



BLIND ASSISTANT SYSTEM USING MACHINE LEARNING

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Abstract: There are millions of people who are blind or partially blind in the world today, and they have a lot of difficulties recognizing people and barriers around them. This research offers a novel machine learning-based blind assistance system that increases the mobility and freedom of people who are visually impaired. Using a convolutional neural network (CNN) architecture and a machine learning (ML) algorithm, we created an intelligent system that can automatically and in real-time distinguish items or barriers in the environment and in persons who are visually impaired. It can accurately identify people in intricate settings with lots of moving objects. By giving visually impaired people access to real-time contextual information about their environment, the suggested technology seeks to empower individuals and help them travel safely.

Index Terms - Blind assistance system, machine learning, visual impairment, object detection, obstacle avoidance, landmark recognition.

I. INTRODUCTION

Millions of people worldwide struggle with visual impairment, which significantly limits a person's movement and independence. Different countries have different classification systems for vision impairments. Visual acuity, or the clarity of vision, and visual fields, or the area from which you are able to perceive visual information while your eyes are stationary and you are looking directly at an object, are the two factors that the World Health Organization (WHO) uses to classify visual impairment. In order to mitigate this issue, developments in machine learning have made it possible to create assistive devices that can help visually impaired people interact with their environment. This research presents a blind assistance system that analyzes visual inputs using machine learning methods.

II. Related Works

Investigate research on navigation systems specifically developed for the blind. This may include GPS-based solutions and obstacle detection technologies. Examine the use of wearable devices, such as smart glasses in assisting the visually impaired with navigation and environmental awareness. This include user studies and feedback on existing blind assistance technologies to understand the practical implications, challenges, and areas for improvement. Explore studies related to user interfaces, accessibility features, and human-computer interaction principles designed specifically for blind users.

III.Methodology

Face Recognition and Object detection is one of those fields that have witnessed great success. The blind assistance system consists of three main components: image acquisition, feature extraction, and decision-making. Image acquisition involves capturing visual information using a camera, while feature extraction techniques extract relevant image features to represent the context. These extracted features are then fed into an intelligent machine learning model, trained on relevant datasets, to identify and classify objects, obstacles, and landmarks. The decision-making component processes the model's output and provides audio or tactile feedback to the user, aiding them in understanding their environment and navigating safely.

IV.AI based visual Aids

Microsoft's Seeing AI software for those with vision impairments is already available. By using this software, a user can hold their phone up to a person and have the phone describe many aspects of the person's appearance, such as age, hair colour, and general mood. You may find out all the information about a product, including its name, expiration date, and other facts, just by pointing your phone at it. Additionally, the programme is capable of reading documents and identifying structure components like lists, headings, and paragraphs.

V.Cognitive Hearing Aids

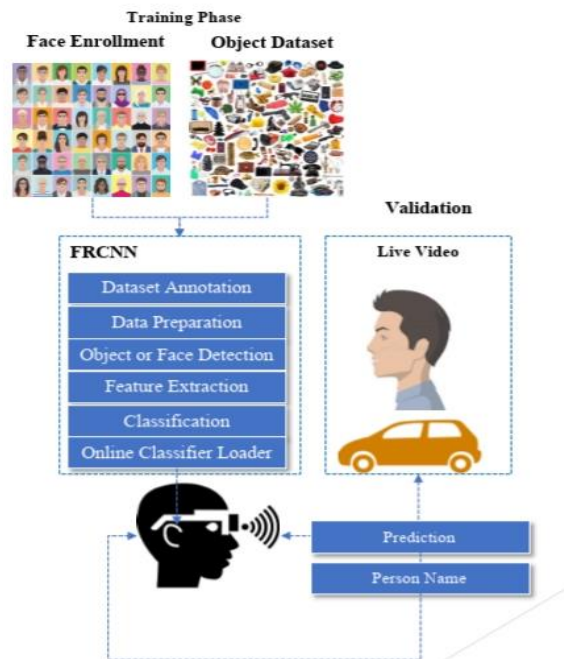
The market for hearing aids has existed for a while. However, everyone's dream wearable accessory is a cognitive hearing aid. In addition to improving hearing, these cutting-edge intelligent hearing aids can detect changes in an individual's mood to determine what they would want to hear at a given time by analysing brain waves. What distinguishes humanity is its capacity to read the human mind and respond accordingly. This means that the gadget can track and tune the user's brain to suppress all other noises except for the specific noises they want to hear when numerous individuals are speaking at once or when one type of voice dominates.

