object detection, and 2020 for Two-Stage object detection.

Using an object detection technique for assisting in the detection of biodegradable materials in waste piles can prove useful because of the clutter and chaos present in their environment, which can cause even the human eye to fail in detecting certain biodegradable items. Furthermore, it can also be used in assisting segregation in many areas of waste management, especially in segregation systems and facilities.

Existing studies use different object detection models in tackling the problem of waste detection

and segregation. One such research, “Detection of Waste Materials Using Deep Learning and Image Processing“, uses object detection to detect waste materials such as cardboard, paper, metal, etc. as an automated framework to limit the incorrect disposal of trash and help segregation.[9]

This study was chosen by the researchers because of the urgency of the community’s waste problem, and the need in taking steps in assisting in the segregation of garbage in order to reduce the methane emissions and environmental damage from accumulated and improper disposal of waste.

To reduce waste delivered into landfills, methods such as recycling and segregation have been implemented by communities. This study aims to add to the effort in segregation by using YOLOv4 to assist in real-time detection of biodegradable materials in clumps of waste.

B. Objectives of the Study

The general objective to determine the success of using YOLOv4 in detecting biodegradable materials in spaces with garbage clutter, this study aims to achieve the following objectives:

- Train a model which will detect biodegradable materials in waste piles.
- Identify the effectiveness of the model in detecting materials that have been deformed or modified.
- Identify the rate of YOLOv4 in falsely detecting or ignoring detection of materials.

C. Significance of the Study

The study will have the following list of contributions:

- In the global context, this study can aid institutions and environmental organizations in using Image Analysis to help determine the biodegradable materials mixed within garbage dumps, waste piles, and landfills.
- To Computer Vision Researchers, this study will be significant to computer vision researchers as this study will guide them in understanding more about the field. The findings of the study will also help future researchers learn more about object detection and its algorithms.
- To Waste Management Engineers, this study will be significant in the field of waste management and segregation because of its focus on the implementation of object detection, which can help their engineers formulate more efficient garbage detection and collection methods on waste piles or landfills.
- To fellow Students and Researchers, this may serve as help for them in their task in finding answers for their own research of object detection and computer vision.

D. Scope and Delimitation

The study will focus on determining the success rate and effectiveness of YOLOv4 in detecting biodegradable materials in a cluttered environment. There are internal and external factors that might affect the result of the detection of biodegradable materials.

Internal focuses on the resolution of the camera in some devices and the speed of which the camera operates on. While external is more about the environment's lighting and the state of the biodegradable material (e.g., the biodegradable material is deformed beyond recognition, the biodegradable material is damaged by chemical substances or modified to some extent). The study will only consider images in .jpg, .jpeg, and .png format for training and testing of images, and .mp4 for video. Furthermore, the study will not include factors such as: a) identification of extremely blurry inputs that are already unrecognizable even by the human eye; b) recognition and classification of the type of biodegradable material detected (i.e. if the detected food object is an apple or an orange); and c) detection in dimly lit or dark places.

E. Conceptual Framework

To successfully attain the desired outcome of the study, certain procedures and requirements will be carefully discussed to conceptualize the project's design and development.

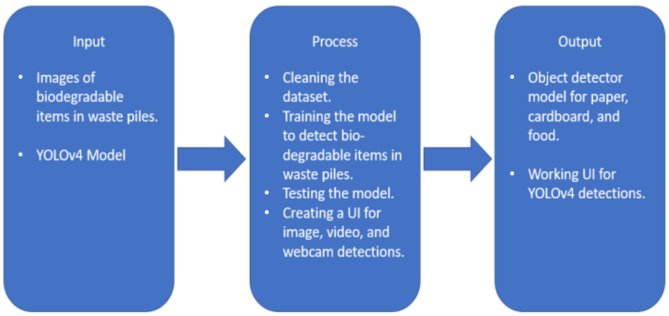


Fig. 1 Conceptual framework of the study

The conceptual framework of the study covers the three parts of the research: the input, process, and output phase.

The input phase includes the collection of biodegradable material datasets from open databases such as Kaggle and the usage of the YOLOv4 for the object detector model. The process phase includes cleaning and pre-processing of the dataset, training of the dataset, the testing and evaluation of the trained model, and the creation of the UI for image, video, and webcam detections. The output phase will be a model which can detect biodegradable materials, as well as an analysis of the effectiveness and success of the detection model in detecting them in waste piles and cluttered environments, and a working UI that can perform YOLOv4 detection processes.

F. *Operational Definition of Terms*

- Algorithm - Algorithm is a procedure of solving a specific problem.
- Image Labeling - Image Labeling is a process of annotating images for model training.
- Computer Vision - Computer Vision is a field of artificial intelligence that focuses on the training of computers in interpreting images and videos.
- Dataset - Dataset is a collection of organized data or values that stores a specific set of data.
- Image Annotations - Image Annotations are predetermined labels created by humans to help train computer vision models.
- Model - A Model is a system or program that attempts to simulate real-world behavior or events with mathematical formulas.
- Object Detection - Object Detection is a computer vision technique that can identify a specific object in images or videos.
- YOLO - YOLO (You Only Look Once) is a real-time object detection model that identifies and classifies an object.

II. REVIEW OF RELATED LITERATURE

A. *Object Detection*

Object detection is a computer vision technique that enables us to recognize and find things in images or videos. Object detection can be used to count objects in a scene and determine and track their location with identification and localization. Object detection generates bounding boxes around observed items, allowing the users to determine where these objects are in a given scene.[10]

Object detection methods are categorized into two types: One-stage networks, which have high inference speeds, and two-stage (or multi-stage) networks which have good localization and recognition accuracy.

