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Article

LidSonic V2.0: LiDAR and Deep Learning-based Green Assistive Edge Device to Enhance Mobility for the Visually Impaired

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Abstract: Over a billion people around the world are disabled, among them, 253 million are visually impaired or blind, and this number is greatly increasing due to ageing, chronic diseases, poor environment, and health. Despite many proposals, the current devices and systems lack maturity and do not completely fulfill user requirements and satisfaction. Increased research activity in this field is required to encourage the development, commercialization, and widespread acceptance of low-cost and affordable assistive technologies for visual impairment and other disabilities. This paper proposes a novel approach using a LiDAR with a servo motor and an ultrasonic sensor to collect data and predict objects using deep learning for environment perception and navigation. We adopted this approach in a pair of smart glasses, called LidSonic V2.0, to enable the identification of obstacles for the visually impaired. The LidSonic system consists of an Arduino Uno edge computing device integrated into the smart glasses and a smartphone app that transmits data via Bluetooth. Arduino gathers data, operates the sensors on smart glasses, detects obstacles using simple data processing, and provides buzzer feedback to visually impaired users. The smartphone application collects data from Arduino, detects and classifies items in the spatial environment, and gives spoken feedback to the user on the detected objects. In comparison to image processing-based glasses, LidSonic uses far less processing time and energy to classify obstacles using simple LiDAR data, according to several integer measurements. We comprehensively describe the proposed system's hardware and software design, construct their prototype implementations, and test them in real-world environments. Using the open platforms, WEKA and TensorFlow, the entire LidSonic system is built with affordable off-the-shelf sensors and a microcontroller board costing less than $80. Essentially, we provide designs of an inexpensive, miniature, green device that can be built into, or mounted on, any pair of glasses or even a wheelchair to help the visually impaired. Our approach affords faster inference and decision-making using relatively low energy with smaller data sizes as well as faster communications for the edge, fog, and cloud computing.

Keywords: visually impaired; smart mobility; sensors; LiDAR; ultrasonic; deep learning; obstacle detection; obstacle recognition; assistive tools; edge computing; green computing; sustainability; Arduino Uno; Smart App

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1. Introduction

There are over 1 billion disabled people today around the world, that is 15% of the world population, and this number is greatly increasing due to ageing, chronic diseases, poor environment, and health, according to the World Health Organisation (WHO) [1]. WHO defines disability as having three dimensions, "impairment in a person's body structure or function, or mental functioning; activity limitation; and participation restrictions in normal daily activities", and that disability "results from the interaction between individuals with a health condition with personal and environmental factors" [2]. Cambridge Dictionary defines disability as "not having one or more of the physical or mental abilities that most people have" [3]. Wikipedia defines physical disability as "a limitation on a person's physical functioning, mobility, dexterity, or stamina" [4]. Disabilities could relate to various human functions including hearing, mobility, communication, intellectual ability, learning, and vision [5]. In the UK, 14.6 million people are disabled [6], that is, over 20% of the population. In the US, 13.2% of the population was disabled according to the 2019 statistics, that is over 43 million people [7]. Similar statistics could be found in various countries around the world, some worse than others, which means that on average, disabled people make up 15% of the population globally.

With 253 million people affected by visual impairment and blindness around the globe, it is the second top disability in the world population after hearing loss and deafness [8]. Four terminologies could be used to identify various rates of loss in vision and blindness, namely, partially sighted, low vision, legally blind, and totally blind [9]. People with partial vision in one or both eyes are considered partially sighted. Low vision relates to a serious visual impairment where visual acuity in the good-seeing eye is 20/70 or lower and cannot be enhanced with glasses or contact lenses. If the best-seeing eye can be corrected to achieve 20/200 then the person is considered legally blind [9]. Finally, totally blind are the ones with a total loss of vision [10]. Even though vision impairment can happen at any point in life, it is more common among older people. Visual impairment could be hereditary. In these kinds of circumstances, it occurs at birth or in childhood [11].

While visual impairment and blindness are among the most disabling disabilities, we know relatively little about the lives of visually impaired and blind individuals [12]. The WHO predicts that the number of people with visual impairments will increase owing to population growth and aging. Moreover, contemporary lifestyles have spawned a multitude of chronic disorders that degrade vision and other human functions [13]. Diabetes and hyperglycemia, for instance, can cause a range of health issues, including visual impairment. Several tissues of the ocular system can be affected by diabetes, and cataracts are one of the most prevalent causes of vision impairment [14].

Behavioral and neurological investigations relevant to human navigation have demonstrated that how we perceive visual information is a critical part of our spatial representation [15]. It is typically hard for visually impaired individuals to orient themselves and move in an unknown location without help [16]. For example, landplane tracking is a natural mobility job for humans, but it is an issue for individuals with poor or no eyesight. This capacity is necessary for individuals to avoid the risk of falling and to alter their position, posture, and balance [16]. Moving up and down staircases, low and high static movable obstacles, damp flooring, potholes, a lack of information about recognized landmarks, obstacle detection, object identification, and dangers are among the major challenges visually impaired people confront indoors and outdoors [17], [18].

The disability and visual impairment statistics in Saudi Arabia are also alarming. Around 3% of people in Saudi Arabia reported the presence of a disability in 2016 [19]. According to the General Authority for Statistics in Saudi Arabia, 46% of all the disabled in Saudi Arabia, that have one disability, are visually impaired or blind, and 2.9% of the Saudi population have disabilities amounting to extreme difficulty [20]. The information provided above highlights the urgent need for research in developing assistive technologies for general disabilities including visual impairment.

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A white cane is the most popular tool used by visually impaired individuals to navigate their environments; nevertheless, it has a number of drawbacks. It needs physical contact with the environment [12], cannot detect barriers above the ground such as ladders, scaffolding, tree branches, and open windows [21], and generates neuromusculoskeletal overuse injuries and syndromes that may require rehabilitation [22]. Moreover, the user of a white cane is sometimes ostracized for social reasons [12]. In the absence of appropriate assistive technologies, visually impaired individuals must rely on family members or other people [23]. However, human guides could be dissatisfying at times since they may be unavailable when assistance is required [24]. The use of assistive technologies can help visually impaired and blind people engage with sighted people and enrich their lives [12].

Smart societies and environments are driving extraordinary technical advancements with the promise of high quality of life [25–28]. Smart wearable technologies are generating numerous new opportunities to enhance the quality of life for all people. Fitness trackers, heart rate monitors, smart glasses, smartwatches, and electronic travel aids are a few examples. The same holds true for visually impaired people. Multiple devices have been developed and marketed to aid visually impaired individuals in navigating their environments [29]. An Electronic Travel Aid (ETA) is a regularly used mobility-enhancing assistive equipment for the visually impaired and blind. It is anticipated that ETAs will increasingly facilitate "independent, efficient, effective, and safe movement in new environments" [30]. ETAs can provide information about the environment through the integration of multiple electronic sensors and have shown effectiveness in improving the daily lives of visually impaired people [31]. ETAs are available in a variety of wearable and handheld devices and may be categorized according to their usage of cellphones, sensors, or computer vision [32]. The acceptance rate of ETAs is poor among the visually impaired and blind population [23]. They are not common among potential users because they have inadequate user interface design, are restricted to navigation purposes, are functionally complex, weighty to carry, expensive, and lack functionality for object recognition even in familiar indoor environments [23]. The low adoption rate does not necessarily indicate that disabled people oppose the use of ETAs; rather, it confirms that additional research is required to investigate the causes of the low adoption rate and to improve the functionality, usability, and adaptability of assistive technologies [33]. In addition, introducing unnecessarily complicated ETAs that may necessitate extensive and supplementary training to learn additional and difficult abilities is not a realistic alternative and is not a feasible solution [22]. Robots can assist the visually impaired in navigating from one location to another, but they are costly along with their other challenges [34]. Augmented reality has been used as a solution for magnifying text and images through a finger wearable applied with a camera to project on a HoloLens [35] but this technology is not suitable for blind people.

We developed a comprehensive understanding of the state-of-the-art requirements and solutions for visually impaired assistive technologies using a detailed literature review (see Section 2) and a survey [36] on this topic. Using this knowledge, we identified the design space for assistive technologies for the visually impaired and the research gaps. We found that the design considerations for assistive technologies for the visually impaired are complex and include reliability, usability, and functionality in indoor, outdoor, and dark environments; transparent object detection; hand-free operations; high-speed real-time operations; low battery usage and energy consumption; low computation and memory requirements; low device weight; and cost-effectiveness. Despite the fact that several devices and systems for the visually impaired have been proposed and developed in academic and commercial settings, the current devices and systems lack maturity and do not completely fulfill user requirements and satisfaction [18,37]. For instance, numerous camera-based and computer-based solutions have been produced. However, the computational cost and energy consumption of image processing algorithms pose a concern for low-power portable or wearable devices [38]. These solutions require large storage and computational resources, including large RAMs to process large volumes of data containing images. This could require substantial processing, communication, and decision-making times, and would also consume energy and battery life. Significantly more research efforts are required to bring innovation, intelligence, and user satisfaction to this crucial area.

In this paper, we propose a novel approach that uses a combination of a LiDAR with a servo motor and an ultrasonic sensor to collect data and predict objects using machine and deep learning for environment perception and navigation. We implemented this approach in a pair of smart glasses called LidSonic V2.0 to identify obstacles for the visually impaired. The LidSonic system consists of an Arduino Uno edge computing device integrated in the smart glasses and a smartphone app that transmits data via Bluetooth. Arduino gathers data, operates the sensors on smart glasses, detects obstacles using simple data processing, and provides buzzer feedback to visually impaired users. The smartphone application collects data from Arduino, detects and classifies items in the spatial environment, and gives spoken feedback to the user on the detected objects. LidSonic uses far less processing time and energy than image processing-based glasses by classifying obstacles using simple LiDAR data, using several integer measurements.

We comprehensively describe the proposed system's hardware and software design, construct their prototype implementations, and test them in real-world environments. Using the open platforms WEKA and TensorFlow, the entire LidSonic system has been built with affordable off-the-shelf sensors and a microcontroller board costing less than $80. Essentially, we provide the design of inexpensive, miniature, green devices that can be built into, or mounted on, any pair of glasses or even a wheelchair to help the visually impaired. Our approach affords faster inference and decision-making using relatively low energy with smaller data sizes. Smaller data sizes are also beneficial in communications, such as those between the sensor and processing device, or in the case of fog and cloud computing, because they require less bandwidth and energy, and can be transferred in relatively shorter periods of time. Moreover, our approach does not require a white cane (although can be adapted to be used with a white cane), and therefore, it allows for hands-free operation.

