Object Detection for Visually Impaired Individuals in Different Weather Conditions

MSc Research Project

Data Analytics

Ankit Kumar

Student ID: x23123061

School of Computing

National College of Ireland

Supervisor: Syed Muhammad Raza Abidi

National College of Ireland

MSc Project Submission Sheet

School of Computing

Student Name:	Ankit Kumar		
Student ID:	X23123061		
Programme:	MSc in Data Analytics	**Year:**	23-24
Module:	MSc Research Project		
Supervisor:	Syed Muhammad Raza Abidi		
Submission Due Date:	12/08/2024		
Project Title:	Object Detection for Visually Impaired Individuals in Different Weather Conditions		
Word Count:	5238, Pages: 15		

I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.
ALL internet material must be referenced in the bibliography section. Students are required to use the Referencing Standard specified in the report template. To use other author's written or electronic work is illegal (plagiarism) and may result in disciplinary action.

Signature: Ankit Kumar
Date: 12/08/2024

PLEASE READ THE FOLLOWING INSTRUCTIONS AND CHECKLIST

Attach a completed copy of this sheet to each project (including multiple copies)	□
Attach a Moodle submission receipt of the online project submission, to each project (including multiple copies).	□
You must ensure that you retain a HARD COPY of the project, both for your own reference and in case a project is lost or mislaid. It is not sufficient to keep a copy on computer.	□

Assignments that are submitted to the Programme Coordinator Office must be placed into the assignment box located outside the office.

Office Use Only	
Signature:	
Date:	
Penalty Applied (if applicable):	

Object Detection for Visually Impaired Individuals in Different Weather Conditions

Ankit Kumar

X23123061

Abstract

Visually impaired people use white cane to navigate through their surroundings. This research presents an object detection system designed to assist visually impaired individuals in different weather conditions. Current models do not account for real-time weather conditions. The objective of this research is to utilize the state-of-the-art YOLOv8 model and integrate weather data with it to enhance object detection accuracy and reliability under various weather conditions. The system was trained on the Pascal VOC 2012 dataset, pre-processed to simulate five major weather types: rainy, snowy, foggy, sunny, and cloudy. By incorporating real-time weather data, the model dynamically adjusts its detection parameters, providing context-aware feedback through audio using Google Text-to-Speech. The results indicate that the model performs optimally under sunny conditions, with a mean average precision (mAP@0.5) of 0.74 and an F1 score of 0.69. Performance under challenging conditions like rain and snow was lower, demonstrating the need for further optimization. The system enhances the navigational safety and independence of visually impaired users by providing real-time, intelligible audio feedback about their surroundings. This research contributes to the field of assistive technology by highlighting the importance of personalized and adaptive systems. Future work includes expanding the dataset, improving preprocessing techniques, integrating with other assistive technologies, and incorporating user feedback for continuous system improvement.

Keywords: Visually Impaired, YOLOv8, Object Detection, Weather conditions, Audio feedback

1 Introduction

According to the WHO, approximately 3.8 percent people in the world are visually impaired (WHO, 2023). Visually impaired people use white cane to navigate through their surroundings. The term white cane was coined by James Briggs in the year 1921 after the traffic accident which made him visually impaired (Project Guiding White, 2011). After the accident, scared Briggs painted his stick white, which would be visible to a motorist from afar. Since then, there have been various research in improving the white cane by integrating sensors to help users navigate. One such research of Hiramoto and colleagues (Hiramoto et al., 2022) proposed an infrared-guided cane to assist visually impaired individuals. The cane uses the infrared sensors to detect obstacles and provides haptic feedback through vibrations.

(Citizeninformation, 2018) Visually impaired people rely on the ability of machines or computer vision to guide them through their surroundings through either voice or haptic feedback. In the research of Abhishek and colleagues (Abishek Kumar et al., 2024), machine learning algorithm was utilized, particularly MobileNet for object recognition and combines mobile app with IoT smart stick to provide real-time object detection, text-to-speech conversion, and emergency communication capabilities.

In the study of Bawdekar and colleagues, a user centric machine, that would convert the text to braille on the go was developed (Bawdekar et al., 2016). With recent advancements in machine learning models, the author wants to take the old research forward and create a machine learning vision using YOLOv8, which currently is the fastest object detection model, with a novel idea of personalizing the user experience with respect to the weather conditions.

Currently, there is no model that integrates weather data before delivering results to the visually impaired users. This research will implement a system that will take the current location of the person and train the model based on the live weather conditions. For instance, if it is raining outside, the model will train on the datasets that have all the rainy images and then provide robust inference on the validation dataset.

Various literatures were studied before arriving at the decision to include the weather data into the object detection loop. Current models, such as those using YOLO, R-CNN, and MobileNet, demonstrate varying degrees of accuracy and efficiency in object detection. Even some research, for example, the one conducted by (Litoriya et al., 2024) lacks comprehensive performance metrics, such as precision, recall, and F1 scores, which are essential for evaluating model effectiveness.