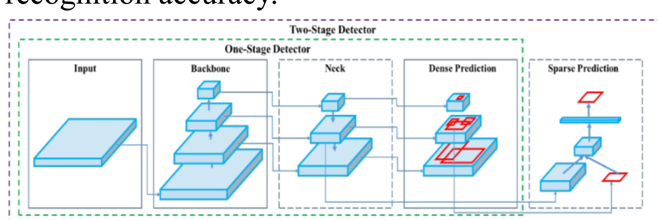


Fig. 2 Architecture of one-stage and two-stage object detectors.[11]

One-stage networks such as YOLO and SSD are significantly faster than two-stage detectors because they do not rely on multiple stages to refine their predictions and perform classifications. Instead, they predict their bounding boxes in a single pass with the help of anchors and grid boxes.[8] This removes the extensive computational cost that comes with having multiple stages in the network, but reduces the accuracy, leaving one-stage networks to struggle in detecting very small objects.

B. *YOLOv4 Model*

Joseph Redmon created the first version of YOLO (You Only Look Once) using a unique architecture called Darknet.[12] The greatest real-time object detectors in computer vision have been built by Darknet, a very flexible research framework implemented in low-level languages, including YOLO, YOLOv2, YOLOv3, and recently, YOLOv4. YOLO's entire detection pipeline is a single network and can be directly optimized end-to-end based on detection performance. The integrated architecture is very fast. A smaller version of the network, Fast YOLO, can handle 155 frames per second. Compared to state-of-the-art detection systems, YOLO has more localization errors but is less likely to predict false alarms in the background.[12]

YOLOv4 was created by A. Bochkovskiy, C. Wang, and H. M. Liao, which enhances YOLOv3 with some changes in architecture and their introduction of bags of freebies and bags of specials, which increases the accuracy with minimal effect on the inference cost.[13] The backbone of YOLOv4 uses CSPDarknet53[13]. CSPResNext50[14] was also considered due to their balanced performance with CSPDarknet53, but the latter was ultimately chosen as the optimal model for the backbone because of its higher receptive field and convolutional layer size. The neck consists of SPP[15] and PAN[16]. The last part of the architecture, the head, uses YOLOv3[17].

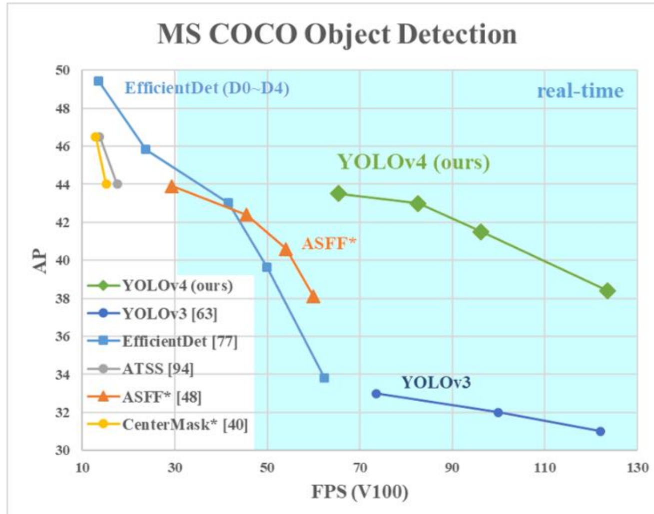


Fig. 3 Comparison with other models. YOLOv4 performs equally well as EfficientDet while operating twice as quickly. YOLOv4 increases the AP of its predecessor by 10% and FPS by 12%.[13]

In [18], the researchers compare YOLOv3 and v4, as well as their improved YOLOv4 version for use in garbage classification with embedded devices in mind, and proves the improvement of YOLOv4's performance over its predecessor. The YOLOv4 results outperformed YOLOv3 in mAP score by 16% and with a 12 FPS lead, and the improved version achieved slightly higher results for FPS, with YOLOv4 having a 4% higher mAP but is 8 FPS behind.

C. *Research on Smart Waste Segregation*

Various research in using smart solutions, such as deep learning technology and artificial intelligence, for use in waste segregation, have been published all throughout the years.

In the study [19], the researchers described several theoretical researches regarding solutions for waste management using digital technologies. For household waste management, they introduced smart dust bins which use artificial intelligence to separate different types of waste as part of their two-phase solution. They also describe an AI chatbot service that allows city residents to inquire about waste sorting, raising their awareness and knowledge in the topic. For city-level waste management, they introduce an alternative version of smart waste bins with sensors that allows garbage collectors to find the most efficient route to collect them, as well as a self-driving garbage truck to make collection itself more efficient.

Another research [20], aims to lessen human intervention in waste segregation due to health risks and to make the process more productive. The research trains the ResNet50, DenseNet169, VGG16, and AlexNet CNN models on ImageNet and compares each of their performance in making predictions and distinguishing types of waste into their own category. The comparison results show that DenseNet169 performs the best out of all the tested models, with AlexNet's performance coming last. In their evaluation of individual classes, cardboard was found to be the best detected item out of all the six classes, with a highest of 1.00 and 0.99 score for precision and recall respectively with DenseNet169. Due to insufficient learning, trash is often misunderstood by the models and is the only class to perform badly in VGG16, with a score of 0.44 and 0.57 for precision and recall. They also found glass to be often confused with other classes, sometimes being misclassified as plastic or metal.