The work presented in this paper is a substantial extension of our earlier system LidSonic (V1.0) [39]. LidSonic V2.0, the new version of the system, uses both machine learning and deep learning methods for classification, as opposed to V1.0 which uses machine learning alone. LidSonic V2.0 provides higher accuracy of 96% compared to 92% for LidSonic V1.0 despite the fact that it uses a lower number of data features (14 compared to 45) and a wider vision angle of 60 degrees compared to 45 degrees for LidSonic V1.0. The benefits of a lower number of features are evident in LidSonic V2.0 requiring even lower compute resources and energy than LidSonic V1.0. We have extended the LidSonic system with additional obstacle classes, provided an improved and extended explanation of various system components, and conducted extensive testing with two new datasets, six machine learning models, and two deep learning models. System V2.0 has been implemented using Weka and TensorFlow platforms (provides dual options for open-source development) compared to the previous system that was implemented in Weka alone. Moreover, this paper provides a much extended, completely new literature review and taxonomy of assistive technologies and solutions for the blind and visually impaired.

We have noted earlier in this section that despite several devices and systems for the visually impaired being developed in academic and commercial settings, the current devices and systems lack maturity and do not completely fulfill user requirements and satisfaction. Increased research activity in this field will encourage the development, commercialization, and widespread acceptance of devices for the visually impaired. The technologies developed in this paper are of high potential and are expected to open new directions for the design of smart glasses and other solutions for the visually impaired using open software tools and off-the-shelf hardware.

The paper is structured as follows. Section 2. explores relevant works in the field of assistive technologies for the visually impaired and provides a taxonomy. Section 3. gives an overview of the LidSonic V2.0 system highlighting its user, developer, and system views. Section 4. gives a detailed illustration of the software and hardware design and implementation. The system is evaluated in Section 5. Conclusions and thoughts regarding future work are provided in Section 6.

2. Related Work

This section reviews the literature relating to this paper. Section 2.1 presents sensor technologies and the types of sensor technologies used in the assistive tools for the visually impaired. Section 2.2 reviews processing methods. Section 2.3 discusses feedback techniques. A taxonomy of functionalities and applications is provided in Section 2.4. Section 2.5 identifies the research gap and justifies the need for this research. A taxonomy of the research on the visually impaired presented in this section is given in Figure 1. An extensive complimentary review of assistive technologies for the visually impaired and blind can be found in our earlier work [39].

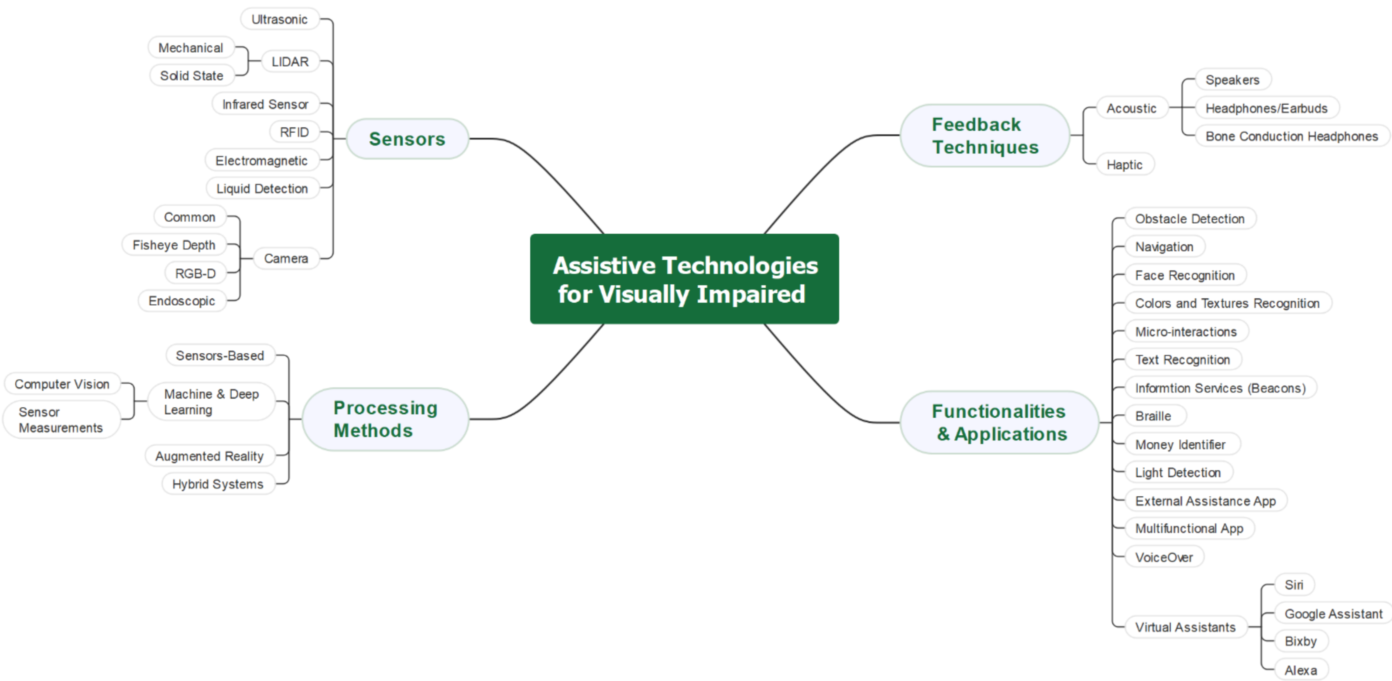

Figure 1. A Taxonomy of Research on Assistive Technologies for the Visually Impaired.

2.1 *Sensor Technologies and Types Used in Assistive Tools*

Sensors are indistinguishable components of cyberphysical systems. They collect knowledge regarding environmental factors as well as non-electrical system parameters and provide the findings as electrical signals. With the development of microelectronics, sensors are possible as compact devices with low costs and have a wide range of applications in different fields, especially in control systems [40]. There are two types of sensors, passive and active sensors. The active sensor needs an incentive to activate. On the contrary, the passive sensor detects inputs and generates output signals directly without external incentive. The classification may be dependent on the sensor's means of detection e.g. electric, biological, chemical, radioactive, etc. [41].

A number of sensors have been employed in the field of visually impaired people. It has been used to solve a wide range of vision issues. The most frequent types of sensors used in assistive devices for the visually impaired are listed in Table 1. It also shows the sensor's function (functionality), type of wearable, and type of feedback.

2.1.1 Ultrasonic Sensors

An ultrasonic sensor is an electronic device that uses ultrasonic sound waves to detect the distance between a target item and transforms the reflected sound into an electric

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signal. Fauzul and Salleh [42] developed a visual assistive technology to assist visually impaired individuals in navigating both indoor and outdoor situations safely and conveniently. A smartphone app and an obstacle sensor are the two major components of the system. To deliver auditory cue instructions to the user, the mobile software makes use of the smartphone's microelectromechanical sensors, location services, and Google Maps. Ultrasonic sensors are used in the obstacle sensor to detect objects and offer tactile feedback. The obstacle avoidance gadget attaches to a standard cane and vibrates the handle at varied intensities according to the nature of the obstructions. The spatial distance and direction of the present position to the intended location are used to produce spatial sound cues. Gearhart et al. [43] proposed a technique to find the position of the detected object using triangulation by geometric relationships to scalar measurements. The authors placed two ultrasonic sensors one on each shoulder angled towards each other five degrees from parallel with a space of 10 inches. However, this technique is too complex to be applied with several objects in front of the sensor. A significant number of research papers in the field of detecting objects, have depended on ultrasonic sensors. Tudor et al. [44] proposed a wearable belt with two ultrasonic sensors and two vibration motors to direct the visual impaired from obstacles. The authors used Arduino Nano Board with an ATmega328P microcontroller to connect and build their system. According to their findings, the authors in [45] found that ultrasonic sensors and vibrator devices are easily operated by Arduino UNO R3Impatto Zero boards. Noman et al. [46] proposed a robot equipped with several ultrasonic sensors and Arduino Mega (ATMega 2560 processor) to detect obstacles, holes, and stairs. The robots may be utilized in indoor environments, however, their use outdoors is not practical.

2.1.2 Lidar Sensors

Light detection and ranging, or LiDAR, is a common remote sensing technique for determining an object's distance. Chitra et al. [47] proposed a hands-free LVU (Lidars and Vibrotactile Units) discrete wearable gadget that helps blind persons to identify impediments. A proper mobile assistance equipment is required. The proposed gadget consists of a wearable sensor strap. Liu et al. proposed HIDA. It is a lightweight assistance system for comprehensive indoor detection and avoidance based on 3Dpoint cloud instance segmentation and a solid-state LiDAR sensor. The authors created a point cloud segmentation model with dual lightweight decoders for semantic and offset predictions, ensuring the system's efficiency. The segmented point cloud was post-processed by eliminating outliers and projecting all points onto a top-view 2D map representation after the 3D instance segmentation.

2.1.3 Infrared (IR) Sensors

An infrared (IR) sensor is an electronic device that monitors and senses the infrared radiation in its surroundings [48]. Infrared signals are similar to RFID in that they use the notion of distant data transfer. As previously stated, the latter uses radio waves, whilst the former uses light signals. Air conditioner remotes and motion detectors, for example, all use infrared technology. Smartphones now come with infrared blasters, allowing users to control any compatible device with an infrared receiver. It is an eye-safe light, which emits pulses and measures the time of reflected light taken to calculate the distance. Every metric of the IR consists of thousands of separate pulses of light that lead to reliable measurements of rain, snow, fog, or dust and can be obtained by an infrared sensor; these measurements are difficult to capture with cameras [22]. In addition, IR has long-range both indoor and outdoor environments, high precision, small size, and low latency. IR sensor can detect up to 14m, 0.5 resolution and 4cm accuracy [12]. IR has medium width among ultrasonic and laser sensors. Laser has a rather narrow scope, and it attracts very narrow space information, which is not large enough for free paths. On the other hand, Ultrasonic sensors have many reflections, so they are limited [49].