VI.Machine learning techniques

This research investigates a number of machine learning methods, like as decision trees, support vector machines (SVMs), and convolutional neural networks (CNNs), that are appropriate for blind assistance systems. These algorithms are taught using transfer learning, supervised learning, or reinforcement learning methods using labelled datasets that contain photos with tagged objects and landmarks. To guarantee a successful design of the blind aid system, the selected algorithms are assessed according to their functionality, precision, and execution duration. The gadget can identify and announce pre-programmed faces of friends and family, recognise and identify objects by colour, and deliver audio explanations of objects like park benches and trees.

VII.Experimental Evaluation

Alternatively, instead of transmitting the extracted regions from the image, Fast R-CNN transmits the full image to ConvNet, which creates regions of interest. On a large dataset, however, quick R-CNN is not quick enough because it also requires selective search to extract the regions. A thorough assessment is carried out utilising data gathered from visually impaired people and real-world settings in order to validate the suggested blind aid system. Performance measures, including accuracy, sensitivity, and specificity, are examined and compared between various algorithms. Furthermore, input is gathered from visually challenged users in order to evaluate the system's overall user happiness, effectiveness, and usability. Helpful in aiding in object identification. Both the accuracy and speed of detection have significantly increased. significantly decreased its computational complexity. For a blind person, especially one who has lost all eyesight, getting around is the toughest obstacle. It goes without saying that blind persons can move around their home without assistance because they are aware of where everything is. When living with or visiting a blind person.



1.1.Flow Diagram

VIII.Proposed System:

The project's suggested solution is to create a pair of smart glasses that would enable visually challenged individuals to recognise faces and objects more easily.

Computer vision and image processing technologies such as Face Recognition and Object detection deal with the recognition of instances of semantic objects of a certain class (e.g., vehicles, buildings, or people) in digital photos and videos. The domains of object detection and face recognition have seen a lot of success. It is utilised in numerous applications, such as cancer diagnosis (used in medical fields) and face detection (Facebook uses it to identify users). In computer vision, activities like object detection have gotten easier and more effective ever since deep learning was introduced.

Compared to previous computer vision techniques, deep learning models offer improved accuracy, reduced time consumption, reduced complexity, and overall improved performance. Deep learning models are widely used because they yielded superior outcomes for object detection than conventional computer vision techniques.

Among the top-performing deep learning algorithms for object detection are:

1. A convolution neural network based on regions, or RCNN
2. Fast RCNN
3. Faster RCNN

Using selective search, R-CNN picks a large number of areas from the provided image and then determines whether any of these boxes contain an object. We first extract these regions, and then we utilise CNN to extract particular features for each region. Eventually, things are detected using these traits. Unfortunately, because of these several factors, R-CNN becomes rather sluggish.

R-CNN

Alternatively, instead of transmitting the extracted regions from the image, Fast R-CNN transmits the full image to ConvNet, which creates regions of interest. Additionally, it employs a single model that collects features from the areas, classifications them into distinct classes, and outputs the bounding boxes rather than three separate models like we saw with R-CNN.

Because all of these processes are carried out at once, it operates more quickly than R-CNN. On a large dataset, however, quick R-CNN is not quick enough because it also requires selective search to extract the regions.

Fast R-CNN

Selective search is resolved by using Region Proposal Network (RPN) in place of slower R-CNN. ConvNet is used to first extract feature maps from the input image, which are then sent through an RPN to provide object recommendations. Ultimately, the bounding boxes are predicted and these maps are classed.