In this research [21], the researchers aim to detect waste using deep-learning based algorithms in natural and urban environments. The researchers use EfficientDet-D2 to localize litter, and EfficientDet-B2 to classify the waste into seven categories. The researchers used 4 different datasets such as Open Litter Map, TrashNet and Waste Pictures for Classification. For the Detection, the researchers used 7 different subsets including Extended-TACO, MJU-Waste, TrashCan datasets and many more. The proposed study achieves up to 70% average precision on detecting waste in natural and urban environments and 75% accuracy on the test dataset.

D. Synthesis and Antithesis

The following are the related literature and studies that share similar ideas and concepts with the research.

The previously mentioned research [8], aims to create an automated waste detection system that uses object detection to categorize the waste material for proper segregation in trash bins. The study uses Faster R-CNN with TensorFlow's Object Detection API for their detection model and was observed to be precise at detection, but took 8.05 seconds to predict a single object and 8.09 for multiple objects. However, because of their limited training dataset, some local waste objects were wrongly predicted, and detections for images containing multiple objects were not consistent. This research is similar to their research with its use of object detection to detect waste materials, however, their approach in detection differs in model and method, using Faster R-CNN and focusing on a generalized dataset of waste materials using images containing mostly single objects for their training dataset.

In [22], the study uses deep learning to make waste segregation and management automated. The study uses YOLOv3 as its model and detects 6 classes of biodegradable and non-biodegradable waste materials. The study also trains YOLOv3-tiny to validate YOLOv3 by comparing their performance and finds that

YOLOv3 performs significantly better than its tiny counterpart but with an increase in prediction time. The similarity of this research is its deep learning approach in detecting waste materials for segregation. However, it differs in their approach, using the predecessor of YOLOv4 and comparing it with its tiny counterpart, and detects both non-biodegradable and biodegradable materials.

In [23], the researchers use hybrid transfer learning for classification, and a fine-tuned Faster R-CNN for object detection region proposals to detect waste throwaway items to assist in recycling. The research also uses data augmentation methods on their dataset to make it larger such as flipping, rotation and shearing, as well as creating images with multiple objects by placing objects at random and single objects at four quadrants. The similarity with this research is their application of data augmentation on their dataset and object detection, while the difference is their use of Faster-RCNN for their detector model and experimentation with hybrid transfer learning.

III. METHODOLOGY

A. *Systems Specification*

The study uses a system with 8GB RAM, a CUDA enabled NVIDIA GeForce 1050TI GPU

with CuDNN, and an Intel Core i3-4170 @3.10GHz CPU, during training and testing of the data. The programming language used for the user interface is Python, together with the PySimpleGUIQt [32] and OS module, and was tested on a Windows 10 operating system.

B. *Data Collection*

The dataset was gathered from three sources: open database websites such as Kaggle, images collected from Google images, and researcher-taken images. For the open database websites, images were gathered from the Garbage Classification Dataset [24], the Waste Classification data dataset [25], and the Non and Biodegradable Material Dataset [26] from Kaggle. The internet images were taken by the researchers using Google Images and other search engine tools. Lastly, researcher-taken images were images taken by the researchers themselves from community waste piles and household garbage.

The images from the dataset range from images with single objects only, to conveyor belts, to images of cluttered garbage and landfills, and usually contain more than one class, or more than one object. Each image was converted to .jpg, if not already in .jpg, and was cropped to scale smoothly into 416x416.

The gathered images were annotated using labelImg, a graphical image annotation tool created by Tzutalin [27], which also allows you to annotate multiple objects in an image.

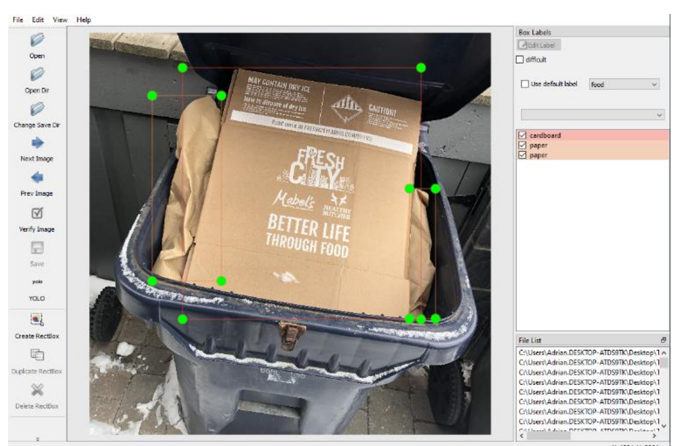
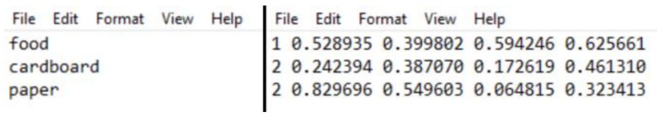


Fig. 4 The labelImg GUI.

The annotations are saved in a .txt format, which contains the class and annotation coordinates of the objects in an image. The classes present in the model are saved in a separate file named clases.txt.



```
File  Edit  Format  View  Help
food
cardboard
paper
```

```
File  Edit  Format  View  Help
1 0.528935 0.399802 0.594246 0.625661
2 0.242394 0.387070 0.172619 0.461310
2 0.829696 0.549603 0.064815 0.323413
```

Fig. 5 The classes.txt file (left) and the .txt file of the labeled image (right). The first digit of a row in the label .txt file is the class of the label and the succeeding numbers are the annotation coordinates.

