# THIRD EYE: OBJECT RECOGNITION AND SPEECH GENERATION FOR VISUALLY IMPAIRED

A Project Report Submitted in Partial Fulfilment of the Requirements for the Degree of

### Bachelor of Technology

in

Computer Science and Engineering

by

Yarlagadda Sai Bhavadeesh (Roll No. 2018BCS0082) Peddi Shwejan (Roll No. 2018BCS0047) Allu Harsha Vardhan (Roll No. 2017BCS0005) Lavanya S (Roll No. 2017BCS0034)



to

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING INDIAN INSTITUTE OF INFORMATION TECHNOLOGY KOTTAYAM-686635, INDIA

November 2021

#### **DECLARATION**

We, Yarlagadda Sai Bhavadeesh (Roll No: 2018BCS0082), Peddi Shwejan (Roll No: 2018BCS0047), Allu Harsha Vardhan (Roll No: 2017BCS0005), Lavanya S (Roll No: 2017BCS0034), hereby declare that, the report entitled "Third Eye: Object Recognition And Speech Generation For Visually Impaired" submitted to Indian Institute of Information Technology Kottayam towards partial requirement of Bachelor of Technology in Computer Science and Engineering is an original work carried out by us under the supervision of Dr. Koppala Guravaiah and has not formed the basis for the award of any degree or diploma, in this or any other institution or university. We have sincerely tried to uphold the academic ethics and honesty. Whenever an external information or statement or result is used then, that have been duly acknowledged and cited.

Kottayam-686635 Yarlagadda Sai Bhavadeesh - 2018BCS0082

November 2021 Peddi Shwejan - 2018BCS0047

Allu Harsha Vardhan - 2017BCS0005

Lavanya S - 2017BCS0034

**CERTIFICATE** 

This is to certify that the work contained in this project report entitled

"Third Eye: Object Recognition And Speech Generation For Vi-

sually Impaired" submitted by Yarlagadda Sai Bhavadeesh (Roll No:

2018BCS0082), Peddi Shwejan (Roll No: 2018BCS0047), Allu Har-

sha Vardhan (Roll No: 2017BCS0005), Lavanya S (Roll No: 2017B-

CS0034) to Indian Institute of Information Technology Kottayam towards

partial requirement of Bachelor of Technology in Computer Science

and Engineering has been carried out by them under my supervision and

that it has not been submitted elsewhere for the award of any degree.

Kottayam-686635

(Dr. Koppala Guravaiah)

November 2021

Project Supervisor

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#### ABSTRACT

Visually impaired people face a lot of difficulties in doing their daily activities. There is a say that, Out of all the five sense organs, eyes are most important. Your eyesight is one of your most important senses: 80% of what we perceive comes through our sense of sight [10]. Visually impaired need the help of either the third person or a stick. These methods are not always fruitful. Detecting and recognizing the objects and generating speech about the objects helps visually impaired in a great way in understanding their surroundings.

We aim to assist the visually impaired to travel independently with the ability to identify objects in their path, and the ability to generate speech describing the objects detected in the scene. The thesis employs training on YOLO (You Only Look Once) v5, Convolutional Neural Network (CNN) model for object detection. YOLO v5 is trained on custom dataset of 15 objects, along with MS COCO 2017 Dataset of 80 objects (95 objects overall). In future, the output of model is converted to audio format and is presented to visually impaired.

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### Chapter 1

### Introduction

Visually Impaired face a lot of difficulties in their daily lives. According to World Health Organization (WHO), at least 2.2 billion people have a near or distant vision impairment. Out of them, 49.1 million people are completely visually impaired. Yet the growth of population is making a substantial improvement in the number of people affected. Notable interregional and gender inequalities exist which highlights the need to scale up vision impairment alleviation efforts at all levels.

Visually impaired always need the help of either a stick or a person. Young children with early-onset severe vision impairment can experience limited language, emotional, social, and cognitive development, with lifelong consequences. Vision impairment critically impacts the quality of life among the adult population. In the case of older adults, vision impairment can contribute to social isolation, difficulty walking, a higher risk of falls and fractures, and a greater likelihood of early entry into nursing or care homes.

Hence, we took up this project to help visually impaired people to recognize their surroundings. In recent years, deep learning has become a more popular technique for solving these problems of identifying objects. The deep learning systems achieve high accuracy rates at a lower cost. Many Convolutional Neural Network (CNN) methods like Single Shot Detector (SSD) and You Only Look Once (YOLO) are used to solve detection and recognition issues. There are other architectures such as Faster R-CNN and Mask R-CNN [37]. In this project, we used the YOLO v5 algorithm. Implemented a custom-made dataset including MS COCO 2017 dataset to attain good accuracy, and performance. After detecting and recognizing the objects, we are planning to generate speech, for the recognized objects. This can be achieved by using Recurrent Neural Network Techniques (RNN).

YOLO is an abbreviation for the term "You Only Look Once". YOLO algorithm detects and recognizes various objects in a picture (in real-time). YOLO uses convolution neural networks to provide real-time object detection. YOLO v5 is faster, more accurate, and light-weight compared to other versions of YOLO. It has been used in various applications such as autonomous car driving, etc. YOLO v5 is one of the best available models for Object Detection at the moment.