Another significant gap is the lack of consideration for environmental factors, such as weather conditions, or lighting conditions, which can drastically impact object detection accuracy. In the research of Jawaid and colleagues, phone camera was used to detect object (Jawaid et al., 2019). In this, the authors conclude that there are varied results in the accuracy of the system based on the lighting conditions. Current systems do not adjust their outputs based on these external conditions, which is a critical oversight given the real-world challenges faced by visually impaired individuals.

To address these gaps, this research should focus on developing more robust and adaptable object detection models that consider environmental factors. This leads to the central research question of this study - “How effectively can YOLOv8 be trained in different weather conditions to provide feedback to visually impaired users?”.

The paper is structured into various sections. Section 2, titled related works discusses various literature that were studied and evaluated to support this research, Section 3 throws light on the research methodology used in the study with the description of the Pascal VOC 2012 dataset and YOLOv8 which is the state-of-the-art model for the proposed solution. Moreover, it encompasses the integration of novel weather data into the system to make it more realistic and discusses about the audio feedback necessary to inform the users about the objects in front of them. In section 4, the system design and implementations, the model architecture with the implementation technique is discussed where the hyperparameter is finalized and loss function is plotted. Section 5 and 6 concludes the research with the results, conclusion and future avenues of this research.

2 Related Works

This section discusses the recent research work done in this domain. Latest peer reviewed research in the field were chosen for comparison and evaluation. This section is divided into two subsections; The first section will discuss and compare the research related to object detection and recognition systems and the second section will throw light on the navigation and mobility assistance systems.

2.1 Object detection and recognition systems

This section discusses the advancements in object detection and recognition system, which is critical component in aiding visually impaired individuals.

A real time object detection method combining YOLOv3, and R-CNN algorithms was developed by (Alagarsamy et al., 2023). The research is based on a specific dataset (VOC 2012) and was only tested on the wildlife animals, which makes it unclears on how well the proposed method would generalize to other objects in real-world scenarios. Future research should focus on broader datasets with various augmentation techniques to validate model's robustness across various object types.

In the research of (Bindamrutha et al., 2023a), real time object detection with voice output using YOLOv4 was introduced. The integration of pyttsx3 for text-to-speech conversion provides immediate audio feedback, enabling users to understand the unfamiliar environments effectively. The research claims that the proposed system can accurately detect the objects and addresses the fact that if an object is in motion and the image gets blurred, then the object detection will not produce desired results. However, it fails to address other potential challenges such as dealing with varying light conditions.

Working on the latest version of YOLO, in another research, (Foysal et al., 2023) enhanced AI-based assistive systems with modified YOLOv7 and YOLOv8 algorithms for multi-class object detection and currency classification. The study reports achieving a mean Average Precision (mAP) of 91.4% and 94.6% for YOLOv7 and YOLOv8 respectively. The dataset had 3064 photos with 20 classes and 295 currency photos. Despite the promising results, the research highlights the need for further evaluations under various environmental condition.

Khekare and colleague (Khekare & Midhunchakkravarthy, 2023), proposed a smart image recognition system for visually impaired people using TensorFlow Lite and the SSD_Mobilenet_v1_1_metadata_1 model. The system can detect 82 object classes and provides real-time voice feedback of the identified objects using google text-to-speech. The research talks about accuracy but lacks in performance evaluation by providing precision, recall, and F1 score. The system's accuracy could be further improved by using various data augmentation techniques.

Dangerous object detection using computer vision was done by (Shah et al., 2021). This is a limited computer vision research where the researchers focused on only five major domains of objects namely sharp objects, danger signs, broken glass, manholes, and fires. The custom dataset comprised of 2500 images, and was evaluated multiple models including YOLOv5, Faster R-CNN, and SSD MobileNet v2. It was concluded that YOLO v5 proved to be the more balanced model as compared to other models.

Nasreen and colleagues (Nasreen et al., 2019), on the other hand, proposed an object detection and narrator system using a CNN trained on ImageNet. They created a web-based application that takes image from the phone as the input and then sends it to the YOLO model on the server side to detect the object. The system is robust as it compares the accuracy of different mobile phone models for example, iphone8, Mi A5, Samsung Galaxy A70 etc. Highest accuracy was achieved by iPhone 8.

After reviewing the research papers on object detection and recognition system, it is evident that it is important to train the dataset in various lighting conditions to make it more robust. Next section will discuss the research papers that offer navigation and mobility assistance solutions.