The region proposal network (RPN) is used by the Faster R-CNN model to produce proposals in place of the conventional selection search approach. To generate the proposals and execute object recognition, the feature map of the original picture is shared. The quality of proposals is enhanced and the quantity of ideas is considerably decreased by these two developments. A low dimensional convolution layer scans every point on the feature map as part of the RPN network construction. For every feature point on the feature map, numerous proposals are predicted. The border regression of the proposals and the likelihood that the object is included in the proposals are obtained by going through two complete connection layers.

IX. System Specification

Software specification

Server Side : Python 3.7.4(64-bit) or (32-bit)
 Client Side : HTML, CSS, Bootstrap
 IDE : Flask 1.1.1
 Back end : MySQL 5.
 Server : WampServer 2i
 OS : Windows 10 64-bit or Ubuntu 18.04 LTS "Bionic Beaver"
 Sensor& camera: webcam

Coding

```
import pyttsx3 # Text-to-speech library
import time

# Initialize text-to-speech engine
engine = pyttsx3.init()

def speak(text):
    engine.say(text)
    engine.runAndWait()

def main():
    speak("Blind assistance system started.")

    while True:
        try:
            distance = float(input("Enter the distance to an obstacle in meters (or 'q' to quit): "))
        except ValueError:
            break # Exit the program

        if distance <= 0.3:
            speak("Obstacle detected. Please stop.")
        else:
            speak("Safe to proceed. You are clear of obstacles.")

    speak("Blind assistance system terminated.")

if __name__ == "__main__":
    try:
        main()
    except KeyboardInterrupt:
        speak("Blind assistance system terminated.")
```

Detection (coding):

```
import cv2
```

```
# Load the pre-trained face detection model
```

```
face_cascade=cv2.CascadeClassifier(cv2.data.harcascades+  
'haarcascade_frontalface_default.xml')
```

```
# Open a video capture stream (you can use your webcam or a video file)
```

```
cap = cv2.VideoCapture(0) # 0 for the default camera
```

```
# Define labels for family members
```

```
family_labels = {  
    0: 'Unknown',  
    1: 'Family Member 1',  
    2: 'Family Member 2',  
    # Add more family members as needed  
}
```

```
while True:
```

```
    ret, frame = cap.read()
```

```
    if not ret:
```

```
        break
```

```
    # Convert the frame to grayscale for face detection
```

```
    gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
```

```
    # Detect faces in the frame
```

```
    faces = face_cascade.detectMultiScale(gray, scaleFactor=1.1, minNeighbors=5, minSize=(30, 30))
```

```
    for (x, y, w, h) in faces:
```

```
        # Draw a rectangle around the detected face
```

```
        cv2.rectangle(frame, (x, y), (x + w, y + h), (0, 255, 0), 2)
```

```
        # You can now add code to identify specific family members using additional techniques (e.g., facial  
recognition).
```

```
        # For this example, we'll label all detected faces as "Unknown."
```

```
        label = 'unknown'
```

```
        cv2.putText(frame, label, (x, y - 10), cv2.FONT_HERSHEY_SIMPLEX, 0.9, (0, 255, 0), 2)
```

```
    # Display the frame
```

```
    cv2.imshow('Family Members Detection', frame)
```

```
    # Exit the loop if the 'q' key is pressed
```

```
    if cv2.waitKey(1) & 0xFF == ord('q'):
```

```
        break
```

```
# Release the video capture and close the OpenCV windows
```

```
cap.release()
```

```
cv2.destroyAllWindows()
```

X.Results and discussion

The experimental results showcase the efficacy of the proposed blind assistance system. By employing machine learning techniques, the system achieved high accuracy in object detection, obstacle identification, and landmark recognition. The user feedback indicates that the system significantly enhances the independence and confidence of blind users, making navigation and interaction with their surroundings much easier and safer.