# Chapter 2

# Literature Survey

Many works have been done on making life better for the visually impaired. There is various equipment for the visually impaired, such as sensor-powered walking sticks, speaking calculators, etc.

Rajwani, Roshan et al.[28] presented a system where the input is taken through an android camera, then the captured image is preprocessed using OpenCV, then the classification and identification is done in Cloud Vision API and it sends the image label. Elmannai, Wafa M and Khaled M. Elleithy. [12] proposed a system where two camera sensors are used for object detection, which is processed using computer vision methods. The remote server handles the image processing. Based on the depth of the image, we can approximately measure the distance between the obstacle and the Visually Impaired person. The Oriented FAST and Rotated BRIEF (ORB) and KNN are used for object detection. Ye, Cang and Xiangfei Qian. [36] In 2018, a 3-D Object Recognition for Visually Impaired people is proposed.

The cane used by blind people is attached with a CV enhanced 3D Camera, it captures a 3D point cloud which is segmented into planar segments, which are then classified using Gaussian Model Mixture and clustered into the target objects. Bashiri, Fereshteh S et al. [6] proposed a system where the input is taken through a Google Glass Device, then the captured image is preprocessed using Convolutional Neural Network, then classification and identification are done using Support Vector Machine Algorithm. Here they used Marshfield Clinic Dataset. Gianani, Sejal et al. [14] came up with a system where the image is captured through a camera device for the input and preprocessed using OpenCV. They have combined both the Single Shot Detector (SSD) framework and the MobileNet architecture to arrive at a fast and efficient deep learning-based method for object detection. Nishajith, A et al. [21] suggested a framework that uses Raspberry Pi which has a Pretrained CNN network. The image is captured through Noir Camera and preprocessing is done through OpenCV and they used Pre-trained object detection model 'ssd\_mobilenet\_v1\_coco\_11\_06\_2017' to classify the objects and text to speech conversion is done using eSpeak. Patel, Charmi T et al. [24] presented a technology where the image is captured through a USB webcam and preprocessing is done and it classifies and identifies the objects using the SVM Algorithm. Further, input from the ultrasonic sensor will be utilized to confirm object detection output. Additionally, an IR sensor will detect small objects near feet. Tosun, Selman and Enis Karaarslan. [33] proposed a system where the image is captured using the android platform and preprocessing is done using OpenCV and Tiny YOLO which is implemented using Tensorflow is used for object detection which gives the audio output.

Wong, Yan Chiew et al. [34] In 2019, an object detection system for visually disabled people based on CNN in real-time has been proposed. To reduce the complex load, regional suggestions from the edges of each image map were generated using the control box algorithm. Then, the suggestions passed through a well-configured CaffeNet model. The object group was filmed by a webcam in real-time and the image feature was removed. Next, a soundbased detector was developed to detect the sight of visually impaired people. Nasreen, Jawaid et al. [20] Proposed a system that can be used to guide visually impaired people for object detection. The developed system takes an image from the back camera and loads it into a website and it passes the image to the server, on the server-side YOLO model is used to detect the objects. Pardasani, Arjun et al. [22] They presented a technology that is wearable like smart glasses and shoes. Both smart shoes and glasses detect the obstacle and pass an audio output to the user. Rahman, Ferdousi et al. citerahman 2019 assistive This paper presents an object detection model using the YOLO algorithm for visually impaired people. MTCNN is utilized for the building model. For Object identification and Facial Recognition, YOLO Algorithm and MTCNN Networking are used, respectively. Shah, Samkit et al. [29] In this paper they compared different detection algorithms to detect multiple objects and they found that Haar Cascade is the fastest and CNN gives more accuracy. Jhinkwan, Piyush et al. [15] They proposed a system that uses a convolutional network combined with fully connected layers. They have used the CIFAR-100 dataset, The model is trained with a backpropagation algorithm to detect the objects in the image. Chen, Xiaobai et al. [11] designed an automatic DCNN quantization algorithm to significantly

reduce data range up to 4 or 5 bits, reducing hardware costs by more than 68% compared to the 16-bit fixpoint model with irreversible accuracy loss. Sun, Minghui et al. [31] proposed a system using Google Tango, a built-in infrared (IR) sensor to collect data.

Afif, Mouna et al. [1] In 2020, introduced YOLO v3, on a custom dataset that has 16 indoor object classes. They attained 73.19% mAP, they focused on indoor navigation. Afif, Mouna et al. [2], later proposed a framework on deep CNN "RetinaNet" for detecting indoor objects, which showed better results than their earlier work. Fang, Wei et al. [13] introduced a method using the Tinier-YOLO model, which is 4 times smaller than Tiny-YOLO v3. trained on PASCAL VOC and COCO datasets. It's faster than other lightweight models. Li, Yongjun et al. [17] In the same year, proposed another version of YOLO, that is YOLO-ACN, which showed better results. They mainly focused on small objects detection. Bhole, Swapnil and Aniket Dhok. [7] Proposed a transfer learning on Single-Shot Detection (SSD) mechanism for object detection, and implemented it for human as well as currency detection. They achieved 90.2% accuracy on currency detection. Yohannes, Ervin et al. [37] introduced a method to assist the visually impaired around an outdoor environment. They designed a model using DarkNet-53 as a backbone, input is taken from a ZED stereo camera, and the model is trained on PASCAL VOC and MS COCO datasets. Joshi, Rashika et al. [16] mentioned a method using Mobile Net SSD, and the images are taken using Jetson Nano, and PiV2 camera, and trained on PASCAL VOC dataset. achieved pretty good results with the proposed model.