C. Transfer Learning

Transfer learning is a method where the knowledge of a previously trained model is reused or repurposed to train a different model. The general features created from training the pre-trained model are transferred to the network of the new model. This is useful in cases where the dataset used for the new model is too small and nowhere near as big an accurate model should have, a problem that is present in the current dataset.[31]

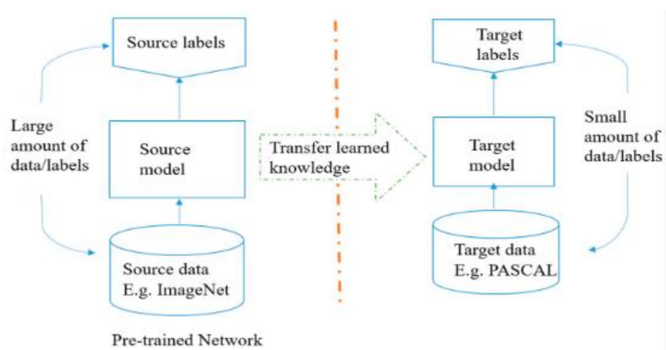


Fig. 6 Transfer Learning conceptual diagram

For object detection, this is achieved by taking a pre-trained model, which are finished models usually trained on very large datasets such as ImageNet, and transferring its trained parameters to the new model.

The research uses YOLOv4's pre trained weight file, which had been trained up to 137 convolutional layers on the MS COCO dataset with 80 different classes. This alleviates the problem of having a very limited dataset by repurposing the pre-trained model and using its learned features for the new tasks set for the new model.

D. Model Training

The researchers will train the model using 80% of the gathered dataset. The model will be trained to detect biodegradable materials commonly found in household waste piles and landfills, specifically food, papers, and cardboard. The model training will be further elaborated in Chapter IV.

E. Model Evaluation

The data will be evaluated using Mean Average Precision (mAP) evaluation metric. It has four sub metrics: Confusion Matrix, Intersection over Union (IoU), Recall, and Precision.

Confusion Matrix

Performance measurement of the predicted and actual detection. True Positive (TP), the prediction matches the ground truth; True Negative (TN), the model does not predict an object that is not part of the ground truth; False Positive (FP), the model predicts but the prediction does not match the ground truth; and False Negatives (FN), the model does not predict an object even though it is part of the ground truth.

Intersection over Union (IoU)

An evaluation metric for measuring the accuracy on particular datasets for detections using bounding boxes. IoU indicates the overlap of the predicted bounding box to the ground truth box, and computed by dividing the area of overlap (overlap of the bounding and ground truth box) by the area of union (area of both boxes).[28]

$$IoU = \frac{TP}{(TP + FP + FN)}$$

Fig. 7 IoU formula.[28]

Precision and Recall

Precision measures the accuracy of the detection by checking how many of the predictions were correct, which is achieved by dividing the number of true positives with the sum of the number of true positives and false positives, while recall measures the competence of the detection in finding all positive detections, which is achieved by dividing the number of true positives with the number of true positives and false negatives.[29]

$$Precision = \frac{TP}{TP + FP}$$

Fig. 8 Precision and recall formula.[29]

F. Outcome

The expected outcome is a model that can detect the aforementioned biodegradable materials in waste piles, landfills, and cluttered environments, and a working user interface for general use.

IV. RESULTS AND DISCUSSION

A. User Interface

The model viewer is placed inside the darknet folder path for it to access darknet. The UI has three buttons for image, video, and webcam processes, which sends a command to darknet to process the image or video based on the button clicked.

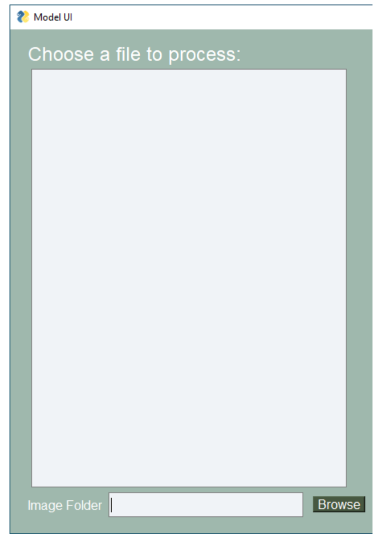


Fig. 9 Left side of the UI

The left side of the UI shows the selection list of all detected available images in your selected folder, which is filtered to only display .jpg, .jpeg, .png, and .mp4 files.

Fig. 10 Right side of the UI

The right side displays the image and the buttons to start darknet's process. Processed videos are saved in the location of the model viewer and will overwrite the previous processed video.

B. *Model Training*

The dataset contains a total of 4,374 images, comprising 1,965 cardboard, 1084 food, 1,587 paper, and 583 negative images. The dataset was trained using the aforementioned system, with its most important pieces being the CUDA enabled NVIDIA GeForce 1050TI GPU with CuDNN and the Intel Core i3-4170 @ 3.10GHz CPU. Due to hardware limitations, the model was limited to a network size of 416x416. The model was trained for 6000 batches, and took a total of 40 hours to finish training. The loss started around 10.0 before dropping to around 5.0-4.0 at the 2400th iteration, where it steadily went down until it plateaued around 3.0 on the 4800th iteration.