2.2 Navigation and mobility assistance systems

After looking at the object detection and recognition system, this section focuses on the navigation and mobility assistance systems. At a macro level, both these subsections are solving the same purpose to help a visually impaired person navigate but this section throws light on the software plus the hardware part that considers haptic feedback as an output option to guide the person. (Hasan et al., 2022) presented a real-time computer vision-based autonomous navigation system using a YOLOv3-trained model to identify objects and obstacles. The system incorporates a novel distance-measuring approach and provides navigation commands through headphones. An example of voice feedback - '*there is a table in front of you at 5 meters*. The camera is installed at the eye level of the user that gives a good surrounding view for object detection. The study does an impeccable job of comparing YOLOv3 and SSD mobileNet v2 by analyzing computation cost of each. The authors conclude that computational cost of YOLOv3 model is 39.3 millisecond per execution (ms/e), which is 59.3 ms/e faster than SSD MobileNet.

While previous research were focusing on the outside world, Senarathna and colleagues (Senarathna et al., 2023) used YOLOv4 as a choice of their object detection and focused on indoor environments, such as study tables, and utilized real-time face detection, object recognition, hand detection, path planning, and voice-guided haptic feedback to enhance the independence of users. The study claims that the proposed system improves object detection but fails to provide accuracy, precision, recall, and F1 score to support the argument.

(Said et al., 2023) introduced a navigation assistance system based on deep learning and NAS. Although they acknowledged the importance of user needs, their research lacked personalization and adaptability aspects. The study demonstrated that the resulting model outperforms the original FCOS model by 2.6% in average precision (AP) while maintaining acceptable computational complexity. The research demonstrated the potential of NAS to automatically search for optimal neural network architectures for object detection tasks, leading to improved performance compared to manually designed architectures. The focus on creating a lightweight and efficient model suitable for embedded devices is a significant contribution.

While other research is focusing on creating a system for object detection that are placed at the eye level, (Ghatkamble et al., 2023) proposed a computer vision system by placing the camera on the shoes that utilized ultrasonic sensors to detect obstacles and provide auditory and tactile feedback. While, the system aims to offer a safe, accurate, and efficient blind steering method, enhancing the mobility and independence of visually impaired individuals, it is an unfeasible option as placing camera on top of shoes is not safe and will increase the wear and tear of the electronic circuit boards overtime.

In another research, (Litoriya et al., 2024) proposed a visual assistant application using YOLO and SSD for object detection and tracking. Their focus on improving existing algorithms is commendable, but the research does not address the challenge of adapting to different environments or lighting conditions, which can significantly impact the performance of object detection systems (Moksyakov et al., 2024).

In conclusion, the literature highlights significant advancements and ongoing challenges in creating assistive technologies for visually impaired individuals. While progress has been made in object detection and navigation systems, many studies still fall short in real-world adaptability, personalization, and thorough performance assessments. The current research seeks to address these issues by using Google Text-to-Speech for real-time feedback and applying various augmentation techniques to enhance model robustness under different lighting conditions and weather conditions. With these pre-processing, this research will develop a more reliable and user-friendly technology.

3 Research Methodology

This section outlines the methodology employed to develop the personalized object detection system for visually impaired individuals. The methodology comprises four components: the dataset used, data pre-processing techniques, the methods applied to build and evaluate the object detection model, and feedback loop with weather data contextual alerts. These components are crucial for ensuring the system's reliability, accuracy, and adaptability to varying conditions

3.1 Dataset

For this research, an industry-standard benchmark for object detection tasks, Pascal VOC 2012 dataset was utilized. The Pascal VOC datasets, particularly the 2012 version, are extensively used in the computer vision community due to their comprehensive annotations, including object bounding boxes and class labels for 20 diverse categories.
Link to the dataset - https://www.kaggle.com/datasets/gopalbhattrai/pascal-voc-2012-dataset

The features of the dataset are summarized in Table 1.

Table 1: Features of Pascal VOC 2012 dataset

Feature	Description
Total Images	1964
Object Categories	20 categories ranging from everyday objects like chairs tables to vehicles and animals
Annotations	Each image is annotated with labels, bounding boxes, and segmentation masks

Research done by (Agrawal et al., 2022; Bindamrutha et al., 2023a; Chandankhede & Kumar, 2022; Foysal et al., 2023; Shah et al., 2021), as discussed in section 2, used Pascal dataset.

After selecting the dataset, the next critical step is data pre-processing. Section 3.2 discusses the pre-processing technique.

3.2 Data pre-processing

Data pre-processing is a critical step to ensure the quality and effectiveness of the machine learning model. Proper pre-processing enhances the dataset, making it suitable for training and ensuring that the model can learn effectively from the input data. The following steps were carried out to preprocess the Pascal dataset. The images were pre-processed based on 5 major weather types namely: Rainy, Snowy, Foggy, Sunny, and cloudy and were stored in respective weather folder. Let's discuss the process to create each type of weather below

1 **Rainy:** To replicate the rainy weather, a function – add_rainy - was added to add the raindrop effects. This function created a rain layer by adding thin blur white lines on top of the image.
2 **Snowy:** Like the rainy image, the snow weather effect was achieved using the add_snowy function, which generated a layer of snow by placing white dots on the image. Gaussian blur was used to soften the effect.
3 **Foggy:** The add_foggy function was created to mimic foggy weather. A white fog layer was blended with the original image using the OpenCV's 'addedweight' function. This gave the images a hazy appearance.
4 **Sunny:** The best way to add a sunny effect to the image is to just brighten the image a bit. The function add_sunny increased the brightness and contrast of the images using the OpenCV's 'convertscaleabs' method.
5 **Cloudy:** Mimicking the cloudy effect was tricky as a lot of cloudy images were taken on the phone camera before concluding reducing the brightness and contrast of the images using the OpenCV's 'convertscaleabs' method.