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2.1.4 RFID sensors

RFID is the abbreviation for Radio Frequency Identification. Data may be transferred and received through radio waves using RFID. In RFID, the sender sends a radio receiver. In this method, the sender is commonly an RFID chip (or an RFID tag) inserted in the object being read or scanned. The receiver, on the other hand, is an electrical device that detects the RFID chip's data. The chip and receiver do not need to be in physical contact because the data is broadcast and received by radio waves. RFID is appealing because of its remote capabilities, but it is also harmful. Because the chip's RFID signal may be read by anybody with an RFID reader, it may lead to an unethical and harmful situation, namely, data theft. The fact that the person using the scanner does not even have to be near the chip/tag increases the danger. Another disadvantage is that each tag has a certain range, which necessitates extensive individual testing, limiting the scope. In addition, the system may be quickly turned off if the tags are wrapped or covered, preventing them from receiving radio signals [50].

An Intelligent Walking Stick for the Blind was proposed by Chaitrali et al. [51]. The proposed navigation system for vision impairment uses infrared sensors, RFID technology, and Android handsets to provide speech output for obstacle navigation. The gadget is equipped with proximity infrared sensors, and RFID tags are implanted in public buildings as well as in the walking sticks of blind people. The gadget is Bluetooth-connected to an Android phone. An Android application is being developed that provides voice navigation based on RFID tag reading and also updates the server with the user's position information. Another application allows family members to access the location of the blind person via the server at any time. The whereabouts of a blind person may be traced at any time, providing further security. Their approach has the disadvantage of not being compacted. When the intelligent stick is within the range of the PCB unit, active RFID tags immediately send location information. It is not necessary for the RFID sensor to read it explicitly.

2.1.5 Electromagnetic Sensors (Microwave Radar)

Adopting a pulsed chirp scheme can reduce the power consumption and preserve high resolution by managing the spatial resolution in terms of the frequency modulation bandwidth. A pulsed signal enables the transmitter to be turned off in the listening time of the echo, thereby significantly reducing the energy consumption [37]. Using a millimeter-wave radar and a typical white cane, electronic travel assistance for blind and visually impaired persons has been proposed[52]. It is a sophisticated system that not only warns the user of possible difficulties but also distinguishes between human and nonhuman targets. Because real-world situations are likely to include moving targets, a novel range alignment approach has been developed to detect minute chest movements caused by physiological activity as vital evidence of human presence. The proposed system recognizes humans in complicated situations with many moving targets, giving the user a comprehensive set of information, including the presence, location, and type of the accessible targets. The authors used a 122 GHz radar board for carrying out appropriate measurements are used to demonstrate the system's working principle and efficacy.

2.1.6 Liquid detection sensors

Research usually contains more than one type of sensor to cover most of the prevalent challenges facing the visual impaired. Ikbal et al. [53] proposed a stick that is equipped with various kinds of sensors to assist in detecting obstacles. One of the obstacles that most jeopardize the visually impaired is water on the floor [54]. Therefore, the authors included a water sensor in their solution in addition to two ultrasonic sensors to detect 180 cm obstacles, one IR sensor to detect stairway gaps and holes on streets, and a temperature sensor for fire alert. The authors connected the entire sensors with an Arduino microcontroller board. This sensor must come into contact with the surface of the water in order to give the result, so it must consider the appropriate wearable. One of the most important uses of a liquid detector for the blind is the sensor that is placed on the cup to prevent it from spilling. To improve navigation safety, the authors present a polarized RGB-Depth (pRGB-D) framework to detect traversable area and water hazards while using polarization-color-depth-attitude information [55].

2.1.7 Cameras

The camera is utilized to gain various functionalities in different technology solutions using machine learning algorithms, such as face recognition, object recognition, and localization, see Table 1**Error! Reference source not found.**. The research has used various types of cameras. The most used types were the common camera and the RGB-Depth camera. The common camera is used mostly in face, emotion, and obstacle recognition. On the other hand, the RGB-D camera has been used in detecting, avoiding obstacles, and mapping to assist in navigation through indoor environments. A depth image is an image channel in which each pixel is related to a distance in the RGB picture between the image plane and the respective point. Adding depth to standard color camera techniques increases both the precision and density of the map. RGB-D sensors have been popular in a variety of visual aid applications due to their low power consumption and inexpensive cost, as well as their resilience and high performance, as they can concurrently sense colour and depth information at video smooth framerate. Because polarization characteristics reflect the physical properties of materials, polarization and associated imaging can be employed for material identification and target detection in addition to color and depth [30]. In the meanwhile, because various polarization states of light act differentially at the interface of an object's surface, polarization has been utilized in a variety of surface measuring techniques. Nevertheless, most industrial RGB-D sensors, such as light-coding sensors and stereo cameras, depend solely on intensity data, with polarization indications either missing or insufficient [55]. This study [56] describes a 3D object identification algorithm and its implementation on a Robotic Navigation Aid (RNA) that allows for real-time detection of indoor items for blind people utilizing a 3D time-of-flight camera for navigation. Then, using a Gaussian-Mixture-Model-based plane classifier, each planar patch is classified as belonging to a certain object model. Finally, the categorized planes are clustered into model objects using a recursive plane clustering process. The approach can also identify various non-structural elements in the indoor environment. This research [57] proposes a new approach to autonomous obstacle identification and classification that combines a new form of sensor, a patterned light field, with a camera. The proposed gadget is compact in size, portable, and inexpensive. As the sensor system is transported in natural interior and outdoor situations over and toward various sorts of barriers, the grid projected by the patterned light source is visible and distinguishable. The proposed solution uses deep learning techniques, including a convolutional neural network-based categorization on individual frames, to leverage these patterns without calibration. The authors improved their method by smoothing frame-based classifications across many frames using lengthy short-term memory units.

Table 1 Types of Sensors Used in Assistive Devices for VI.

Sensor Name	Works	Purpose of Sensor	No. of Sensors	Weight	Wearable /Assistive	Feedback Method
IR Sensors	[58]	Touch down, Touch up sensor	2	Light	Mounted on top of a finger	Acoustic
	[49]	Detect obstacles, stairs	2	Light	Cane	Acoustic
IMU	[58]	Recognize gestures and sense movements	1	Light	Mounted on top of a finger	Acoustic
Ultrasonic Sensors	[23]	Detect obstacles up to the chest level	5	Light	Cane	Acoustic, Vibration
	[59]	Detect obstacles	2	High	Guide dog robot and portable robot	Acoustic
	[45]	Detect obstacles	5	Fair	Mounted on the head, legs, and arms	Buzzer, Vibration
	[44]	Detect obstacles	2	Fair	Belt	Vibration
ToF Distance Sensors	[12]	Detect obstacles	7	High	Belt	Vibration Belt
Microwave Radar	[37]	Detect obstacles	1	Light	Mounted into a cane	Acoustic, Vibration
Wet Floor Detection Sensors	[53]	Detect wet floors	1	Light	Cane	Buzzer
Bluetooth	[60]	Informing about indoor environments	3	Light	Beacon transmitter, smartphone	Acoustic
Laser Pointer	[61]	Detect obstacles	1	Light	Belt	Vibration belt
Cameras	[58]	Localize the hand touch	1	Light	Mounted on top of a finger	Acoustic
	[62]	Emotion recognition	1	Light	Clipped on to spectacles	Vibration belt
	[59]	Obstacle recognition (traffic light, cones, bus, etc.)	2	High	Guide dog robot and portable robot	Acoustic
	[63]	Localization system	1	Low	Head level (helmet), chest level (hanged)	Location in a Map
RGB-D Cameras	[61]	Detect obstacles	1	Light	Smartphone simulate a cane	Vibratory Belt
	[64]	Avoid obstacles, localization system for indoor navigation	1	Light	Glass, tactile vest, smartphone	Haptic Vest (4 Vibration Motors)
Endoscopic Cameras	[65]	Identify clothing colors, visual texture recognition	1	Light	Mounted on top of a finger	Acoustic
Compass	[66]	Indoor navigation	1	Light	Optical head-mounted (Glass)	Acoustic

2.2 *Processing Methods*

Researchers have used a range of processing methods for assistive technologies. Recent years have seen an increase in the use of machine learning and deep learning methods in various applications and sectors, including healthcare [67–69], mobility [70–72], disaster management [73,74], education [75,76], governance [77], and many other fields [78]. Assistive technologies are no different and have begun to increasingly rely on machine learning methods. This section reviews some of the works on processing methods for assistive technologies, both machine learning-based methods and other methods.

There are numerous ideas and methods that have been proposed to solve the problems and challenges facing the blind. Katzschmann et al. [12] incorporated several sensors and feedback motors in a belt to produce an aiding navigation system, called Array of Lidars and Vibrotactile Units (ALVU), for visually impaired people. The authors have developed secure navigation, which is effective in providing detailed feedback to a user about the obstacles and free areas around the user. Their technique is made up of two components: a belt with a distance sensor array and a haptic array of feedback modules. The haptic strap that goes around the upper abdomen provides input to the person wearing ALVU, which allows them to sense the distance between themselves and their surroundings. As the user approaches an impediment, they have greater pulse rates and a higher vibration force. The vibration and pulses stop once the user has overcome the obstacle. However, this kind of feedback is primitive and cannot define, for the user, the type of obstacle that they should avoid. Moreover, it does not determine whether the obstacle should or should not be avoided. In addition, wearing two belts may not be easy and comfortable for the user. Meshram et al. [23] designed a NavCane that detects and avoids obstacles from the floor up to the chest level. It can also identify water on the floor. It has a user button to send auto alerts through SMS and email for emergencies. It provides two kinds of feedback, tactile feedback by using vibration and auditory feedback by the headphones. However, the device cannot identify the nature of the objects and cannot detect obstacles above chest level.

Hong et al. [79] proposed a solution for blind people based on two haptic wristbands in order to provide feedback to objects. Using a Lidar, Chun et al. [80] proposed a detection technique that reads the distances of deferent angles, then measures the predicted obstacles by comparing those reading.

Using the Internet of Things IoT, Machine Learning, and Embedded Technologies, Mallikarjuna et al. [34] developed a low-cost visual aid system for object recognition. The image is acquired by the camera and then forwarded to the Raspberry Pi. To classify the image, the Raspberry Pi is trained using the Tensor Flow Machine Learning Framework and Python programming. However, their technique takes a long period of time (5s to 8s) to inform the visually impaired individual about the item in front of them.