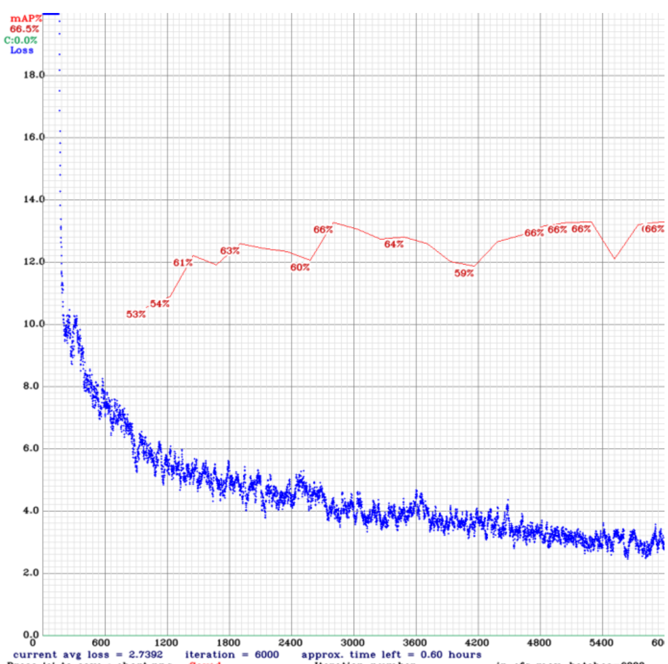


Fig. 11 Model training graph

C. *Model Testing*

The system used the same hardware as the one used for training and was tested on a total of 760 images. The model made 9845 detection counts with 2633 being the unique truth counts. The class with the highest average precision is food at 74.62%, having 515 true positives and 122 false positives.

Class	AP (Average Precision)	TP (True Positive)	FP (False Positive)
food	74.62%	515	122
cardboard	69.28%	708	350
paper	55.51%	334	159

Table. 1 Detection results from test dataset

The detection results show the average precision for a class and its true positive and false positive count. True positives occur when the model makes a positive prediction that matches the ground truth, while false positives occur when the model makes a positive prediction that doesn't match any ground truths.

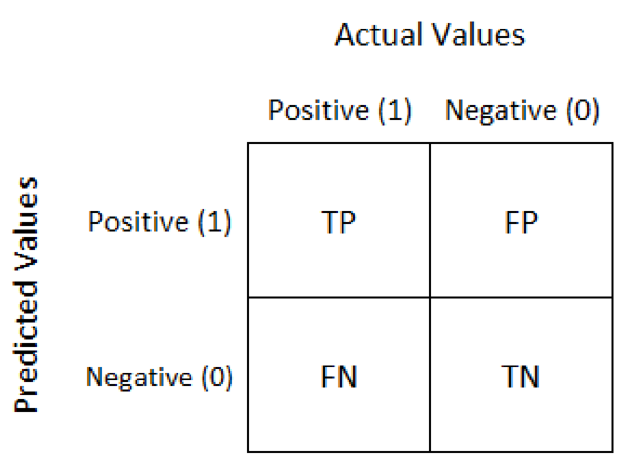


Fig. 12 Confusion Matrix.[30]

From the overall results, the model has a mAP@.50 of 66.47%, Precision of 0.71%, Recall of

0.59%, average IoU of 59.16% and has a total detection time of 56 seconds.

mAP@.50 (Mean Average Precision)	Prec-ision	Recall	Average IoU	Total Detect-ion Time
66.47%	0.71%	0.59%	59.16%	56s

Table. 2 Overall model performance from test dataset

D. Detection Results

Test Image 1

Test Image 2

Test Image 3

Test Image 4

Test Image 5

Test Image 6

Fig. 13 Detection results on images from the test dataset

Fig. 13 shows the detection results of the model in various settings. The model can accurately detect objects in an image or video, but can still confuse, misidentify, or ignore objects depending on their angle in the image. Furthermore, the model may sometimes detect parts of a single object as a separate object, such as in Test Image 3, if the part looks disjointed from the body or if the part connecting to the main object is occluded.

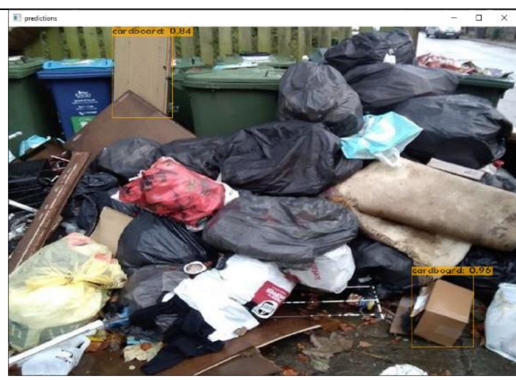
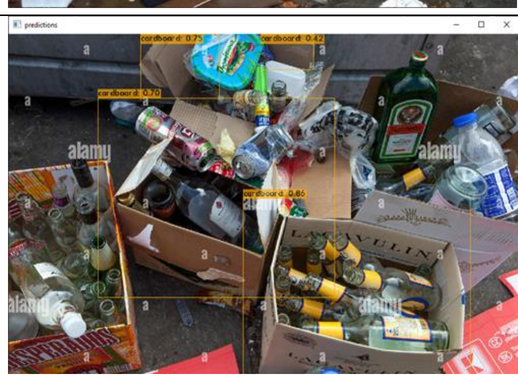
Test Image 7	
Test Image 8	
Test Image 9	

Fig. 14 Test Images showing misidentifications and ignored objects

Shown in Fig. 14 are the instances where the model confuses, misidentifies, or ignores objects, which can occur depending on the object's orientation, angle, or appearance in the image. Confusion usually occurs to objects with similar appearance to other classes, such as wood or brown paper bags and cardboard. This can be seen in Test Image 8, where a piece of wood is detected as cardboard. Similarly, colored or white cardboard can sometimes be detected as paper if not enough context of the object is seen. Furthermore, because some objects included in the classes can differ in appearance for other regions or countries, the model may ignore some objects not included in the dataset. This can be observed in Test Image 9, where a cardboard is ignored because of its different color as well as angle. The model performance on real-time detection ranged between 13-14 FPS and averaging at 13.1 FPS, and 15-15.9 FPS for video feeds, averaging at 15.7 FPS.