Figure 1 below shows the original image with the processed images for different weather conditions.

Figure 1: Original vs Processed images

After pre-processing the images and storing them in different folders for easy access, the final count of total images available for training increased and below is the table, Table 2, that highlights that change.

Table 2: Summary of Pre-processed Dataset

Before Pre-Processing	
Total Images in dataset	1963
After Pre-Processing	
Type of Weather	**Total Images**
Rainy	1963
Snowy	1963
Foggy	1963
Sunny	1963
Cloudy	1963
Total Images in Dataset	**9815**

3.3 Methods

In recent advancements in real-time object detection, YOLOv8, introduced by Ultralytics, has shown significant improvements over previous models by achieving higher accuracy and faster inference speeds. Khow and colleagues did an experiment on the Pascal VOC2012 dataset and achieved a mAP score of 85.6% indicating superior performance compared to the recent models (Khow et al., 2024). The model maintains high inference speed and demonstrates significant potential in distance estimation tasks.

The object detection system was built using the YOLOv8 (You Only Look Once) model, known for its high speed and accuracy as discussed above. This section outlines the methodology used, detailing the model architecture, training process, integration of weather data, evaluation metrics, and user feedback.

3.3.1 Transfer Learning and Hyperparameter Tuning

Transfer learning is a powerful technique in machine learning where the model developed for a specific task is reused for a second task. Various research studied and referenced before in the literature review section (Section 2) have used transfer learning. To mention a few - (Bindamrutha et al., 2023b; Foysal et al., 2023; Ghatkamble et al., 2023b; Jawaid Nasreen et al., 2019) - have used the transfer learning method to boost their results.

In this study, transfer learning was employed to enhance the performance of YOLOv8 model on the Pascal VOC 2012 dataset. Before the training of the model, hyperparameters were tuned and the best combination of the hyperparameter was chosen. The hyperparameters are shown in Table 3.

Table 3: Hyperparameters

Hyperparameter	Values
Epochs	[10, 20]
Learning Rates	[0.001, 0.01, 0.1]
Batch Sizes	[16, 32, 64]
Image Sizes (pixels)	[640, 800, 1024]

3.3.2 Weather Data Integration

A novel aspect of this research is the integration of weather data to personalize the object detection system. Real-time weather data was obtained from a reliable API, such as OpenWeatherMap (OpenWeatherMap.org, 2012). This data includes information on weather conditions like rain, fog, sunny etc. As discussed in section 3.2, the images were pre-processed for each weather type and were stored in different folders. Once real-time weather information is fetched, the model is validated on the images corresponding to that weather. This ensures the object detection system adapts based on the weather, enhancing its accuracy and reliability in diverse weather conditions.

3.3.3 Evaluation Metrics

The performance of the model was evaluated using several standard metrics to ensure comprehensive assessment:

1. **Precision and Recall**: These metrics measure the accuracy (precision) and completeness (recall) of the detected objects. Precision is the ratio of true positive detections to all positive detections, while recall is the ratio of true positive detections to all actual objects.
2. **F1 Score**: The F1 score provides a balance between precision and recall, calculated as the harmonic mean of the two. It is a useful metric for evaluating the overall effectiveness of the model.
3. **Mean Average Precision (mAP)**: mAP is used to evaluate the model's performance across all object categories. It is calculated by averaging the precision scores at different recall levels, providing a comprehensive measure of the model’s detection capabilities. This metric is crucial for understanding how well the model performs in detecting objects under various conditions.

3.3.4 Audio Feedback

The implementation of audio feedback in object detection system is designed to provide visually impaired users with real-time, intelligible information about their surroundings. This was achieved by using Google Text-to-Speech (gTTS) library. The process involves running inferences on a set of images and generating natural language descriptions.

4 Design and Implementation

This section discusses the model design and the implementation. This section is divided into two parts namely: design and implementation.

4.1 Design

A pre-trained YOLOv8 model was selected due to its state-of-the-art performance and efficiency in real-time applications. Figure 2 depicts the model architecture of this research. Firstly, the Pascal VOC 2012 data is pre-processed to create images for different weather conditions. Then, these are stored in different folders labeled as Snowy, Rainy, Cloudy, Foggy, and Sunny. After tuning the hyperparameters, the YOLOv8 pre-trained model is used to train the model on weather-specific dataset. During the inference phase, the real time weather data is fetched from the weather API and the system selected appropriate weather-specific trained weights to perform object detection, ensuring robust performance under different weather conditions.