Gurumoorthy et al. [81] proposed a technique using the rear camera of a mobile phone to capture and analyze the image in front of the visually impaired. To execute tasks related to computer vision, they benefit from Microsoft Cognitive Services. Then, give image feedback to the user through Google talkback. This technique needs a mobile internet service to be performed. Additionally, it is hard for the visually impaired to take a proper picture. A similar solution of sending the picture to the cloud to be analyzed is proposed by [33] however, the authors capture the image through a camera mounted into the white cane. The authors also proposed a solution for visually impaired people's mobility, which comprises a smart folding stick that works in tandem with a smartphone app with interconnection mechanisms based on GPS satellites. Navigational feedback is presented to the user as a voice output as well as to the visually impaired family/guardians via the smartphone application. Rao and Singh [82] developed an obstacle detection method using computer vision using a fisheye camera that is mounted onto a shoe. The photo is transmitted to a mobile application that uses TensorFlow Lite to classify the picture and alert visually impaired users about potholes, ditches, crowded places and staircases. It gives a vibration notification. In addition, an ultrasonic sensor was mounted with a servo on the front part of the shoe, to detect nearby obstacles. A vibration motor has been used inside the shoe for feedback.

2.3 *Feedback Techniques*

People with standard vision depend on feedback that they gain from vision. They perceive more through vision than through hearing or touch. It is something that the visually impaired lack. Therefore, ETAs must be able to provide sufficient input on the perceived knowledge about the world of the user. Furthermore, feedback should be swift and not conflict with hearing and feeling [61].

2.3.1 Haptics

The feature of haptic methods for the visually impaired person that can give more interaction methods for the other human sensors such as hearing and do not interfere with it. It has been noticed in the studies that the visually impaired have higher memorization abilities and recognition of haptic tasks [83]. The advantages of haptic feedback are high privacy because only the person can observe the stimuli, useful in high-noise environments, and expand the person's experience as an additional communicational channel. [84]. Buimer et al. [62] presented an experiment to recognize facial emotion and sent the feedback through a vibration belt to the user. The authors convey the information of each six emotions by having six vibration units in a belt. Even though the experiment has accuracy problems, the satisfactory results of this method have been studied on eight visually impaired people. Five of them found that the belt was easy to use and could interpret the feedback while conversing with another person. While the other three found its use difficult. Gonzalez-Canete et al. have proposed Tactons, they identified sixteen applications with different vibration signals to be distinguished from each other. The authors found that musical techniques for haptic icons are more recognizable and can be further distinguished. In addition, adding complicated vibrotactile sensations to smartphones is a significant benefit for users with any kind of sensory disability. The authors measured the recognition rate of the VI users and non-VI users. They found that non-VI users score higher rates, especially with identifying applications that they are familiar with, but when they use the reinforcement learning stage in which they give some feedback to the users the recognition rate in the VI users increased [84].

2.3.2 Acoustic

Masking auditory signals by binaurally re-displaying environmental information through headphones or earbuds, blocking vital environmental signals on which many visually impaired people rely for secure navigation [22]. Currently, bone transmitting helmets enable the user to obtain 3D auditory feedback, leaving the ear canal open and enabling the user with free eyes, hands, and mind. The algorithm reduces sound production that does not indicate a change to further minimize the auditory output. Thus, the audible output sound is only produced when the user is confronted with an impediment, limiting possibly irritating sounds to a minimum. [85].

2.4 Functionalities and Applications

We review the necessary functions and applications that the visually impaired use to solve difficult matters for them. These applications are obstacle detection, navigation, face recognition, colours, and textures recognition, micro-interactions, text recognition, informing services, and Braille displayer and printer. Next, a detailed review is presented.

2.4.1 Obstacle Detection

A lot of research and studies focused on obstacle detection due to its significance to the visually impaired as it considers a major challenge for them. An ETA using a microwave radar to detect obstacles up to the head level due to the vertical beam of the sensor, has been presented in [37]. To overcome the issue of power consumption, the authors switched off the transmitter during the listening time of the echo. Moreover, the pulsed chirp scheme was adapted to manage the spatial resolution. To improve the precision of the indoor blind guide robot's obstacle recognition, Du et al. [86] presented a sensor data fusion approach based on the D-S evidence theory of the genetic algorithm. The system uses ultrasonic sensors, infrared sensors, and Lidar to collect data from the surroundings. The optimized weight is replaced in D-S evidence theory for data fusion under the premise of determining the weight range of various sensors using the genetic algorithm. In practice, weighing and fusing evidence requires determining the weight of evidence. Their technique has an accuracy of 0.94 for indoor obstacle identification. Bleau et al. [87]

present EyeCane that can identify four kinds of obstacles: cube, door, post, and step. However, its bottom sensor failed to properly identify objects on the ground, making downwards navigation more dangerous.

2.4.2 Navigation

Regarding navigation, it may be divided into two main categories, internal and external navigation, because the set of techniques used in each one is different from the other. For example, Global Positioning System (GPS) is not suitable for indoor localization due to the power of satellite signals that become weak and cannot determine whether, is it close to a building or a wall [88]. However, some studies developed techniques that may apply to both.

AL-Madani et al. [88] adopted a fingerprinting localization algorithm with fuzzy logic type-2 to navigate indoors in rooms with six BLE (Bluetooth Low Energy) beacons. The algorithm calculation was done on the smartphone. The algorithm achieved 98.2% in indoor navigation precision and an accuracy of 0.5 m on average. Jafri et al. [89] have benefited from Google Tango Project to serve the visually impaired. The Unity engine's built-in functionalities in the Tango SDK were used to build a 3-D reconstruction of the local area, then a Unity collider component was connected with the user who used it for obstacle detection by determining its relationship with the reconstructed mesh. Indoor navigation assistance with an optical head-mounted screen that directs the visually impaired is presented in [66]. The program creates indoor maps by monitoring a sighted person's activities inside of the facility, develops and prints QR code location markers for locations of interest, and then gives blind users vocal direction. Pare et al. [90] investigate a smartphone-based sensory replacement device that provides navigation direction based on strictly spatial signals in the form of horizontally spatialized sounds. The system employs numerous sensors to identify impediments in front of the user at a distance or to generate a 3D map of the environment and provide audio feedback to the user. A navigation system based on binaural bone-conducted sound was proposed by [91]. The system does the following to correctly direct the user to their desired point. Initially, the best bone-conduction device to use is described, as well as the best contact circumstances between the device and the human skull. Second, using the head-related transfer functions (HRTFs) acquired in the air-borne sound field, the fundamental performance of sound localization replicated by the chosen bone-conduction device with binaural sounds is validated. A panned sound approach is also approved here, which may accentuate the sound's location.

iMove around and Seeing Assistant [92][93] enable its users to know their current location, including street address, receive immediate area details (Open Street Map), manage their points, manage paths, create automated paths, and navigate to the selected point or path, and exchange newly generated data with other users. The app can use voice commands to facilitate the control of the program. Seeing Assistant Move has an exploration mode that utilizes a magnetic compass to measure direction correctly, which transmits this knowledge using clock hours. Also, it has a source-light detector that allows the user to interact with devices that use a diode as an information tool. For people that are fully blind, the light source detector is extremely useful. When leaving the house or planning to sleep, the blind consumer would never leave a turned-on lamp. In order to be able to accommodate signalling devices (such as diodes, and control lights), the program has a feature that helps a user to detect a blinking light. This can be used to indicate whether or not a device is turned on, or whether or not a battery level is low or high. On the other hand, lots of speech correlated with the user position is registered iMove around the app. A note of speech is played at any time the user is near the position where it was captured. BlindExplorer [94] utilize the 3D sounds as an auditory stimulus, which offers the app a type of feedback that helps a consumer to travel to the route, destination, or the right direction without needing to visualize the screen and without moving their eyes off the ground. RightHear[95] is a virtual access assistant that helps users easily navigate new environments. It has two modes indoor and outdoor. It locates the visually impaired current location and nearby points for an indoor and outdoor environment. However, indoor locating is limited by supported locations.

Ariadne GPS [96] has a feature that makes the app suitable for the visually impaired. Namely, it uses VoiceOver in the app to inform about the street names and numbers that are around the user by touching them. By simply placing the finger on the device's screen, the user would be told about the streets while viewing the map and moving it. The user location is in the middle of the screen and what is in front of the user is in the top half of the screen, and the location in the bottom half of the screen is behind the user. This app reports on the user's position at all times. It has a monitor function while activating it, it informs about the user's location continuously. BlindSquare [97] is a self-voicing software, combined with third-party navigation applications, that provides detailed points of interest and intersections for navigating both outside and inside designed especially for the visually impaired, blind, deafblind, and partially sighted. To determine what data is most important, BlindSquare has some special algorithms and then talks to the user with high-quality speech synthesis. The app can be controlled by voice commands. The Voice Command feature is a paid service that demands that credits be bought for continuous use. Voice Command Credits are available on the App Store as an in-app purchase.

2.4.3 Face and Emotion Recognition

Morrison et al. [98] have investigated the technological needs of the visually impaired through tactile ideation. The findings were critical for people with visual disabilities and pointed to the need for social information such as face recognition and emotion recognition. In addition, social engagement and watching what others are doing, and simulating a variety of visual skills, such as object recognition or text recognition, were important abilities. The importance of knowing people's emotions was discussed in [62]. The authors used computer vision technology to solve the problem. Their system uses face recognition applications to capture six basic emotions. Then it conveys this emotion to the user by means of a vibration belt. The proposal faced several challenges involving the light conditions, the movements of the person opposite the user and facing the camera directly while capturing the pictures. Therefore, the recognition accuracy was affected. The authors did not present any numerical accuracy information in their paper.

2.4.4 Colors and Textures Recognition

Medeiros et al. [65] present a finger-mounted wearable that can recognize colors and visual textures. They developed a wearable device that included a tiny camera and a co-located light source (an LED) that was placed on the finger. This technology allows users to obtain color and texture information by touch, allowing them to glide their fingers across a piece of clothing and combine their understanding of physical materials with automated aural input regarding the visual appeal. The authors used a special camera for this purpose. To identify visual textures, they used a machine-learning approach, while color identification was done superpixel segmentation to help with higher cognizing of clothing appearance.

Color Inspector [99] was developed to help distinguish color blind and other visually disabled people by analyzing live footage to explain the color in view and to recognize complicated colors. It supports Voice Over that can audibly read the color. Color Reader [100] allows for the real-time identification of colors by solely pointing the camera at the object. The app has a feature to read the colors in the Arabic language. ColoredEye [101] provides different color categories with different color descriptions, such as BASIC with 16 fundamental colors, CRAYOLA with 134 fun pigments and DETAILED with 134 descriptive colors.