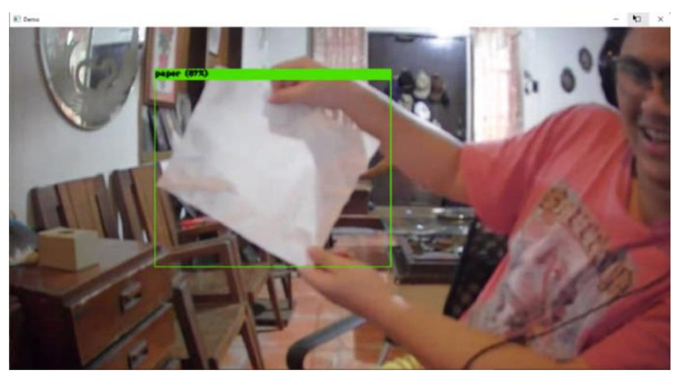


Fig. 15 Real-Time Detection

V. SUMMARY OF FINDINGS, CONCLUSIONS, AND RECOMMENDATIONS

A. Summary of Findings

This part of the paper summarizes the findings from the study:

- The trained model has a mean average precision score of 66.47%. The model has an average precision of 74.62% for food, 69.28% for cardboard, and 55.51% for paper.
- The model can successfully detect objects but can still ignore or confuse some objects. The model may also make separate detections for a single object if it is occluded.
- The model runs at an average of 13.1 frames per second in real-time detection and 15-15.9 frames per second for video feeds on a NVIDIA GeForce 1050TI GPU.
- The functions of the user interface work as intended and are simple enough to be used by people who are not very tech-literate.

B. Conclusions

The study concludes the following:

- The model is trained on 4,374 images from the gathered datasets [24][25][26] containing biodegradable materials (food, cardboard and paper objects). The model can detect these materials properly with small errors and misidentifications.
- For real-time testing, the researchers conclude that the 13-14 frames per second performance is acceptable considering that the GPU used to test the model is not a high-end piece of hardware.
- Out of all the detections for food, 122 were FPs (false positives) and 515 were TPs (true positives); cardboard had 350 FPs and 708 TPs, and paper had 159 FPs and 334 TPs.
- Overall, the study was able to create a model that can detect biodegradable materials, deformed or modified. From the results of the study, the researchers conclude that using the model to help with waste segregation is feasible to make it efficient and lessen human contact with waste objects.

C. Recommendations

The study recommends the following:

- To improve the precision of the model for deformed objects and lessen its false detections, the model should be trained with more images that contain these types of objects. Furthermore, because certain objects may have a different appearance in other countries, these objects should be included in the dataset to increase the robustness of the model.
- To improve the model's FPS performance, for detection in video feeds and in real-time, higher quality and more powerful hardware should be used, especially for the GPU.
- It is recommended to test one image or video at a time when testing on lower-end systems.
- To increase efficiency during testing, automatic processing of an entire folder could be integrated into the functions of the user interface.

REFERENCES

[1] “The myth of biodegredation - eco-products.” [Online]. Available: https://www.ecoproducts.com/images/pdfs/talking_points/Biodegradation.pdf. [Accessed: 23-Jul-2022].

[2] “Composting to avoid methane production,” Agriculture and Food. [Online]. Available: https://www.agric.wa.gov.au/climate-change/composting-avoid-methane-production#:~:text=Inefficient%20composting%20processes%20can%20result,of%20nuisance%20odours%20and%20complaints. [Accessed: 23-Jul-2022].

[3] “Causes of climate change,” Climate Science Investigations South Florida - Causes of Climate Change. [Online]. Available: http://www.ces.fau.edu/nasa/module-4/causes/methane-carbon-dioxide.php. [Accessed: 22-Jul-2022].

[4] Myhre, G., D. Shindell, F.-M. Bréon, W. Collins, J. Fuglestvedt, J. Huang, D. Koch, J.-F. Lamarque, D. Lee, B. Mendoza, T. Nakajima, A. Robock, G. Stephens, T. Takemura and H. Zhang, 2013: Anthropogenic and Natural Radiative Forcing. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

[5] Iea, “Methane tracker 2020 – analysis,” IEA. [Online]. Available: https://www.iea.org/reports/methane-tracker-2020. [Accessed: 23-Oct-2022].

[6] N. Tyagi, “Introduction to yolov4,” Analytics Steps. [Online]. Available: https://www.analyticssteps.com/blogs/introduction-yolov4. [Accessed: 03-Nov-2022].

[7] S. Achary, “Yolov4 - Speed & Accuracy,” Medium, 23-May-2020. [Online]. Available: https://medium.com/analytics-vidhya/yolov4-speed-accuracy-9f11c301334d#:~:text=YOLOv4%20is%20twice%20as%20fast%20as%20EfficientDet%20with%20comparable%20performance.&text=Compared%20with%20the%20previous%20YOLOv3,fast%20and%20accurate%20object%20detector. [Accessed: 03-Nov-2022].

[8] A. Lohia; K. D. Kadam; R. R. Joshi, and A. M. Bongale, "Bibliometric Analysis of One-stage and Two-stage Object Detection" (2021). Library Philosophy and Practice (e-journal). 4910.

[9] A. Mitra, “Detection of waste materials using deep learning and image processing,” thesis.

[10] “Object detection guide,” Fritz. [Online]. Available: https://www.fritz.ai/object-detection/#:~:text=Object%20detection%20is%20a%20computer%20vision%20technique%20that%20works%20to,move%20through. [Accessed: 16-Nov-2022].

[11] “Object detection: The reference architectures in medical imaging,” IMAIOS. [Online]. Available: https://www.imaios.com/en/resources/blog/introduction-to-the-most-common-deep-learning-architectures-for-object-detection-in-medical-imaging. [Accessed: 17-Dec-2022].