Atikur Rahman and Sheikh Sadi. [27] In 2021, proposed an IoT-enabled

Automated Object Recognition where they used SSD Model, SIFT, and MS COCO dataset. Balachandar, Santhosh et al. [5] They proposed a scheme where a multi-view object tracking (MVOT) system is used in this proposed system to address multiple cameras monitoring recording videos. And by combining the knowledge contained in the videos, a powerful and accurate framework is developed. Each segmented group of objects in one view is mapped to the corresponding group in another view using the Yolo V3 algorithm These agreeing sets corresponded to blob gatherings, Which allow data to be exchanged between cameras. These images are transformed into voice output after they are captured by the camera. Mansi Mabendru and Sanjay Kumar Dubey. [19] In this paper a system is developed using two different algorithms i.e. Yolo and Yolo\_v3 and tested under the same criteria to measure the accuracy and performance. In the YOLO Tensor flow, the SSD Mobile Net model and in Yolo\_v3 Darknet model are used. To get the audio Feedback gTTS (Google Text to Speech), the python library is used to convert statements into audio speech. To play the audio pygame python module is used. Kanchan Patil et al. [25] They proposed a wearable device with a Virtual assistant system for the visually impaired person, Total of five components they merged into one system in this project. The navigation through these components is possible through hardware buttons and voice-over commands given by the user. There are many deep learning methodologies and core libraries of python language used for programming. Mohana Priya et al. [4] In this paper a voice-based image caption generation is a task that involves the NLP (natural language processing). The combination of CNN and LSTM is considered the best solution in this project; the main target of this proposed research work is to obtain the perfect caption for an image. After obtaining the description, it will be converted into text and the text into a voice. Annapoorani et al. [3] You Only Look Once (YOLO) a Real-Time Object Detection is deployed in this paper, Image classification techniques are used to identify the features of the image and Indian currency recognition module is developed to identify the denominations. The text description of the recognized object will be sent to the Google Text-to-Speech API using the gTTS package. Sandeep Pandasupuleti et al. [23] In this paper they proposed Voice Translation and Image Recognition using VCC, LSTM, and Flickr\_8k dataset.

Table 2.1: Trends & Technologies discussed in literature

Paper Title	Authors	Methods	Pros & Cons
Proposed System	Rajwani, Roshan,	Android Camera,	Since the output
on Object Detec-	Dinesh Purswani,	OpenCV, Google	is through An-
tion for Visually	Paresh Kalinani,	Cloud Vision API,	droid application,
Impaired People.	Deesha Ramchan-	Compare it with	it should have
[28]	dani, and Indu	Microsoft COCO	enough battery.
	Dokare	Dataset and give	
		output.	

Table 2.1: Trends & Technologies discussed in literature ... Contd.

Paper Title	Authors	Methods	Pros & Cons
A Highly Accurate	Elmannai, Wafa	Two camera Sen-	Accuracy of 96%,
and Reliable Data	M., and Khaled M.	sors, Computer	Used a mother-
Fusion Framework	Elleithy	Vision Methods,	board connected
for Guiding the		Oriented FAST and	with various sen-
Visually Impaired.		Rotated BRIEF	sors like gyro,
[12]		(ORB) and KNN	compass, GPS,
		Algorithm.	music, FEZ Spider
			board.
3-D Object Recog-	Ye, Cang, and Xi-	3D Camera(White	Trained on all in-
nition of a Robotic	angfei Qian	Cane), Planar Seg-	door objects Accu-
Navigation Aid for		ments, Gaussian	racy over 90%
the Visually Im-		Model Mixture	
paired [36]			
Object Detection	Bashiri, Fereshteh	Marshfield Clinic	Limited number of
to Assist Visually	S, Eric LaRose,	Dataset, Google	objects (ex: doors,
Impaired People:	Jonathan C. Bad-	Glass Device, CNN	stairs, signs etc.,)
A Deep Neural	ger, Roshan M.	Model, Support	Accuracy over 98%
Network Adven-	D'Souza, Zeyun	Vector Machine	
ture. [6]	Yu, and Peggy	Algorithm	
	Peissig.		

Table 2.1: Trends & Technologies discussed in literature ... Contd.

Paper Title	Authors	Methods	Pros & Cons
JUVO - An Aid	Gianani, Sejal,	Camera,Image	Few objects in
	, , ,	, ,	3
for the Visually Im-	Abhishek Mehta,	Capturing and Pre-	Dataset. Indoor
paired [14]	Twinkle Motwani,	processing, Object	Environment, Ac-
	and Rohan Shende	detection Us-	curacy of 99.61%
		ing OpenCV,	
		SSD Framework,	
		MobileNet Archi-	
		tecture	
Smart Cap-	Nishajith, A., J.	Raspberry Pi Noir	90 classes of objects
Wearable Visual	Nivedha, Shilpa S.	Camera, OpenCV	in Dataset.
Guidance System	Nair, and J. Mo-	Processing, COCO	
For Blind. [21]	hammed Shaffi.	Model,eSpeak.	
Multisensor –	Patel, Charmi	USB Web-	It can be used
based Object De-	T., Vaidehi J. Mis-	cam,Preprocessing,S	tattiisti cault door envi-
tection in Indoor	try, Laxmi S.	Analysis,SVM	ronment but it is
Environment for	Desai, and Yogesh	Classifier.	tested for indoor
Visually Impaired	K. Meghrajani.		environment only.
People [24]			

Table 2.1: Trends & Technologies discussed in literature ... Contd.