2.4.5 Micro-interactions

Micro-interaction is the animations and configuration adjustments that occur when a user interacts with something [102]. There are four parts to setting micro-interactions: First, a micro-interaction is started when a trigger is engaged. Second, triggers can be

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started by the user or by the system. Then, a user-initiated trigger requires the user to take action. In a system-initiated trigger, the software recognizes the presence of particular criteria and takes action. When a micro-interaction is initiated, rules dictate what occurs next. Finally, feedback informs individuals on what is going on. Feedback is whatever a user sees, hears, or feels during a micro-interaction. The meta-rules of the micro-interaction are determined by Loops and Modes [103]. A device mounted on a finger has been presented by Oh et al. [58] to leverage physical gestures to facilitate the micro-interaction of some common and daily applications such as setting the alarm, and finding and opening an app. The authors carried out a survey to study the efficiency of their methods.

2.4.6 Text Recognition

One of the important things that we must consider is how to use this feature, and how to convey the important information only not all of the information detected around [104]. The blob is a collection of pixels whose intensity is different from the other nearby pixels. Although the MSER (Maximally Stable External Region) can detect the blob faster, SWT (Stroke Width Transform) algorithm can detect characters from an image with no separate learning process [104]. Shilkrot et al. [105] developed FingerReader, a supporting reading system for visually impaired people to assist impaired persons in reading printed texts with a real-time response. This gadget is a close-up scan device that may be worn on the index finger. As a result, the gadget reads the printed text a single line at a time and then provides haptic feedback and audible feedback. Text Extraction Algorithm, which is integrated with Flite Text-To-Speech, was utilized by [106]. The proposed technique uses a close-up camera to retrieve the printed text. The trimmed curves are then matched with the lines. The 2D histogram ignores the repeated words. The program then defines the words from the characters and transmit them to ORC. As the user continues to scan, the identified words are recorded in a template. As a result, the system keeps note of those terms in the event of a match. However, when the user deviates from the current line, they get audible and tactile feedback. Moreover, if the device does not discover any more printed text blocks, the visually impaired get signals via tactile feedback informing them of the line's ending. SeeNSpeak [107] supports voice over and can interpret text audibly from the photographs of books, newspapers, posters, bottles, or any item with text. The app can also use a wide range of target languages to translate the detected text.

2.4.7 Information Services

In the context of location-based services, a beacon is a tiny hardware device that allows data to be transmitted to mobile devices within a certain range. Most apps require that receivers have Bluetooth switched on, that they download the corresponding mobile app and have location services turned on. Moreover, they require that the receiver accept the sender's messages. Beacons are frequently mounted on walls or other surfaces in the area as a small standalone device. Beacons can be as basic as sending a signal to nearby devices, but they can also be Wi-Fi and cloud-connected, with memory, and processing resources. Some are equipped with temperature and motion sensors [108]. Perakovic et al. [60] used the beacon technology to inform the visually impaired with required information, such as notifying them about possible obstacles, locating an object, informing them about a facility, discounts, or navigation in indoor environments.

2.4.8 Braille Display and Printer

Braille technology is an assistive technology that helps blind or visually impaired individuals to perform basic tasks such as writing, Internet searching, Braille typing, text processing, chatting, file downloading, recording, electronic mail, song burning, and reading [109]. There is a major challenge because of the high cost of some current braille technologies or the large and heavy format of some braille documents or books with embossed paper. Braille is a representation of the alphabet, numbers, marks of punctuation, and symbols composed of cells of dots. In a cell, there are 6-8 possible dots and a single letter, number, or punctuation mark is created by one cell.

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Displayer is an electromechanical mechanism for viewing braille characters, commonly utilizing round-tipped pins lifted through holes on a flat surface is often called a refreshable braille display or braille terminal. The visually impaired use it instead of a monitor. Via the braille display, they can insert commands and text, and it conveys text and images from the screen to them by modifying or refreshing the braille characters on the keyboard. They can browse the internet, draft documents, and use a computer in general. Up to 80 characters from the screen can be shown on a braille display, which can be updated when the user moves the cursor across the monitor using the command keys, cursor routing keys, or Windows and screen reader controls. Braille displays of 40, 70, or 80 characters are typically available. In most occupations, a 40-character display is appropriate and sufficient.

There are other important devices for the visually impaired that can be used, especially in the case of learning or employment in the office are the Refreshable Braille Display and Braille Embosser. A braille printer or a braille embosser is a device that uses solenoids to regulate embossing pins, it extracts data from computing devices and embosses the information on paper in braille. It produces tactile dots on hard paper, rendering written documents that are clear to the blind. Depending on the number of characters depicted, the cost of braille displays varies from $3,500 to $15,000. In 2012, sixty-three studies aimed at finding new ways to refreshable braille were explored by the Transforming Braille Group. Orbit Reader 20 is the result with a 20-cell refreshable braille display [110] that costs currently $599. However, Orbit Reader 20 has the basic version and has limited braille characters.

Special braille paper is needed for braille embossers, which is heavier and more expensive than standard printer paper. More pages with the same volume of data are used for braille printing than pages written on a standard printer. They are sluggish and noisier as well. Some braille printers are capable of printing single or double-sided pages. Although embossers are relatively simple to use, they can be messy and can differ a bit from one device to another in the quality of the finished product [111]. Braille displays range in price from $3,500 to $15,000, depending on the number of characters depicted. The cost of a braille printer is relative to the volume of braille it generates. Small-volume braille printers cost between $1,800 and $5,000, whereas large-volume printers cost between $10,000 and $80,000 [112].

2.4.9 Money Identifier App

A software that can recognize the denomination of banknotes for currencies. Cash Reader: Bill Identifier [113] is an app that can identify a wide range of currencies. However, it needs a monthly payment subscription. MCT Money Reader [114] is another app that can recognize currency including Saudi Riyal with a cost of 58.99 SR for lifetime recognition.

2.4.10 Light Detection

The Light Detector [115] translates into sound any natural or artificial light source it encounters. The software locates the light by aiming the mobile camera in its direction. Depending on the strength of the light, the user can notice a greater or lower tone. It is useful for the visually impaired to find if the lights at home are on or off or to find out if the shades are drawn by moving the device upwards and downwards.

2.4.11 External Assistance App

Be My Eyes [116] is an app in which blind or visually impaired users can request help from sight volunteers. Once the first sighted user accepts the request, a live audio and video call is established between the two parties. With a back-camera video call for the blind or visually impaired, the sighted aide can now assist the blind or visually impaired. However, the app depends on an insufficient number of volunteers and has privacy issues because the users share videos and personal information during the connection.

2.4.12 Multifunctional App

Sullivan+ (blind, visually impaired, low vision) [117] depends on the camera shots on the mobile and analyzes them using the AI mode that automatically seeks the top results that match the pictures taken. The app supports the following functions: Text recognition, Face recognition, Image description, Color recognition, Light brightness, and Magnifier. However, face and object recognition need further improvements. Visualize-Vision AI [118] makes use of different neural networks and AI to identify pictures and texts. The software is meant as visual assistance to the visually disabled, while still providing a developer mode that enables various AIs to be explored. Another app that can identify an object using artificial neural networks [119].

A visually impaired person can find an object by calling the object and the app finds it. Seeing Assistance Home [120] lets users use an electronic lens for partially visually impaired persons, color identification, light source detection and can scan and produce barcodes and QR codes. VocalEyes AI [121] can assist the visually impaired in the following functions: object recognition, reading text, describing the environments, label brands and logos, face recognition, emotions classification, age recognition, and currency recognition. LetSee [122] has three functions, money recognition that supports several currencies but does not support the Saudi Riyal, plastic card recognition, and light measurement tools to help locate sources of light, such as spotlights, cameras, or windows. The higher brightness of the light the louder sound the user hears. TapTapSee [123] supports: object recognition, barcode and QR code reading, Auto-focus notification, and Flash toggle. Aipoly Vision [124] provides its utility with monthly fees of 4.99 USD for full object recognition features. The software also has the functions of currency recognition, text reading, color recognition, and light detection. However, the software is only supported in designated iPhones and iPads devices.

2.4.13 VoiceOver

For visually impaired people, voice-over is one of the most useful functions. VoiceOver is a gesture-based screen reader. The user can utilize a mobile device even if they cannot see the screen. VoiceOver provides auditory explanations of what is on the screen.

On an iPhone, for example, when the user touches the screen or drags his finger over it, VoiceOver says the name of whatever the user touches, including icons and text. To interact with an item, such as a button or link, or to go to another item, the user can use VoiceOver gestures. VoiceOver creates a sound when the user goes to a new screen, then picks and speaks the name of the first item on the screen (typically in the top-left corner). VoiceOver tells the user when the display changes to the landscape or portrait orientation, the screen dims or locks, and what's active on the Lock Screen when the user wakes up his iPhone [125].

The voice-over on iOS communicates with the user through a variety of "gestures," or motions made with one or more fingers on the screen. Many gestures are location-sensitive—sliding one's finger around the screen, for example, reveals the screen's visual contents as the finger passes over them. This allows visually impaired users to explore an application's actual on-screen layout. A person can activate a selected element by double-tapping—similar to double-clicking a mouse—in the same way as a sighted user would. VoiceOver can also switch off the display yet keep the touch screen responsive, conserving battery life. This function is known as the "Screen Curtain" by Apple [126].

2.4.14 Virtual Assistant Apps (Voice Commands)

Virtual Assistants can help the visually impaired because of their ability to control their mobile due to voice commands. Here we have investigated the three most popular and recent virtual assistants: Siri, Google Assistant, and Bixby. One of the main concerns that we checked is privacy.

Siri

Siri is an assistant that uses voice queries and a natural-language user interface to respond to queries, make recommendations and take action by delegating requests to a

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set of Internet services [127]. Siri assists in a series of tasks, such as phone calls, messaging, setting alarms, timers, and reminders, handling device settings, getting directions, scheduling events and reminders, previewing the calendar, running smart homes, making payments, playing music, checking facts, making calculations and/or translating a phrase into another language [128]. However, some of the functions need to be visualized to be completed, because the assistant is designed for sighted people, not for the visually impaired. It needs improvements so it can satisfy their needs. Siri provides various languages, including Arabic.