[12] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You only look once: Unified, real-time object detection,” 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016.

[13] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, "YOLOv4: Optimal Speed and Accuracy of Object Detection", arXiv:2004.10934

[14] C.-Y. Wang, H.-Y. M. Liao, I.-H. Yeh, Y.-H. Wu, P.-Y. Chen, and J.-W. Hsieh, “CSPNet: A new backbone that can enhance learning capability of CNN,” arXiv.org, 27-Nov-2019. [Online]. Available: https://arxiv.org/abs/1911.11929. [Accessed: 17-Dec-2022].

[15] K. He, X. Zhang, S. Ren, and J. Sun, “Spatial pyramid pooling in deep convolutional networks for visual recognition,” arXiv.org, 23-Apr-2015. [Online]. Available: https://arxiv.org/abs/1406.4729. [Accessed: 17-Dec-2022].

[16] S. Liu, L. Qi, H. Qin, J. Shi, and J. Jia, “Path Aggregation Network for instance segmentation,” arXiv.org, 18-Sep-2018. [Online]. Available: https://arxiv.org/abs/1803.01534. [Accessed: 17-Dec-2022].

[17] J. Redmon and A. Farhadi, “Yolov3: An incremental improvement,” arXiv.org, 08-Apr-2018. [Online]. Available: https://arxiv.org/abs/1804.02767. [Accessed: 17-Dec-2022].

[18] Q. Chen and Q. Xiong, “Garbage classification detection based on improved Yolov4,” Journal of Computer and Communications, 30-Nov-2020. [Online]. Available: https://www.scirp.org/journal/paperinformation.aspx?paperid=106526. [Accessed: 17-Dec-2022].

[19] R. Hynninen, I. Liehu, J. Lähteinen, I. Pekonen, "Utilizing Digital Technologies for Waste Management", 10.13140/RG.2.2.27209.67689

[20] G. S. Susanth, et. al., “Garbage Waste Segregation Using Deep Learning Techniques“, 2021 IOP Conf. Ser.: Mater. Sci. Eng. 1012 012040

[21] S. Majchrowska, A. Mikołajczyk, M. Ferlin, Z. Klawikowska, M. A. Plantykow, A. Kwasigroch, and K. Majek, “Deep learning-based waste detection in natural and Urban Environments,” Waste Management, vol. 138, pp. 274–284, 2022.

[22] S. Kumar, D. Yadav, H. Gupta, O. P. Verma, I. A. Ansari, and C. W. Ahn, “A Novel YOLOv3 Algorithm-Based Deep Learning Approach for Waste Segregation: Towards Smart Waste Management,” Electronics, vol. 10, no. 1, p. 14, Dec. 2020, doi: 10.3390/electronics10010014. [Online]. Available: http://dx.doi.org/10.3390/electronics10010014

[23] H. N. Kulkarni and N. K. S. Raman, “Waste Object Detection and Classification.” [Online]. Available: https://cs230.stanford.edu/projects_fall_2019/reports/26262187.pdf.

[24] M. Mohamed, “Garbage classification (12 classes),” Kaggle, 24-Jan-2021. [Online]. Available: https://www.kaggle.com/datasets/mostafaabla/garbage-classification?resource=download. [Accessed: 16-Nov-2022].

[25] S. Sekar, “Waste classification data,” Kaggle, 16-Jun-2019. [Online]. Available: https://www.kaggle.com/datasets/techsash/waste-classification-data. [Accessed: 16-Nov-2022].

[26] R. Zamzamy, “Non and biodegradable material dataset,” Kaggle, 12-Jun-2021. [Online]. Available: https://www.kaggle.com/datasets/rayhanzamzamy/non-and-biodegradable-waste-dataset?resource=download. [Accessed: 16-Nov-2022].

[27] Tzutalin, “heartexlabs / labelImg,” GitHub. [Online]. Available: https://github.com/heartexlabs/labelImg. [Accessed: 16-Nov-2022].

[28] Kukil, “Intersection over union IOU in object detection segmentation,” LearnOpenCV, 11-Nov-2022. [Online]. Available: https://learnopencv.com/intersection-over-union-iou-in-object-detection-and-segmentation/. [Accessed: 16-Nov-2022].

[29] Kukil, “Intersection over union IOU in object detection segmentation,” LearnOpenCV, 11-Nov-2022. [Online]. Available: https://learnopencv.com/intersection-over-union-iou-in-object-detection-and-segmentation/. [Accessed: 16-Nov-2022].

[30] A. Ragan, “Taking the confusion out of confusion matrices | by Allison Ragan ...” [Online]. Available: https://towardsdatascience.com/taking-the-confusion-out-of-confusion-matrices-c1ce054b3d3e. [Accessed: 16-Nov-2022].

[31] M. Z. Alom, T. M. Taha, C. Yakopcic, S. Westberg, P. Sidike, M. S. Nasrin, M. Hasan, B. C. Van Essen, A. A. Awwal, and V. K. Asari, “A state-of-the-art survey on Deep Learning Theory and Architectures,” Electronics, vol. 8, no. 3, p. 292, 2019.

[32] MikeTheWatchGuy, “PySimpleGUIQt,” PyPI. [Online]. Available: https://pypi.org/project/PySimpleGUIQt/. [Accessed: 12-Jan-2023].

APPENDICES

APPENDIX A: CURRICULUM VITAE

ADRIAN MIGUEL CORTEZANO

DATA SCIENCE MAJOR

A graduating computer science student looking to develop his skills and gain professional experience in software and web development.