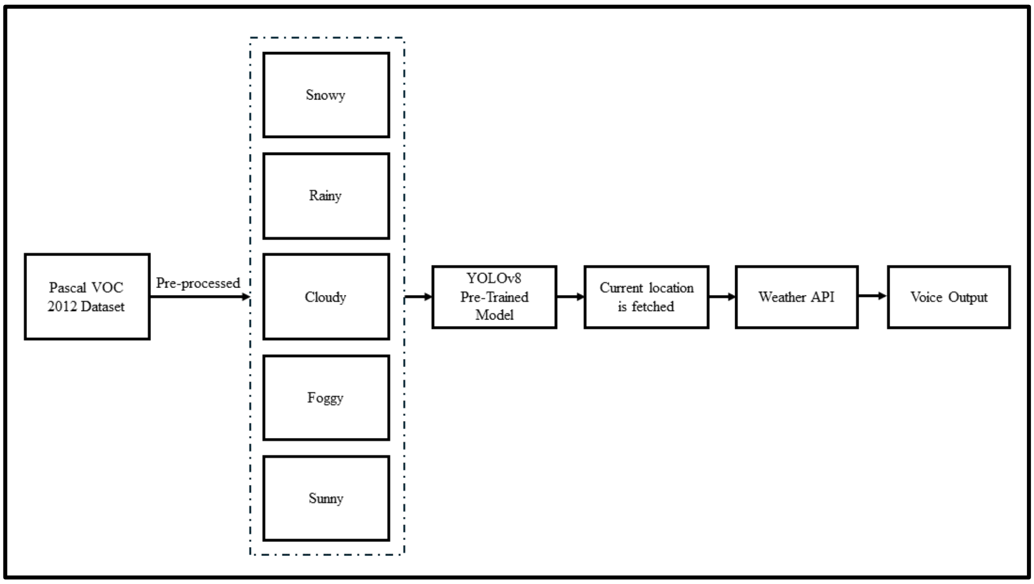

Figure 2: Model Architecture

4.2 Implementation

For implementing this research project, Google Colab pro+ environment was set-up with 500 compute units. The NVIDIA A100 GPU was used as it offers highest performance, enabling faster training and inference for AI models.

The Pascal dataset was downloaded in google drive and was mounted in Colab environment for reusability. As discussed in section 3.2, the dataset was pre-processed and the size of overall data was increased, catering to different weather conditions and saved in different folders in the drive itself. Post pre-processing, appropriate hyperparameter combination was chosen as depicted in table 4. Figure 3 below shows the loss graph which helped in choosing the hyperparameter. After carefully studying the graph, the parameter that best suited the need is described in table 4.

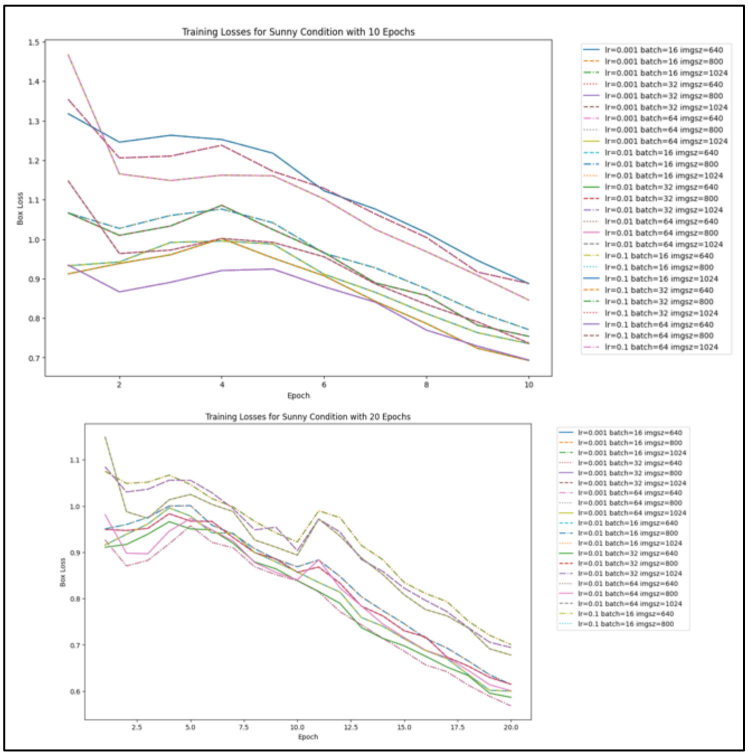

Figure 3: Losses for 10 epochs and 20 epochs for different learning rates

Table 4: Chosen hyperparameter for the model

Hyperparameter	**Values**
Epochs	20
Learning Rates	0.001
Batch Sizes	16
Image Sizes (pixels)	640

YOLOv8 pre-trained model was used to train the model with the set hyperparameter for maximum efficiency. The model was trained on each of the weather-specific-pre-processed dataset and the weights file was saved in the specific weather folders. This decision was made to increase the reproducibility of the code. This gives another researcher a chance to use these datasets and then add more images in specific weather folders to make the system more robust.