Apple notes that Siri searches and requests are paired with a specific identifier and not an Apple ID, thus personal information is not stored for sale to advertisers or organizations. Apple declares that users can reset the identifier by turning Siri off and back on at any point, essentially restarting their interaction with Siri, which would erase user data associated with the Siri identifier. The terms say personal information can only be used by Apple to provide or enhance third-party applications for their products, services, and ads. Private data would not be exchanged with third parties for marketing purposes on their own. However, and for whatever reason, Apple can use, pass, and reveal non-personal information. This means Apple's sites, internet platforms, mobile software, email messages, and third-party product ads use monitoring tools to help Apple better identify customer behavior, inform the business about the areas of its website accessed by the users, and promote and evaluate the efficacy of advertising and searches. Users may see advertisements dependent on other details in third-party applications, however, the Apple ID of a child also gets a non-target advertisement on such platforms. The terms of Apple state that the protection of children is a significant priority at Apple for everyone. Apple provides parents with the information they need to determine what would be best for their child.

Google Assistant

Google Assistant is a virtual assistant that is powered by artificial intelligence created by Google and is mostly available on smartphones and smart home platforms. Google Assistant can be reached from its website, which can be downloaded from the iOS App Store and the Google Play Store. According to privacy, Google Account is designed with on/off data controls, allowing users to choose the privacy settings that suit them. In addition, as technology advances, Google's terms note that its privacy policies often change, meaning that privacy is still a user-owned individual option. The terms state that Google can use the personal information of users to provide ads to third parties but report that it does not sell the personal information of users to third parties. Moreover, the terms state that Google can show targeted ads to users, but that users can alter their preferences, choose whether their personal information is used to make ads more applicable to them, and turn on or off such advertising services. The terms also state that Google enables particular collaborators to use their cookies or related technology to retrieve information from a user's account or computer for advertisement and measurement purposes. Google's rules, though, note that they would not display a child's customized advertising, meaning advertisements are not be focused on the information coming from a child's account.

The terms of Google note that all of its services allow users to connect with other trustworthy and untrusted users, and exchange information with other people, such as others with whom a user can chat or share content. If a user has a Google Account, their profile name, profile photo, and activities that a user takes on Google or on third-party applications that are linked to their Google Account can appear. In addition, information about a child, including name, photo, email address, and transactions from Google Play, can be exchanged with members of a family community using Google Family Link. These terms and conditions note that Google does not gather or use data for advertising purposes in the Google Cloud or G Suite services and that there are no commercials in the G Suite or Google Cloud Platform. Finally, the terms of Google note that it does not send users personalized advertisements on the basis of specific categories, such as religion, race, health, or sexual orientation.

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Bixby

For Samsung devices, Bixby [129] is an intelligent digital assistant that hears and records what users desire and works with their favorite applications. Bixby Vision's Scene description function describes what is displayed on the screen. Personalize Bixby lets the assistant learn the user preferences from their usage to facilitate the utility in the future. In addition, Bixby can handle smart devices with voice commands, while attaching the apps to SmartThings. The user can change the TV channel or turn the light on/off.

There is a privacy notice that tells what is recorded and saved. The information that Bixby requires—and it will not work until the user gives permission—is a username, birthdate, phone number, email, device identifiers, voice commands, health information and any information that has been provided through the application, such as the user's interaction with the app. In addition, some of the information could be sent to an external third party to convert the voice command into text. Some of Samsung's services allow users to communicate with others, and those other users may view information stored or displayed in the user's account on the social networking service they are connecting to. In addition, Samsung can use third-party monitoring technology for a range of purposes including evaluating the usage of its services and (in combination with cookies) delivering user-relevant content and advertising. Some third parties may be serving to advertise or keeping track of which advertisements users see, how frequently they see those advertisements, and what users do in response. The terms note that only restricted representatives of Samsung's Bixby voice service team can access and otherwise process personal data in accordance with their job or contractual duties. Nevertheless, the terms do not reveal how common security measures in the sector, such as encryption, are used to secure sensitive details in transit or at rest [130]. The word Bixby is not easy to be pronounced in Arabic. Currently, Bixby does not support the Arabic language.

Alexa

Alexa began as a smart speaker equipped with Alexa software, capable of listening to user questions and answering with replies. Over time, more household gadgets were interconnected through Alexa and operated by smartphones from anywhere. Amazon first built the Alexa platform to work as a digital assistant and entertainment device, but its application and use grew to IoT, online searching, smart office, and smart home features, substantially improving the way the average person interacts with technology [131]. To make it easier to interact with Alexa, the developers provide a set of tools, APIs, reference solutions, and documentation [132].

2.5 Research Gap

We provide a comparison of LidSonic V2.0 with related works in Table 2. In Column 2, the technologies used by the particular works are mentioned inside their respective rows. In column three, we discuss work settings (i.e., whether they were indoor or outdoor). After that, the studies were examined for detecting transparent objects' features. We checked if the gadget is hands-free. It is critical to know if the device can operate at night, which is documented in Column 7. We also noted whether or not machine learning techniques were used in the research. We also looked into the different forms of feedback they provided and whether they used verbal feedback. In addition, checked the processing speed because the solution requires real-time and quick data processing. It is also discussed whether the gadget has low energy consumption. We also looked at the device's cost-effectiveness and if it was inexpensive. We also looked at whether or not the solutions given require low memory, as well as their weights. The various studies related to and satisfied the requirements for some of the system's needed features. All of these aspects of system design are addressed in our work. To claim maturity and robustness, further system optimizations and assessments are required. A detailed comparison of LidSonic V1.0 that also applies to LidSonic V2.0 is provided in [39].

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Table 2 System Aspects and a Comparison with related works.

Research	Technology	Environment		Transparent Object Detection	Handsfree	Functioning in Dark	ML/DL	Vocal Feedback	High-Speed Processing	Low Energy Consumption	Low Cost	Low Memory Usage	Lightweight
		Indoor	Outdoor										
[133]	Solid-state LiDAR Sensor, RealSense L515(Lidar Depth Camera), Laptop	✓	×	×	✓	-	✓	✓	×	×	×	×	✓
[47]	Lidars, Vibrotactile Units	✓	✓	×	✓	×	✓	✓	×	×	✓	×	✓
[134]	Ultrasonic, PIR motion sensor, Accelerometer, Smartphone	✓	✓	✓	✓	✓	×	✓	✓	✓	✓	✓	✓
This Work	**TF-mini LiDAR, Ultrasonic**	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

We have noted earlier that despite several devices and systems for the visually impaired being developed in academic and commercial settings, the current devices and systems lack maturity and do not completely fulfill user requirements and satisfaction. Essentially, in this work, we provide the design of inexpensive, miniature, green devices that can be built into, or mounted on, any pair of glasses or even a wheelchair to help the visually impaired. Our approach affords faster inference and decision-making using relatively low energy with smaller data sizes. Smaller data sizes are also beneficial in communications, such as those between the sensor and processing device, or in the case of fog and cloud computing, because they require less bandwidth and energy, and can be transferred in relatively shorter periods of time. Moreover, our approach does not require a white cane (although can be adapted to be used with a white cane), and therefore, it allows handsfree operation. Increased research activity in this field will encourage the development, commercialization, and widespread acceptance of devices for the visually impaired.

3. A High-Level View

In this section, we present a high-level view of the LidSonic V2.0 system, the user view, the developer view, and the system view, in Sections 3.1 to Sections 3.3. A detailed description of the system design is provided in Section 4.

3.1 User View

Figure 2 shows the user view. The user puts on the LidSonic V2.0 gadget, which is fixed in a glass frame. The user installs the LidSonic V2.0 smartphone app after downloading it. The Bluetooth connection between the LidSonic V2.0 mobile app and the LidSonic V2.0 device is used. LidSonic V2.0 is intensively trained in both indoor and outdoor settings. The user wanders around in both indoor and outdoor surroundings, allowing the LidSonic V2.0 gadget to be further trained and validated. Furthermore, a visually impaired person's family member or a volunteer may go around and retrain and check the gadget as needed. The gadget has a warning system in case the user encounters any impediments. When the user encounters an obstacle, a buzzer gets activated. Additionally, the system may provide vocal input such as "Ascending Stairs" to warn the user of an impending challenge. By pressing the prediction mode screen, the user may also hear the result. A user or his/her assistant can also use voice commands to label or relabel an obstacle class and create a dataset. This enables the validation and refining of the machine learning model, such as revising an object's label if it was incorrectly categorized.

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Figure 2. LidSonic: A User's View.

3.2 *Developer View*

Developing modules as seen in Figure 3 starts with constructing the LidSonic V2.0 device. A Lidar sensor, ultrasonic sensor, servo, buzzer, laser, and Bluetooth are all connected to an Arduino Uno CPU to build the LidSonic V2.0 gadget. Then, using an Arduino sketch, we combine and handle the different components (sensors and actuators) as well as their communication. The LidSonic V2.0 smartphone app was created with Android Studio (LidSonic V2.0). We created the dataset module to help in dataset generation. Then, using the chosen Machine or Deep learning Module to construct and trains the models. We utilized the Weka library for machine learning and the TensorFlow framework for deep learning models. Bluetooth is used to create a connection between the LidSonic V2.0 device and the mobile app, which is also used to send data between the device and the app. The Google Speech-to-Text and Text-to-Speech APIs were used to develop the speech module.

The developer wears the LidSonic V2.0 device and walks around to create the dataset. The LidSonic V2.0 device provides sensor data to the smartphone app, which classifies obstacle data and generates the dataset. To verify our findings, we used the metrics shown in the Figure 5 validation module. The developer put on the trained LidSonic V2.0 gadget and went for a walk to test it in operational mode. The developer observed the system's buzzer and vocal feedback. The dataset can be expanded and recreated by the developers, users, or their assistants to increase accuracy and precision.

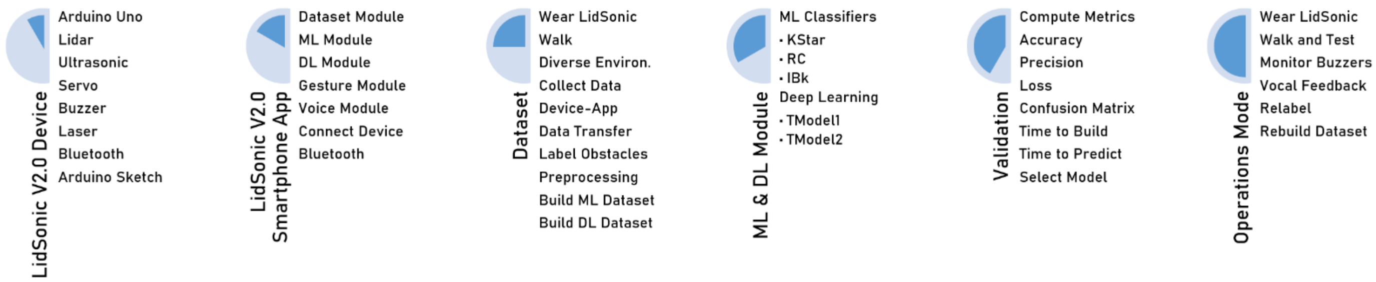

Figure 3. LidSonic: A Developer's View.