Paper Title	Authors	Methods	Pros & Cons
Real-Time Object	Tosun, Selman, and	Camera, OpenCV	Only 20 classes in
Detection Appli-	Enis Karaarslan	Processing, Tiny	the dataset, Man-
cation for Visually		YOLO Tensor-	ual selection.
Impaired People:		Flow, Audio	
Third Eye. [33]		Output, COCO	
		Dataset	
Convolutional Neu-	Y.C. Wong, J.A.	Cnn, Used edge box	The object detec-
ral Network for Ob-	Lai, S.S.S. Ranjit,	algorithm, Caffnet	tion models faced
ject Detection Sys-	A.R. Syafeeza, N.	model, softmax Ci-	difficulty in clas-
tem for Blind Peo-	A. Hamid	far10 dataset has	sifying the object
ple. [34]		been used	from a picture of ul-
			timate scale
Object Detection	Jawaid nasrren,	Used YOLO.It nar-	Results showed
and Narrator for	warsi, Arif, Asad	rates to the user.It	that the accuracy
Visually Impaired	ali shaikh, Yahya	was trained on Im-	is varying de-
People. [20]	Muhammad, Mon-	agenet dataset	pending on phone
	aisha abdullah.		camera quality and
			the light effects.
			iPhone and Sam-
			sung have better
			results than others.

Table 2.1: Trends & Technologies discussed in literature ... Contd.

Paper Title	Authors	Methods	Pros & Cons
Smart Assistive	Arjun Pardasani,	Open CV, Image	Both the devices
Navigation Devices	Prithviraj N Indi,	processing, Used	have been devel-
for Visually Im-	Sashwata Banerjee,	Smart glass and	oped by using sim-
paired People. [22]	Aditya Kamal,	shoes	ple, cheap sensors.
	Vaibhav Garg		Their motive is to
			make both the de-
			vices as a part of
			the user's regular
			and frequently used
			objects
An Assistive Model	FerdousiRahman,	Open CV, YOLO	The object de-
for Visually Im-	IsratJahanRitun,	algorithm, Deep	tection process
paired People	NafisaFarhin, Ji-	learning	achieved 6-7 FPS
using YOLO and	aUddin		processing with an
MTCNN [26]			accuracy rate of
			63-80%

Table 2.1: Trends & Technologies discussed in literature ... Contd.

Paper Title	Authors	Methods	Pros & Cons
CNN based Auto-	Samkit Shah ,	Haar cascade,	When processed on
Assistance System	Jayraj Bandariya	CNN,Deep learn-	CPU, Haar cascade
as a Boon for	, Garima Jain ,	ing COCO 2017	is the fastest al-
Directing Visually	Mayur Ghevariya ,	data Set was used	gorithm, but CNN
Impaired Person.	Sarosh Dastoor		gives more accu-
[29]			rate results when
			detecting multiple
			objects simultane-
			ously for real time
			applications
Object Detection	Piyush Jhinkwan	Deep learn-	It was trained
Using Convolution	, Vaishali In-	ing,CNN, Back	with dropout and
Neural Networks	gale , Shubham	propagation algo-	data augmentation
[15]	Chaturvedi	rithm. For training	to achieve better
		CIFAR-100 dataset	results.
		was used	

Table 2.1: Trends & Technologies discussed in literature ... Contd.

Paper Title	Authors	Methods	Pros & Cons
A 68 mw 2.2	Xiaobai Chen, Jin-	Deep convolutional	reducing hardware
Tops/w low bit-	glong Xu	network, low-bit,	cost by over 68%
width and mul-		multiplierless	compared to the 16
tiplierless DCNN			bit fixpoint model
object detection			with negligible ac-
processor for vi-			curacy loss
sually impaired			
people. [11]			
"Watch Your	MINGHUI SUN	Google Tango,	The system cannot
Step": Precise	PENGCHENG	built-in infrared	correctly distin-
Obstacle Detection	DING , JIAGENG	(IR) sensor to	guish complex
and Navigation	SON , MIAO	collect data	situations such as
for Mobile Users	SONG5 , AND		obstacles leaning
Through Their	LIMIN WANG		against a wall
Mobile Service [31]			
Research on Small	Qiwei Xu, Runzi	YOLO v3, 2080 Ti	Improvised YOLO
Target Detection in	Lin, Han Yue,	machine, Dataset	v3 and it showed
Driving Scenarios	Hong Huang, Yun	used is Apollo	better results com-
Based on Improved	Yang, Zhigang Yao	Scape (Baidu's	pared to YOLO
Yolo Network. [35]		autopilot dataset).	v3. Accuracy is
			84.76%.

Table 2.1: Trends & Technologies discussed in literature ... Contd.