The novel idea of integrating the weather API to give weather specific information in a speech format is the last stage of the implementation. Already discussed in section 3.3.2, weather API key was generated and then used in the code to fetch the current location and the current weather condition. The weather condition are more than just the 5 categories that is being used in the project. Table 5 depicts the weather mapping into the 5 categories.

Table 5: Weather mapping to project's weather categories

Weather	Weather Subset
Sunny	clear, sun, sunny, mostly sunny, partly sunny, fair
Cloudy	cloud, overcast, mostly cloudy, partly cloudy
Foggy	mist, fog, haze, misty
Rainy	rain, drizzle, showers, thunderstorm, light rain, heavy rain
Snowy	snow, sleet, blizzard, snow showers, light snow, heavy snow

After mapping of the weather data, the current location is taken by the API and the weather is returned. Based on the weather, the inference was run by picking the weights from the specific weather folder and then the description of the image was converted to audio using the Google Text-to-speech (gTTS). The text to speech function was optimized to make it sound more conversational. If, more than three objects of similar type were found, instead of saying 10 people are in front of you, the model will say – 'There is a group of people in front of you'.

5 Results and Conclusion

This section discusses the results and conclusion of the project.

5.1 Results

After training the model, the validation was done for all the images in the 5 weather folders with appropriate weather weight file. Table 6 below shows the results of the inference.

Table 6: Model Performance

condition	mAP@0.5	mAP@0.5:0.95	F1 Score	Precision	Recall
sunny	0.74	0.55	0.69	0.74	0.64
cloudy	0.71	0.52	0.68	0.71	0.66
foggy	0.72	0.55	0.69	0.72	0.67
rainy	0.72	0.54	0.68	0.72	0.64
snowy	0.71	0.51	0.68	0.71	0.65

After this, current location was set to 'Mumbai' for testing purposes and the current weather that was fetched was in real-time – 'Rainy'. So, making inferences on all the rainy images, Figure 4 below shows the models' predictions with bounding boxes on the images. The model gives output in the voice format. For example, the description of the car image below is – *"There is 1 car in front of you"*.

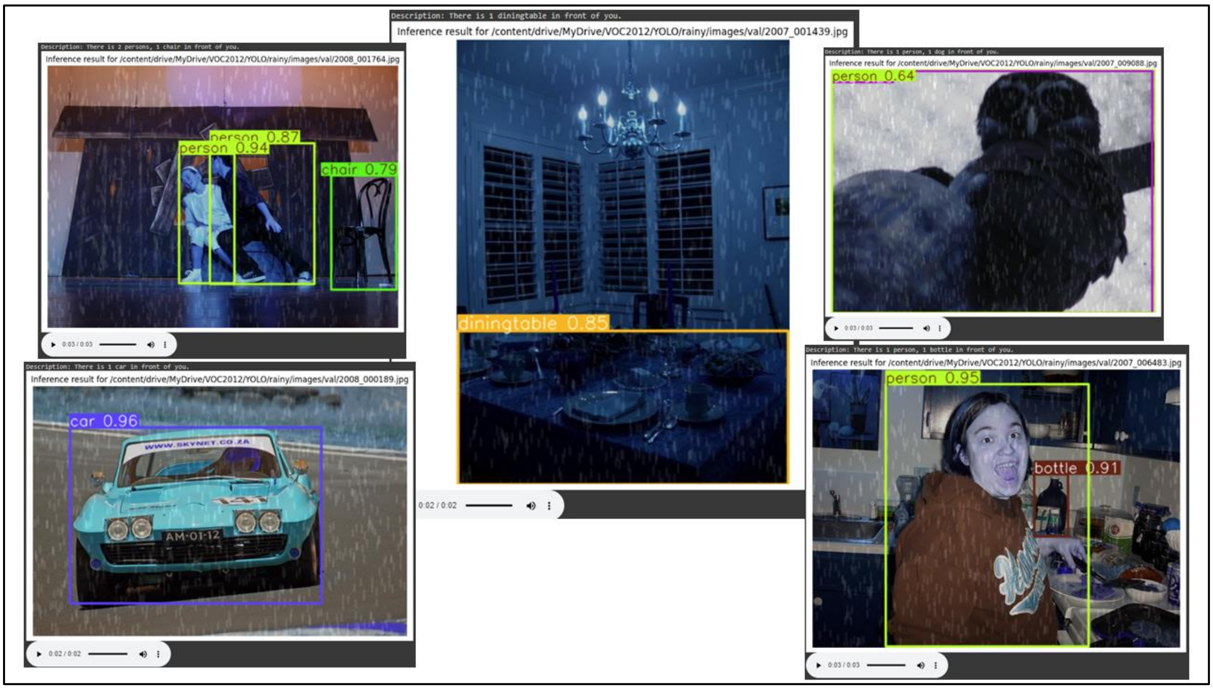

Figure 4: Inferring on Rainy images (current weather set: Rainy)

5.2 Conclusion

The research successfully developed a YOLOv8 object detection model, that adapts to the current weather conditions, for visually impaired individuals. The addition of speech output using Google's TTS makes it a practical system for everyday use.