3.3 *System View*

LidSonic V2.0 detects hazards in the environment using various sensors, analyses the data using multiple channels, and issues buzzer warnings and vocal information. With the use of an edge device and an app that collects data for recognition, we propose a technique for detecting and recognizing obstacles. Figure 4 presents a high-level functional overview of the system. When the Bluetooth connection is established, the data is collected from the Lidar and ultrasonic sensors. An obstacle dataset should be established if the system does not have one. The dataset is created using Lidar data only. Two distinct channels or procedures are used to process the data. First, using simple logic by the Arduino unit. The sensors operated by the Arduino Uno controller unit offer the essential data for visually impaired people to perceive the obstacles surrounding them. It processes the ultrasonic and basic LiDAR data for rapid processing and feedback through a buzzer. The second channel is to use deep learning or machine learning techniques to analyze LiDAR data via a smartphone app and produces vocal feedback. These two channels are unrelated to one another. The recognition process employs deep learning and machine learning approaches and is examined and evaluated in the sections below.

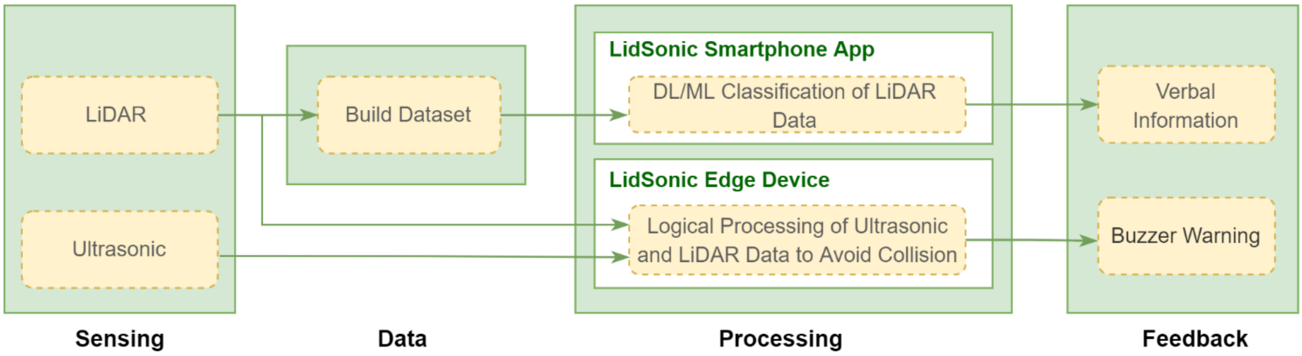

Figure 4. LidSonic V2.0 Overview (Functional).

Figure 5 depicts a high-level architectural overview of the system. Hardware, machine learning and deep learning models, software, datasets, validation, and platform are all part of the system. The hardware includes all of the components required by the LidSonic V2.0 gadget. We created several models using ML and DL techniques that are explained further in Section 4. The system makes use of two software: one for controlling the sensors and performing the obstacle detection tasks with an Arduino skitch device and another for recognition tasks with the smartphone app. The accuracy, precision, loss, time to train a model, time to predict an object, and confusion matrix were employed as validation metrics in this work. Depending on the type and performance of the classifier, the system can be used on a variety of platforms, including edge and cloud. In the next section, we'll expand on this system perspective with comprehensive diagrams and methods.

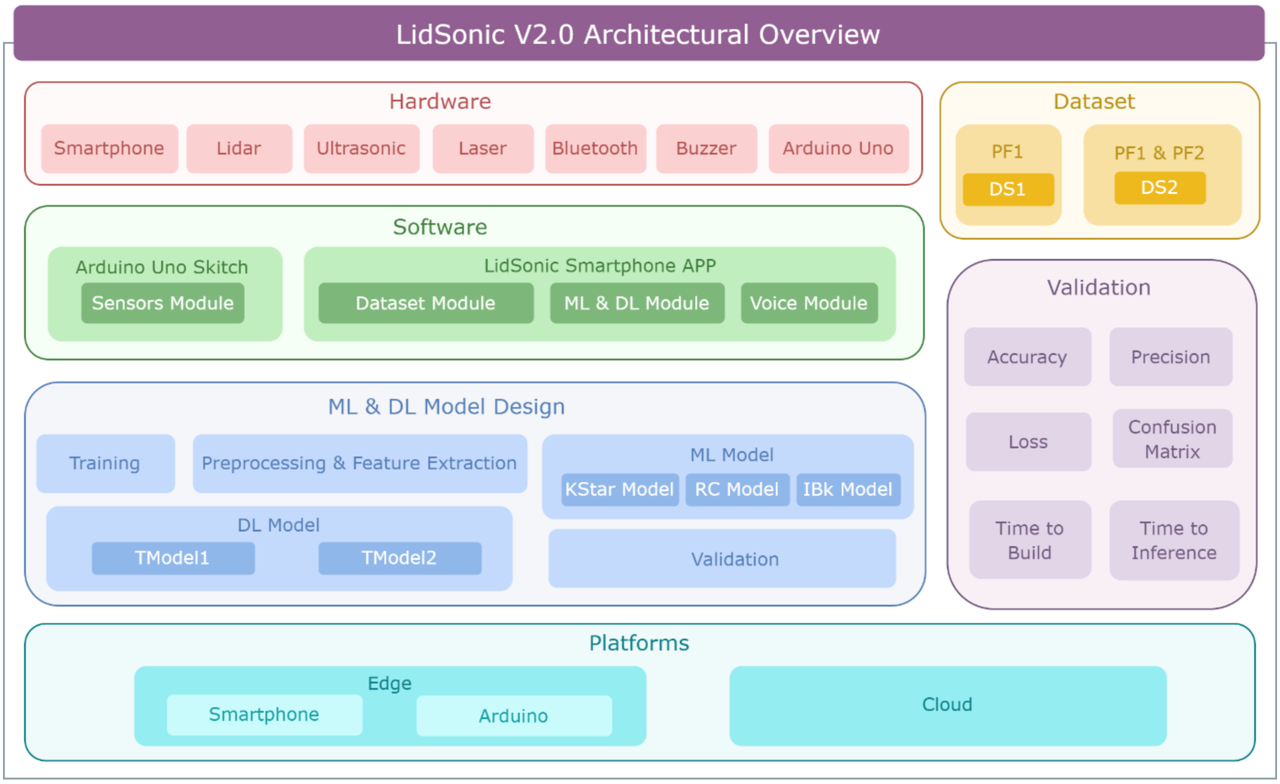

Figure 5. LidSonic V2.0 Overview (Architectural).

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4. Design and Implementation

This section explains in detail the LidSonic V2.0 System's design. The hardware components and design are described in Section 4.1. Section 4.2 provides an overview of the system's software design. The sensors module is illustrated in Section 4.3 and Dataset, and Machine & Deep Learning Modules are explained in Sections 4.4 and 4.5, respectively.

4.1 System Hardware

The system incorporates the following hardware components, as shown in Figure 6. TFmini Plus LiDAR, Ultrasonic sensor, Bluetooth, Arduino Uno, and the user's smartphone. A servo, buzzer, and power bank to operate the device.

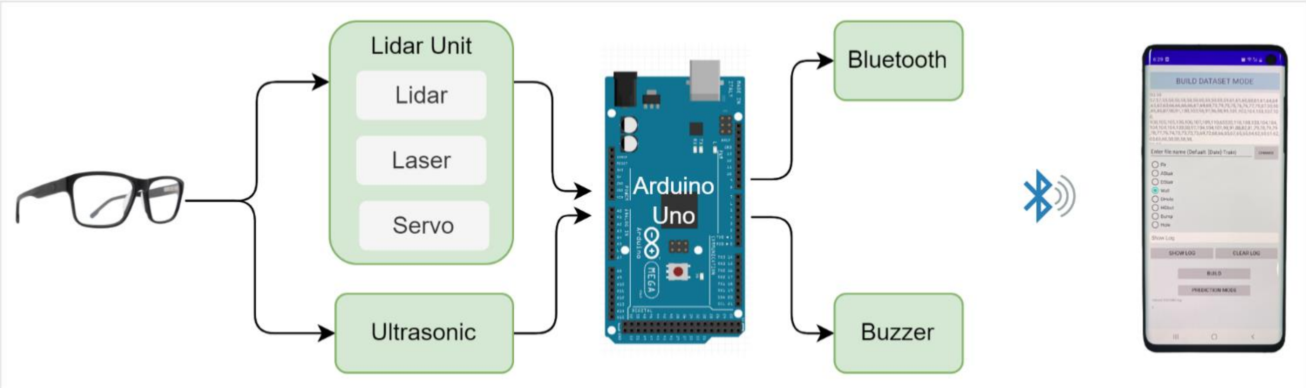

Figure 6. System Hardware.

Figure 7 displays a photo of the LidSonic V2.0 gadget, which includes smart glasses with sensors and an Arduino Uno board. The LidSonic V2.0 device's central nervous system is the Arduino Uno microcontroller unit, which is used to integrate and manage the sensors and actuators, as well as to transfer sensor data to the smartphone app through Bluetooth. It is configured to control how servo motions, sensors, and other components interact. The Lidar Unit contains the TFmini Plus LiDAR sensor [135] that is connected with a Servo, and Laser as a unit. The laser beam is installed above the TFmini Plus LiDAR and helps to indicate where the Lidar is pointed so that we may scan and categorize various things in order to build a valid dataset. The data collected by the TFmini Plus LiDAR from its spatial environment is transferred to the Arduino unit. Some of this information is used by Arduino to detect obstacles and activate the buzzers as needed, while other information is relayed through Bluetooth to the smartphone app. The servo that controls the movement of the two devices holds both the TFmini Plus LiDAR and the laser. The ultrasonic sensor is capable of detecting a wide range of obstructions. It is also utilized to compensate for the TFmini's LiDAR's inadequacies by recognizing transparent obstructions in the route of visually impaired people. The ultrasonic sensor detects objects at 30 degrees and a detection range of 0.02m-4.5m [136]. The Arduino unit analyzes the data from the ultrasonic sensor, and if an item is detected, the buzzer is actuated. The buzzer sounds distinct tones to notify visually impaired persons of different sorts of things detected by the sensors. The buzzer and sound frequencies or tones are controlled by the Arduino CPU based on the identified items. A microphone for user instructions, Bluetooth for interfacing with the LidSonic V2.0 device, and speakers for vocal feedback regarding detected objects are all included in the smartphone app's hardware.