Paper Title	Authors	Methods	Pros & Cons
Tinier-YOLO: A	Wei Fang, Lin	Tinier-YOLO-v3,	Faster runtime
Real-Time Object	Wang, Peiming	PASCAL VOC	speed compared to
Detection Method	Ren	(2007 + 2012),	other lightweight
for Constrained		COCO.	models. But, is
Environments. [13]			suitable for embed-
			ded systems (Low
			accuracy).
YOLO-ACN: Fo-	Yongjun Li, Shasha	YOLO-ACN, MS	Doesn't improve
cusing on Small	Li, Haohao Du, Li-	COCO, Infrared	performance much
Target and Oc-	jia Chen, Dong-	pedestrian dataset	with the proposed
cluded Object	ming Zhang, Yao Li	KAIST, NVIDIA	method, compared
Detection. [17]		Tesla K40.	to YOLO v3. fo-
			cused on small
			objects detection.
Object Recognition	Rashika Joshi,	MobileNetSSD	Got pretty good
and Classification	Meenakshi Tri-	(SSD - Single	accuracy, but the
System for Visually	pati, Amit Kumar,	Shot-Detector),	dataset is small,
Impaired. [16]	Manoj Singh Gaur.	PASCAL VOC	not sufficient. Only
		2007.	for embedded sys-
			tems.

Table 2.1: Trends & Technologies discussed in literature ... Contd.

Paper Title	Authors	Methods	Pros & Cons
An Evaluation of	Mouna Afif, Riadh	RetinaNet	Attained 84.61%
RetinaNet on In-	Ayachi, Yahia Said,	(ResNet,	mAP. Focused
door Object Detec-	Edwige Pissaloux,	DenseNet, VG-	on only indoor
tion for Blind and	Mohamed Atri	GNet based), Self	navigation. the
Visually Impaired		prepared Dataset	number of objects
Persons Assistance		(Contains 8000	it can detect is very
Navigation. [2]		images).	small. Got good
			results with pro-
			posed algorithm.
Indoor object de-	Mouna Afif, Riadh	YOLOv3,	Attained 73.19%
tection and recog-	Ayachi, Edwige	DarkNet-53.	mAP, and it's only
nition for an ICT	Pissaloux, Yahia	Dataset contains	focused on indoor
mobility assistance	Said, Mohamed	8000 images and	navigation. Used
of visually impaired	Atri	contains 16 indoor	pretrained model
people. [1]		object classes.	and trained on the
			new dataset.

Table 2.1: Trends & Technologies discussed in literature ... Contd.

D Till A 41 D 0 G			
Paper Title	Authors	Methods	Pros & Cons
Robot Eye: Auto-	Ervin Yohannes,	Self-designed	Accuracy is 81%,
matic Object De-	Paul Lin, Chih-	model (DarkNet-53	better than YOLO
tection and Recog-	Yang Lin, Timothy	based), ZED Stereo	v3. Used PASCAL
nition Using Deep	K. Shih	camera, PASCAL	VOC for classes,
Attention Network		VOC, MS COCO	and mixed MS
to Assist Blind Peo-		datasets.	COCO. No-of
ple. [37]			classes are too
			small
Deep Learning	Swapnil Bhole,	PASCAL VOC	Added currency
based Object De-	Aniket Dhok	2007 dataset,	detection to the
tection and Recog-		SSD, Inception v3	dataset and
nition Framework		model.	achieved 90.2%
for the Visually-			acc. But the
Impaired. [7]			dataset contains
			only 20 classes.
IoT Enabled Au-	Md. Atikur Rah-	laser sensors ,	Yolo accuracy is
tomated Object	man , Muhammad	Single Shot Detec-	95.99 and SSD
Recognition for the	Sheikh Sadi	tor (SSD) model,	88.89%(YOLO)
Visually Impaired.		SIFT,MS COCO	seems to be better
[27]		dataset	compare to SSD

Table 2.1: Trends & Technologies discussed in literature ... Contd.

Paper Title	Authors	Methods	Pros & Cons
Deep Learning	Balachandar, San-	Yolov3,Cameras,M	They have
Technique Based	thosh, Suriyakr-	VOT,COCO	used(videocon
Visually Impaired	ishna, Vigensh,	dataset	camera)its intra
People Using	Usharani, Manju		camera grahic
YOLO V3 Frame-	Bala		which does not
work Mechanism.			highlights the fea-
[5]			tures properly and
			exactly tally the
			model
Real Time Object	Mansi Mahendru,	Tensor flow, SSD,	Yolo accuracy is
Detection with Au-	Sanjay Kumar	Yolo, Yolo_v3,	78.99 and yolov3
dio Feedback using	Dubey	gTTS, Deep Learn-	92.89% (seems to
Yolo vs. Yolo_v3		ing	be better compare
[19]			to (yolo)
Guidance System	Kanchan Patil ,	gTTS, Yolo v3,	chat-bot can-
for Visually Im-	Avinash Kharat,	Pyttsx, AIML,	not recognize
paired People. [25]	Pratik Chaud-	Vice over chatbot	the command in
	hary , Shrikant		noisy environment,
	Bidgar , Rushikesh		chat-bot may get
	Gavhane		confused between
			voice of an user
			and person nearby.

Table 2.1: Trends & Technologies discussed in literature ... Contd.