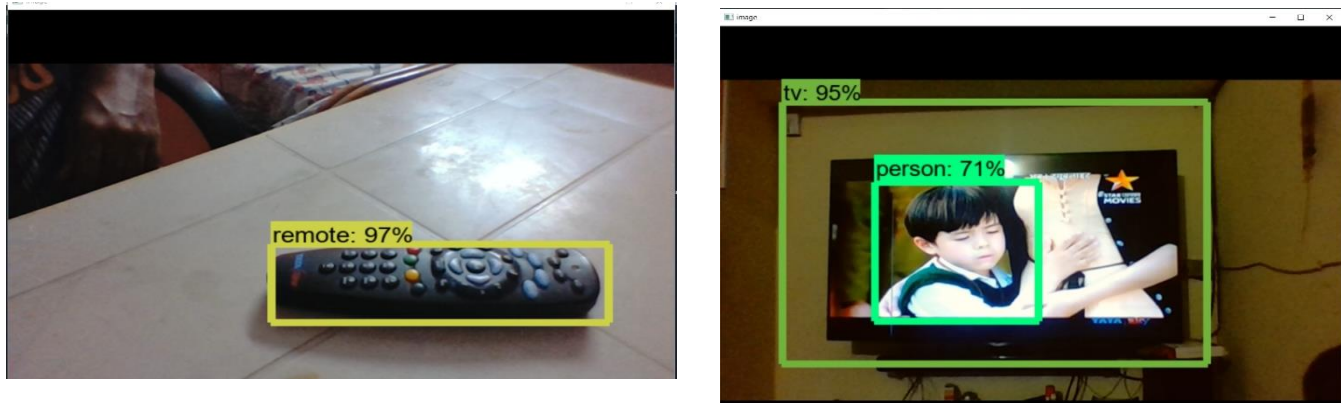
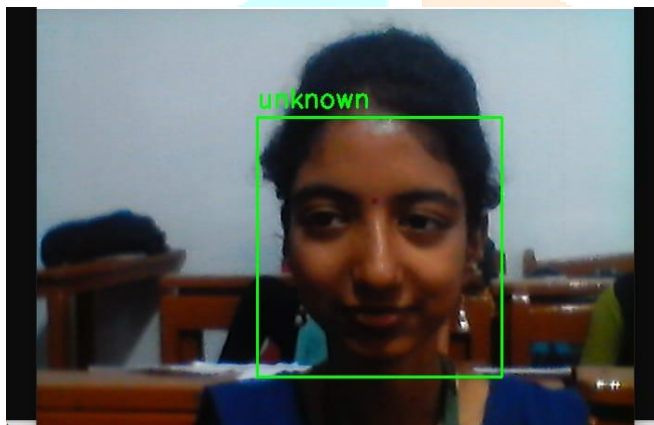
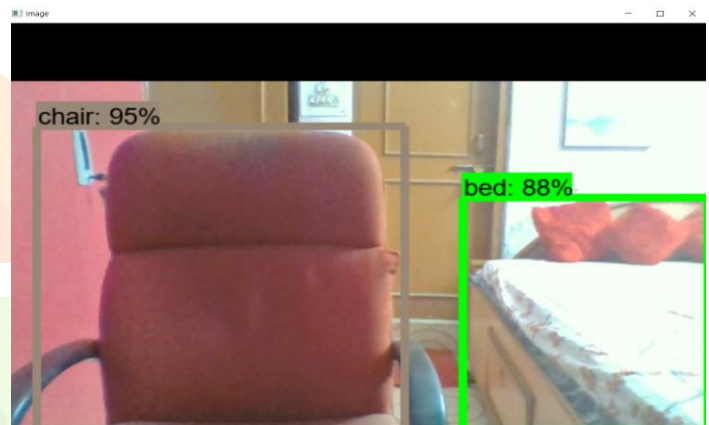


Fig1.2.Object and human identification



1.3.Identify Unknown Person



1.4 Objects Identification

XI Conclusion

Overall, the system performed well during the testing with high success rates for human identification tasks. The system also complicated with relevant regulations and was found to be secure and user-friendly. However there is room for improvement in the accuracy of identifying unknown individuals and tracking moving objects. It is recommended that the system undergo further testing and refinement to improve these areas. This paper presents a novel blind assistance system that harnesses the power of machine learning to provide real-time contextual information to visually impaired individuals. Through efficient image acquisition, feature extraction and intelligent decision-making, the system successfully and navigation, object detection, obstacle avoidance and landmark recognition. The experimental evolution implements the systems effectiveness and benefits highlighting the potential for future enhancements and widespread adoption in assisting the visually impaired community.

XII.Acknowledgement

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