Despite promising results, limitations were observed as shown in Table 6 above. The sunny condition achieved highest mAP@0.5 and F1 score, indicating better performance under optimal conditions.

Foggy conditions on the other hand, showed high precision and recall, demonstrating the model's robustness against low visibility. Accuracy of cloudy and rainy was reasonable but performance was low signifying a need of improvement and hyperparameter training for specified weather type. Snowy conditions had the lowest mAP and F1 score which is due to the challenging nature of detecting objects during snow.

All these limitations highlight the need for further optimization and more comprehensive training data. Overall, this research contributes to the growing field of assistive technologies, emphasizing the importance of adaptive personalized systems for visually impaired. The findings are accurate and encourage further exploration in this area, which will make the system more robust.

6 Future Perspectives

We will focus our future research on designing and implementations of the below mentioned strategies to further augment our model:

1. **Expanded Dataset:** a more diverse and extensive dataset, like COCO dataset, may be used to cover a broader range of objects. This will increase the model's generalizability and robustness.
2. **Advanced Pre-processing Technique:** As of now, for snowy and Rainy images, the flakes and rain were added artificially using the code. It can be enhanced by making sure it is closer to the actual photo taken in the rain with more heavy rain drops which will make the learning more robust.
3. **Hyperparameter Tuning:** As the hyperparameter was tuned only for 10 and 20 epochs, it can further be trained on different epochs (up to 50) and then the loss curve must be plotted and the best hyperparameter must be selected for the training purpose.
4. **Multi-Language support:** With increase in the AI and different platforms, it will be easy to convert the English text to any other language, according to the user's understanding, and then converted to speech.

By addressing some of these future directions, the research can significantly advance in the field of assistive technologies, offering robust and user-friendly solutions to the visually impaired individuals.

References

Abishek Kumar, G., Surya, G., & Sathyadurga, V. (2024). Echo Guidance: Voice-Activated Application for Blind with Smart Assistive Stick Using Machine Learning and IoT. 2024 International Conference on Advances in Data Engineering and Intelligent Computing Systems, ADICS 2024. https://doi.org/10.1109/ADICS58448.2024.10533517

Agrawal, P., Jain, G., Shukla, S., Gupta, S., Kothari, D., Jain, R., & Malviya, N. (2022). YOLO Algorithm Implementation for Real Time Object Detection and Tracking. 2022 IEEE Students Conference on Engineering and Systems, SCES 2022. https://doi.org/10.1109/SCES55490.2022.9887678

Alagarsamy, S., Rajkumar, T. D., Syamala, K. P. L., Niharika, C. S., Rani, D. U., & Balaji, K. (2023). An Real Time Object Detection Method for Visually Impaired Using Machine Learning. 2023 International Conference on Computer Communication and Informatics, ICCCI 2023. https://doi.org/10.1109/ICCCI56745.2023.10128388

Bawdekar, K., Kumar, A., & Das, R. (2016). TEXT TO BRAILLE CONVERTER. IJECET_07_04_007 International Journal of Electronics and Communication Engineering and Technology, 7(4), 54–61. www.jifactor.com

Bindamrutha, T., Likhitha, A., Reddy, S. A., Reddy, G. V., & Priya, S. S. (2023a). A Real-time Object Detection System for the Visually Impaired. ViTECoN 2023 - 2nd IEEE International Conference on Vision Towards Emerging Trends in Communication and Networking Technologies, Proceedings. https://doi.org/10.1109/ViTECoN58111.2023.10157345

Bindamrutha, T., Likhitha, A., Reddy, S. A., Reddy, G. V., & Priya, S. S. (2023b). A Real-time Object Detection System for the Visually Impaired. ViTECoN 2023 - 2nd IEEE International Conference on Vision Towards Emerging Trends in Communication and Networking Technologies, Proceedings. https://doi.org/10.1109/ViTECoN58111.2023.10157345

Chandankhede, P., & Kumar, A. (2022). Visually Impaired Aid using Computer Vision to read the obstacles. JOURNAL OF ALGEBRAIC STATISTICS, 13(3), 4467–4481. https://publishoa.com

Citizeninformation. (2018). Mobility training for people with visual impairments. https://citizensinformation.ie/en/travel-and-recreation/transport-and-disability/mobility-training-for-people-with-a-visual-impairment/

Foysal, N. U., Thamid, T. J., Uddin, M. S., Islam, M. F., Islam, M. N., & Faisal, F. Al. (2023). Advancing AI-based Assistive Systems for Visually Impaired People: Multi-Class Object Detection and Currency Classification. 2023 International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD), 438–442. https://doi.org/10.1109/ICICT4SD59951.2023.10303628