Paper Title	Authors	Methods	Pros & Cons
Building A Voice	Mohana priya R,	NLP ,CNN, LSTM	The dataset is
Based Image Cap-	Dr.Maria Anu, Di-	(Long short term	small. For better
tion Generator	vya	memory) , RNN	accuracy could be
with Deep Learn-		(recurrent neural	used big dataset
ing. [4]		network) flicker	, According to
		dataset,Accuracy	current trends, it's
		90%	not sufficient
Blind - Sight: Ob-	A. Annapoorani,	YOLO, COCO	Live object recog-
ject Detection with	Nerosha Senthil	Dataset, gTTS	nition system can-
Voice Feedback. [3]	Kumar, Dr. V.		not perform future
	Vidhya		learning which is a
			demerit.
Image Recognition	Sandeep Pa-	Flickr_8k dataset,	Dataset is very
and Voice Trans-	supuleti, Lahari	VGG, LSTM	small, the imple-
lation for Visually	Dadi, Manikumar		mentation can be
Impaired. [23]	Gadi, R. Krish-		enhanced by giving
	naveni		a greater number
			of images and
			text datasets with
			shorter captions for
			training

### Chapter 3

# **Proposed Work**

YOLO is an algorithm that uses neural networks to provide real-time object detection. This algorithm is popular because of its speed and accuracy. It has been used in various applications to detect traffic signals, people, parking meters, and animals.

YOLO is an algorithm based on regression, instead of selecting the interesting part of an image, it predicts classes and bounding boxes for the whole image in one run of the algorithm. Ultimately, we aim to predict a class of an object and the bounding box specifying object location.

### 3.1 Methods

The project uses YOLO algorithm that provides real-time object detection using neural networks and YOLO has different versions.

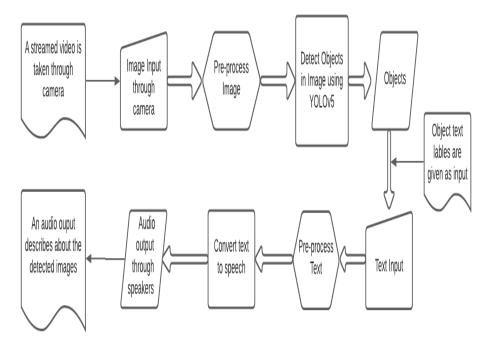


Figure 3.1: Schematic diagram of proposed system

#### 3.1.1 YOLO

YOLO first takes an input image, the framework then divides the input image into grids (say a 3 X 3 grid). Image classification and localization are applied on each grid. YOLO then predicts the bounding boxes and their corresponding class probabilities for objects.

We will divide each image into different grids. For example we divide an image into 3 x 3 grids and there are a total of 3 classes which we want the objects to be classified into. Let's say the classes are Pedestrian, Car, and Motorcycle respectively. So, for each grid cell, the label y will be an eight-

dimensional vector: pc defines whether an object is present in the grid or not (it is the probability) bx, by, bh, bw specify the bounding box if there is an object c1, c2, c3 represent the classes. So, if the object is a car, c2 will be 1 and c1 & c3 will be 0, and so on. We will run both forward and backward propagation to train our model.

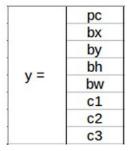


Figure 3.2: Eight Dimensional Vector

#### 3.1.2 YOLO v1

YOLOv1 is a single-stage object detection model. Object detection is framed as a regression problem to spatially separated bounding boxes and associated class probabilities. A single neural network predicts bounding boxes and class probabilities directly from full images in one evaluation. Since the whole detection pipeline is a single network, it can be optimized end-to-end directly on detection performance.

#### Limitations

• YOLO v1 has difficulties in detecting small objects that appear in groups.

- YOLO v1 has difficulties in detecting objects having unusual aspect ratios.
- YOLO v1 makes more localization errors compared to Fast R-CNN.

#### 3.1.3 YOLO v2

The major improvements of this version are better, faster and more advanced to meet the faster R-CNN which is also an object detection algorithm which uses a Region Proposal Network to identify the objects from the image input and SSD(Single Shot Multibox Detector).

#### **Improvements**

- Batch Normalization: it normalizes the input layer by altering slightly and scaling the activations. mAP increased by 2%.
- Higher Resolution Classifier: Input changed from 224\*224 to 448\*448
   mAP increased by 4%.
- Anchor Boxes: are designed to detect objects in the same grid.
- Fine Grained Features: Divides the image into 13\*13 grid cells which helps identifying small objects, unlike V1.
- Multi Scale Training: Model is trained on different sizes of objects for the same images.
- Darknet 19: YOLO v2 uses Darknet 19 architecture with 19 convolutional layers and 5 max-pooling layers and a softmax layer for classification objects. Darknet is a neural network framework written in C

language and CUDA. It's really fast in object detection which is very important for predicting in real-time.

Results: At 67 FPS, YOLOv2 can give an mAP of 76.8 while at 40 FPS
the detector gives an accuracy of 78.6 mAP, better than the state-ofthe-model such as Faster R-CNN and SSD while running significantly
faster than those models.

#### 3.1.4 YOLO v3

The previous version has been improved for an incremental improvement which is now called YOLO v3. As many object detection algorithms are been there for a while now the competition is all about how accurate and quickly objects are detected. YOLO v3 has all we need for object detection in real-time with accurately and classifying the objects.