EDUCATION

2004-2012 **Primary School**
Paco Catholic School

2012-2018 **Secondary School**
Mary Immaculate Parish Special School

2018-Present **Bachelor of Science in Computer Science**
Adamson University

TECHNICAL SKILLS

Object-Oriented languages	Python, C#, Java
Markup languages	HTML, CSS
Others	Database with MSSQL, software quality assurance
Research	Machine learning, object detection using YOLOv4

CERTIFICATIONS

April 2022 **Enterprise Design Thinking Practitioner**
Issued by IBM

May 2022 **Scrum Foundation Professional Certificate - SFPC™**
Issued by CertiProf

December 2022 **Flexisource "IT Forum 2022"**
Issued by Adamson University

CONTACT

0965-735-6365
cdricncdricn@gmail.com
Las Pinas City, Metro Manila
https://www.linkedin.com/in/adrian-cortezano-95b749254/

Arniel Reyes

DATA SCIENCE MAJOR

Graduating student from Adamson University who aspires to develop and hone his skills and gain professional experience in the corporate world.

arniel.reyes10@gmail.com 0923-682-8058 in linkedin.com/in/arniel-reyes-b21948239

Technical (IT) SKILLS

Data Management Database design & Management, Data Quality Assessment, Data Analysis, Pattern Identification, Visualization of data Insights

Computer Science Proficient in computer programming major in Python, knowledgeable in visual basic, C#, C++, MySQL, System administration, Advanced Microsoft Excel Functions

Research Advance YoloV4, Computer Vision, Machine learning

Computer Hardware Identify hardware such as Pc components and electronics

WORK EXPERIENCE

TOPSERVE SERVICE SOLUTIONS
Technical Support
01/2018 – 02/2018

- Worked as an IT technical support for the company.

IGT SOLUTIONS
Travel Agent
12/2019 – 05/2020

- Worked as a reservations and ticketing agent and name correction for Expedia Group Philippines.

EJR Data Processing
Data extraction specialist
11/2022 – 12/2022

- Worked as a data extractor for a German client.

EDUCATION

PRIMARY SCHOOL – SENIOR HIGHSCHOOL (STEM TRACK)
PACO CATHOLIC SCHOOL
2003-2018

BACHELOR OF SCIENCE IN COMPUTER SCIENCE
ADAMSON UNIVERSITY
2018-PRESENT

PROFESSIONAL CERTIFICATES

SCRUM FOUNDATION PROFESSIONAL (2022)
Online course

FORTINET NSE 3 ASSOCIATE
Online course

IBM ENTERPRICE DESIGN THINKING PRACTITIONER (2022)
Online course

Denver Ryan Lim Sebolino

Bachelor of Science in Computer Science

+63 9771005781

denversebolino@gmail.com

Sta. Mesa, Manila

PERSONAL INFORMATION

Currently taking BS Computer Science in Adamson University. My goal is to learn more on the field of computer science and to contribute to the society.

ACADEMIC QUALIFICATIONS

Philippine Pasay Chung Hua Academy / 2006-2018
2269 A. Luna St. Pasay City

Adamson University / 2018-2023
Ermita, Manila

TECHNICAL QUALIFICATIONS

Programming Language: *Python, Java, C#*

Scripting Language:
HTML, CSS, Javasript

Databases:
Microsoft SQL Server

Others:
Object Oriented Programming

CERTIFICATIONS

IT Forum 2022 "Flexisource IT Seminar"
Adamson University

Fortinet NSE 3 Associate
Online Course

+63 9065649371

Christian Pacis Bautista

bautista.christian.pacis@gmail.com

Lot 10 Blk 5 Summerfield Subd. Brgy. San Jose, Antipolo City

Bachelor of Science in Computer Science

PERSONAL INFORMATION

To pursue a job opportunity in a competitive environment that will push my boundaries and broaden my knowledge in the field of computer science while allowing me to contribute to the company's dynamics.

ACADEMIC QUALIFICATIONS

SACRED HEART CATHOLIC SCHOOL OF CAINTA
2012 – 2016

SIENA COLLEGE OF TAYTAY
2016 – 2018

COMPUTER SCIENCE | ADAMSON UNIVERSITY
2018 – CURRENT

TECHNICAL QUALIFICATIONS

Programming Language: *Python, Java, C#, C++*

Scripting Language:
HTML, CSS, JavaScript

Databases:
Microsoft SQL Server

CERTIFICATIONS

IT Forum 2022 "Flexisource IT Seminar"
Adamson University

Fortinet NSE 3 Associate
Online Course

Vince Yuan F. Gabinete

Bachelor of Science in Computer Science

+63 9279742568

vinceyuan123@yahoo.com

Imus, Cavite

PERSONAL INFORMATION

To develop into a highly effective specialist in the field of information technology by utilizing my technical knowledge and abilities to promote both professional and personal growth as well as the success of the firm.

ACADEMIC QUALIFICATIONS

Harrell Horne Integrated School
2012 – 2016

Far Eastern – University Manila
2016 – 2018

COMPUTER SCIENCE | ADAMSON UNIVERSITY
2018 – 2023

TECHNICAL QUALIFICATIONS

Programming Language: *Python, Java, C#*

Scripting Language:
HTML, CSS, Javasript

Databases:
Microsoft SQL Server

Others:
Object Oriented Programming

CERTIFICATIONS

IT Forum 2022 "Flexisource IT Seminar"
Adamson University

Fortinet NSE 3 Associate
Online Course

WORK EXPERIENCE

Customer Service Representative
Amazon
Three E-com Center, Bayshore Ave.,
Pasay, Metro Manila

September 06, 2021 - PRESENT