Ghatkamble, R., Ratish Kumar, K., John Hrithik, S., Harshith Kumar, J., & Sujan, P. S. (2023a). Computer Vision and IoT-Based Smart System for Visually Impaired People. 2023 International Conference on Artificial Intelligence and Applications, ICAIA 2023 and Alliance Technology Conference, ATCON-1 2023 - Proceeding. https://doi.org/10.1109/ICAIA57370.2023.10169589

Ghatkamble, R., Ratish Kumar, K., John Hrithik, S., Harshith Kumar, J., & Sujan, P. S. (2023b). Computer Vision and IoT-Based Smart System for Visually Impaired People. 2023 International Conference on Artificial Intelligence and Applications, ICAIA 2023 and Alliance Technology Conference, ATCON-1 2023 - Proceeding. https://doi.org/10.1109/ICAIA57370.2023.10169589

Hasan, M. Z., Sikder, S., & Rahaman, M. A. (2022). Real-Time Computer Vision Based Autonomous Navigation System for Assisting Visually Impaired People using Machine Learning. 2022 4th International Conference on Sustainable Technologies for Industry 4.0, STI 2022. https://doi.org/10.1109/STI56238.2022.10103268

Hiramoto, T., Araki, T., & Suzuki, T. (2022). Infrared Guided White Cane for Assisting the Visually Impaired to Walk Alone. Proceedings - International Conference on Machine Learning and Cybernetics, 2022-September, 276–280. https://doi.org/10.1109/ICMLC56445.2022.9941336

Jawaid Nasreen, Warsi Arif, Asad Ali Shaikh, Monaisha abdllah, & Yahya Muhammad. (2019). Object Detection and Narrator for Visually Impaired People (6th ed.). IEEE International conference on Engineering Technologies and Applied Sciences (ICETAS). https://doi.org/https://doi.org/10.1109/ICETAS48360.2019.9117405

Khekare, G., & Midhunchakkravarthy. (2023). Smart Image Recognition System for The Visually Impaired People. 2023 International Conference on Energy, Materials and Communication Engineering, ICEMCE 2023. https://doi.org/10.1109/ICEMCE57940.2023.10434130

Khow, Z. J., Tan, Y. F., Karim, H. A., & Rashid, H. A. A. (2024). Improved YOLOv8 Model for a Comprehensive Approach to Object Detection and Distance Estimation. IEEE Access, 12, 63754–63767. https://doi.org/10.1109/ACCESS.2024.3396224

Litoriya, R., Bandhu, K. C., Gupta, S., Rajawat, I., Jagwani, H., & Yadav, C. (2024). Implementing Visual Assistant Using Yolo and SSD for Visually-Impaired Persons. Journal of Automation, Mobile Robotics and Intelligent Systems, 17(4), 79–87. https://doi.org/10.14313/jamris/4-2023/33

Litoriya, R., Chandra Bandhu, K., Gupta, S., Rajawat, I., Jagwani, H., & Yadav, C. (2024). Implementing Visual Assistant using YOLO and SSD for Visually-Impaired Persons. Journal of Automation, Mobile Robotics and Intelligent Systems, 79–87. https://doi.org/10.14313/jamris/4-2023/33

Moksyakov, A., Wu, Y., Gadsden, S. A., Yawney, J., & AlShabi, M. (2024). Object Detection and Tracking with YOLO and the Sliding Innovation Filter. Sensors, 24(7). https://doi.org/10.3390/s24072107

OpenWeatherMap.org. (2012). Open Weather Map. https://openweathermap.org/

Project Guiding White. (2011, April 5). History Of The White Cane. https://guidingwhite.wordpress.com/history-of-the-white-cane/

Said, Y., Atri, M., Albahar, M. A., Ben Atitallah, A., & Alsariera, Y. A. (2023). Obstacle Detection System for Navigation Assistance of Visually Impaired People Based on Deep Learning Techniques. Sensors, 23(11). https://doi.org/10.3390/s23115262

Senarathna, P., Pigera, I., Dodanduwa, S., De Silva, H., Amarakoon, T., & Thelijjagoda, S. (2023). Machine Learning Based Assistive Technology for Object Detection and Recognition for Visually Impaired Individuals. Proceedings of the 2023 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems, ICSES 2023. https://doi.org/10.1109/ICSES60034.2023.10465424

Shah, H., Shah, R., Shah, S., & Sharma, P. (2021). Dangerous Object Detection for Visually Impaired People using Computer Vision. Proceedings - 2021 1st IEEE International Conference on Artificial Intelligence and Machine Vision, AIMV 2021. https://doi.org/10.1109/AIMV53313.2021.9670992

WHO. (2023, August 10). Blindness and vision impairment. https://www.who.int/news-room/fact-sheets/detail/blindness-and-visual-impairment