#### **Improvements**

- Bounding Box Predictions: Uses Logistic Regression to predict the objectiveness score.
- Class Predictions: Uses Logistic classifiers instead of softmax, by doing in so we can have multi-label classification.
- Feature Pyramid Networks.
- Darknet-53 Architecture: has 53 convolutional layers.

#### 3.1.5 YOLO v4

YOLOv4's architecture is composed of CSPDarknet53 as a backbone, spatial pyramid pooling additional module, PANet path-aggregation neck and YOLOv3 head. CSPDarknet53 is a novel backbone that can enhance the learning capability of CNN. The spatial pyramid pooling block is added over CSPDarknet53 to increase the receptive field and separate out the most significant context features. The PANet is used as the method for parameter aggregation for different detector levels instead of FPN used in YOLO v3.

#### Improvements

- YOLOv4 is twice as fast as EfficientDet (competitive recognition model) with comparable performance.
- YOLO v4 is also based on the Darknet and has obtained an AP value of 43.5 percent on the COCO dataset along with a real-time speed of 65 FPS on the Tesla V100, beating the fastest and most accurate detectors in terms of both speed and accuracy.
- In addition, AP (Average Precision) and FPS (Frames Per Second) increased by 10% and 12% compared to YOLOv3

#### 3.1.6 YOLO v5

So, it said to be that YOLO v5 is extremely fast and lightweight than YOLO v4, while the accuracy is on par with the YOLO v4 benchmark.

YOLO V5 is written in Pytorch framework.

Pytotch inferences are very fast that before releasing YOLOv5, many other AI practitioners often translate the YOLOv3 and YOLOv4 weights into ultralytics Pytorch weight.

#### **Improvements**

- YOLO v5 is different from all other prior releases, as this is a PyTorch implementation rather than a fork from the original Darknet.
- Same as YOLO v4, the YOLO v5 has a CSP backbone and PANet neck.
- The major improvements include mosaic data augmentation and autolearning bounding box anchors.

### 3.2 Why YOLO v5

YOLO v5 is nearly 90 percent smaller than YOLO v4. So, it said to be that YOLO v5 is extremely fast and lightweight than YOLO v4, while the accuracy is on par with the YOLO v4 benchmark. So we decided to use YOLO V5.

#### 3.3 Dataset

Training, Validation and Testing of proposed model YOLO v5 are done on a custom prepared dataset combined with MS COCO 2017 Dataset [18]. MS COCO 2017 dataset contains 80 different object classes likely, person, dog, chair, potted plant, etc. In addition, we added 15 more different object classes

such as switchboard, pillow, locker, keys, open door, closeddoor, window, direction board, postbox, pole, shop, manhole, tree, upstairs, downstairs. Which are not mentioned in MS COCO 2017 Dataset (95 classes overall). These objects are relevant to Indian atmosphere. For each object class, we added 30 - 50 images, all together we added 500 images to dataset. By overall images we considered for doing image detection is 5000.

#### 3.3.1 Annotation tool

We used makesense as [30] a data annotation tool to annotate our new dataset. Makesense provides a lot more flexibility than other tools in adding labels list, most of the other tools automatically order the labels alphabetically. But, makesense follows the order we provide, and it is also possible to download the annotated images in YOLO format. So, this is the reason why we choose makesense as our annotation tool.

#### 3.3.2 YOLO format

To train & validate on YOLO algorithm, we need a specific format of dataset, As shown in figure 3.1. In the images folder, we further need to divide it into 3 different folders namely, train, val, test, and save respective images in those folders. similarly for labels folder, here all the labels will be text files. And finally, we need to specify the paths of all the images in respective folders, in their respective text files (train.txt, val.txt, test.txt).

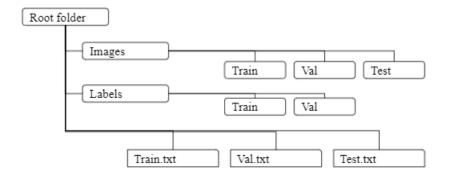


Figure 3.3: Dataset folder structure

### 3.4 Algorithm

#### 3.4.1 YOLO v4

YOLO stands for You Only Look Once. It's an object detection model used in deep learning use cases. YOLO belongs to the family of One-Stage Detectors (You only look once - one-stage detection). One-stage detection (also referred to as one-shot detection) is that you only look at the image once. YOLO v4 [9] claims to have state-of-the-art accuracy while maintaining a high processing frame rate. It achieves an accuracy of 43.5% AP for the MS COCO with an approximately 65 FPS inference speed on Tesla V100.

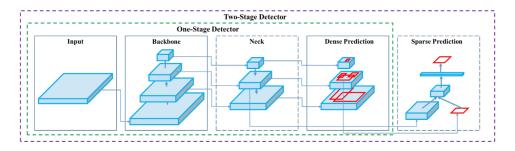


Figure 3.4: YOLO v4 Architecture

In object detection, high accuracy is not the only holy grail anymore. The four parent blocks, after the input image: Backbone (Dense Block & DenseNet, CSP, (CSPDarknet53); Neck (FPN, SPP); Head (Dense Prediction)-used in one-stage-detection algorithms such as YOLO, SSD, etc; Sparse Prediction-used in two-stage-detection algorithms such as Faster-R-CNN, etc (not in YOLOv4).

#### 3.4.2 YOLO v5

YOLO an acronym for 'You only look once', is an object detection algorithm that focuses on detecting objects in images which divides images into a grid system. Each cell in the grid is responsible for detecting objects within itself. YOLO v5 is one of the best available models for object detection at the moment. The great thing about this Deep Neural Network is that it is very easy to retrain the network on our own custom dataset.

#### Architecture

The network architecture of YOLO v5 [32]. It consists of three parts: Backbone: CSPDarknet, Neck: PANet, Head: YOLO Layer. The data are first input to CSPDarknet for feature extraction and then fed to PANet for feature fusion. Finally, YOLO Layer outputs detection results (class, score, location, size).

Object Detector will have a backbone for pre-training it and a head to predict classes and bounding boxes. The Backbones can be running on GPU or CPU platforms. The Head can be either one-stage (e.g., YOLO, SSD, RetinaNet)

for Dense prediction or two-stage (e.g., Faster R-CNN ) for the Sparse prediction object detector. Object detectors have some layers (Neck) to collect feature maps, and it is between the backbone and the Head.

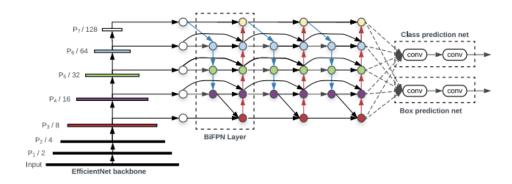


Figure 3.5: EfficientDet architecture

## Chapter 4

## **Experimental Results**

We carried out our training, validation, and testing on the google colab platform. Weights & Biases [8] is used to track the training and validation process for visualization.

### 4.1 Training

Tesla K80 with 12 GB RAM, Powered by google colab is used for training the YOLO v5 model, With the help of PyTorch and PyTorch-Cuda libraries, Coded in python. The model is trained on the dataset mentioned for 50 epochs, With a batch size of 8. Here are The class loss, Box loss, Object loss results for the training set.

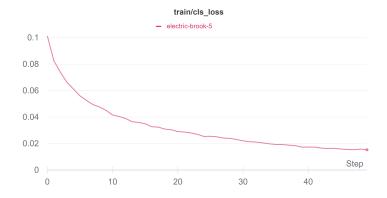
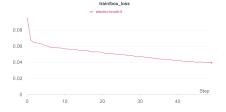


Figure 4.1: Training: Class loss vs number of epochs



0.065 0.065 0.055 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05

Figure 4.2: Training: Box loss vs number of epochs

Figure 4.3: Training: Object loss vs number of epochs

## 4.2 Validaton

Validation is done on each training epoch with a batch size of 16, for 50 epochs after each training epoch. Here are the class loss, Box loss, Object loss results for the validation set.

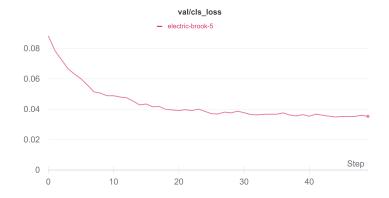


Figure 4.4: Validation: Class loss vs number of epochs



0.054
0.052
0.05
0.048
0.046
0.044
0.044
0.046
0.040
0.040
0.040
0.040
0.040
0.040

Figure 4.5: Validation: Box loss vs number of epochs

Figure 4.6: Validation: Object loss vs number of epochs

### 4.3 Evaluation metrics

Model is evaluated based on Precision, Recall, MAP (mean Average Precision).

### 4.3.1 Precision

Precision is one indicator of a machine learning model's performance – the quality of a positive prediction made by the model. Precision refers to the number of true positives divided by the total number of positive predictions (i.e., the number of true positives plus the number of false positives).

#### 4.3.2 Recall

A recall is a metric that quantifies the number of correct positive predictions made out of all positive predictions that could have been made.

Unlike precision that only comments on the correct positive predictions out of all positive predictions, Recall indicates missed positive predictions.

### 4.3.3 mean Average Precision (mAP)

The mean Average Precision or mAP score is calculated by taking the mean AP over all classes and/or overall IoU thresholds, Depending on different detection challenges that exist.



Figure 4.7: Evaluation metric: Precision vs number of epochs

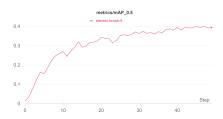


Figure 4.9: Evaluation metric: mAP\_0.5 vs number of epochs

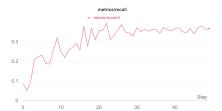


Figure 4.8: Evaluation metric: Recall vs number of epochs



Figure 4.10: Evaluation metric: mAP\_0.5:0.95 vs number of epochs

## Chapter 5

# Conclusion & Future Work

We are able to achieve precision as 0.55, recall as 0.37, and mAP as 0.4, with the proposed model. our model YOLO v5 is able to detect 95 different objects, with high confidence. with this model now we are able to detect objects those are most required for the visually impaired in their daily life.

### 5.1 Improvising model accuracy

As part of our further work, we try to improve our model accuracy, precision, and recall. And, we also try to make our model detect more objects those are helpful for the visually impaired in their daily life.

## 5.2 Speech generation

After achieving the convincing metrics, we further move on to convert the detected objects into voice messages, using Recurrent Neural Network (RNN) Architectures. Speech generation gives a better experience to the visually impaired, by letting them know about their surroundings.

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