(a) (b)

Figure 7. (a) LidSonic V2.0 device and a glass **(b)** LidSonic V2.0 device mounted into a glass frame.

TFmini-S LiDAR

A laser diode emits a light pulse, which is used in a LiDAR. Light strikes and is reflected by an item. A sensor detects the reflected light and determines the time of flight (ToF). The TF-mini-S device is based on the OPT3101 and is a high-performance single-point short-range LiDAR sensor manufactured by Benewake [137]. It is based on long-range proximity and distance sensor analog front end (AFE) technology based on ToF [137]. A TFmini-S LiDAR operates on the networking protocol UART (TTL)/I2C, can be powered by a conventional 5 V supply, and has a total power consumption of 0.6 w.

The TFmini-S LiDAR has a refresh rate of 1000 Hz and a size range of 10 cm to 12 m. It provides a ±6 cm accuracy between 0.1 m and 6 m, and a 1 percent accuracy between 6 m and 12 m. The operational temperature range is around 0 °C to 60 °C. The range of angles is 3.5° [138]. Data from the TFmini-S LiDAR may be collected quickly and precisely. There are no geometric distortions in the LiDAR, and it may be utilized at any time of day or night [138]. When no item is identified within a 12 m range, the sensor sends a value of 65,535.

The TFmini-S has the advantages of being inexpensive cost, having a tiny volume, low energy consumption, and many interfaces to satisfy various requirements, but it has the disadvantage of not detecting transparent objects such as glass doors (we used an ultrasonic sensor to compensate for it). It improves the outdoor efficiency and accuracy of various degrees of reflectivity by detecting stable, accurate, sensitive, and high-frequency ranges. Few studies have been conducted on utilizing LiDAR to assist the visually impaired and identify their needs. The gadgets that aid the visually impaired make use of a very expensive Linux-based LiDAR [139].

Ultrasonic Sensor

An ultrasonic sensor is one of the best tools for detecting barriers because of its cheap prices, low energy consumption, sensitivity to practically all types of artifacts [40], and the ultrasonic waves may be transmitted up to a distance of 2 cm to 300 cm. Furthermore, ultrasonic sensors can detect items in the dark, dust, smoke, electromagnetic interference, and tough atmospheres [140].

A transducer in an ultrasonic sensor transmits and receives ultrasonic pulses, which carry information about the distance between an item and the sensor. It sends and receives signals using a single ultrasonic unit [41]. The HC-SR04 ultrasonic sensor has a < 15° effective angle, a resolution of 0.3 cm, a frequency of operation of 40 kHz, and a measurement angle of 30°. The range limit of ultrasonic sensors is reduced when they are reflected off smooth surfaces, when they have a low incidence beam, and when they open narrowly. Optical sensors, on the other hand, are unaffected by these issues. Nonetheless, the optical sensors' shortcomings include that they are sensitive to natural ambient light and rely on the optical properties of the object [37]. Sensors are often employed in industrial systems to calculate object distance and flow velocity. ToF is the time it takes for an ultrasonic wave to travel from the transmitter to the receiver after being reflected by an object. Equation (1) may be used to calculate the distance from the transmitter, where c is the velocity of the sound [141].

$$d = [c \times (\text{ToF})]/2$$

Infrared sensors and lasers are outperformed by ultrasonic sensors. Infrared sensors cannot work in the dark and produce incorrect findings when there is no light. However, there are inherent drawbacks that restrict the application of ultrasonic instruments to mapping or other jobs requiring great accuracy in enclosed spaces. Due to sonar cross-talk, they are less reliable and have reduced range, large beam coverage, latency, and update rates [12]. The receiver detects an undetectably tiny volume of the reflected energy if the obstacle surface is inclined (i.e., surfaces formed in triangles or rough edges), which causes ultrasonic range estimations to fail [142].

4.2 System Software

The LidSonic V2.0 system consists of the LidSonic V2.0 device and the LidSonic V2.0 Smartphone App see Figure 8. The LidSonic V2.0 device's Sensors Module contains software that controls and manages the sensors (Lidar and ultrasonic sensors) and actuators (servo and laser beam). This module is also in charge of the basic logical processing of sensor data in order to generate buzzer alerts regarding discovered items.

The smartphone app's Dataset Module is in charge of collecting data from the LidSonic V2.0 device and appropriately storing the dataset, including the labels. The Machine and Deep Learning Module is located in the smartphone app and allows to train, infer, and evaluate models. Two Google APIs are used by the Voice Module. The Text-To-Speech API is used to give audio feedback from the smartphone app, such as spoken input on adjacent objects identified by the sensors using mobile speakers. The Google Speech-to-Text API is used to transform user voice instructions and evaluate them so that the app may take relevant actions, such as labeling and relabeling data objects.

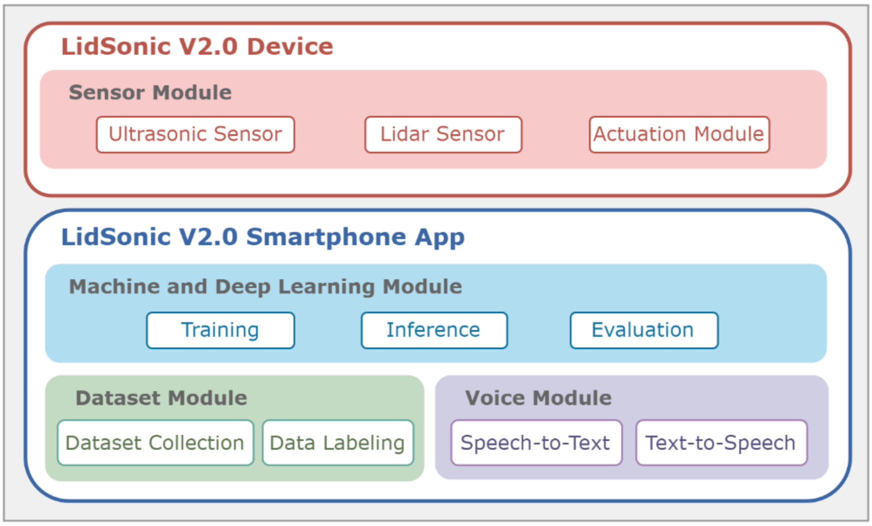

Figure 8. LidSonic V2.0 Software Modules.

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Algorithm 1: The Master algorithm: LidSonic V2.0

Input: VoiceCommands [Label, Relable, VoiceOff, VoiceOn, Classify],
AIType [ML, DL]
Output: LFalert, HFalert, VoiceFeedback
1. ServoSensorsModuleSubSystem (Angle, Position)
2. LaserSensorsModuleSubSystem ( )
3. UD2O ← UltrasonicSensorsModuleSubSystem ( )
4. [LD2O, LDO] ← LiDARSensorsModuleSubSystem ( )
5. FeedbackType ← ObsDetWarnSensorsModuleSubSystem ( )
6. **switch** (AIType) **do**
7. **case:** ML
8. [MLDataset] ← MLDatasetModule (LDO, Label, Relable)
9. [MOL, VoiceCommands] ← MLModule (MLDataset, VoiceCommands)
10. **case:** DL
11. [DLDataset] ← DLDatasetModule (LDO, Label, Relable)
12. [DOL, VoiceCommands] ← DLModule (DLDataset, VoiceCommands)
13. **End switch**
14. VoiceModule (VoiceCommands, VoiceFeedback)

The Master algorithm is given in Algorithm 1. The array VoiceCommands (various commands sent to the LidSonic V2.0 System) and AIType are the Master algorithm's inputs. AItype indicates the type of classification approach to be conducted, either Machine Learning (ML) or Deep Learning (DL). Label, Relabel, VoiceOff, VoiceOn, and Classify are the VoiceCommands. The user gives the system the Label and Relabel voice commands to Label or Relabel an object observed by the system. The commands VoiceOff and VoiceOn are used to switch voice commands on and off, if the user simply wants to hear the buzzer sound that alerts them when an object is close rather than hearing the names of all the things being recognized in the surroundings. When the user wants to identify a specific obstacle, they can use the voice command Classify; this command can be used even if the vocal feedback is turned off. The Master algorithm produces three outputs: LFalert, HFalert, and VoiceFeedback, which are used to notify the user about various items through a buzzer or voice instruction.

The LidSonic V2.0 system operates different modules and subsystems for numerous purposes, as shown by the Master algorithm. The ServoSensorsModuleSubSystem, a subsystem of the Sensors module, uses angle and position as inputs to determine the servo starting position and motion, as well as control the position of the LiDAR sensor; the LaserSensorsModuleSubSystem, which displays the position that the LiDAR is pointing (this is only for development purposes, and assist the developer know the object being scanned by the LiDAR); The UltrasonicSensorsModuleSubSystem returns the data output from the ultrasonic sensor, "UD2O" (user's distance to object computed based on the data from the ultrasonic sensor); the LiDARSensorsModuleSubSystem returns two outputs from the LiDAR sensor, "LD2O" (user's distance to object computed based on the data from the LiDAR sensor) and "LDO" (user's distance to object (LiDAR data object that contains detailed data about the objects); the ObsDetWarnSensorsModuleSubSystem, which returns "FeedbackType" and detects objects and informs the user about them via buzzers and voice feedback; MLDatasetModule provides the Weka datasets labeled "MLDataset" after receiving the inputs "LDO", "label", and "relabel"; DLDatasetModule provides CSV files “DLDataset”; MLModule returns "MOL" (object level, below or above the floor) and "VoiceCommands."; DLModule returns “DOL” (object level, below or above the floor) and "VoiceCommands."; and the VoiceModule, which transforms speech to text and vice versa using VoiceCommands and VoiceFeedback as inputs. In the next sections, more algorithms, pictures, and text are used to describe the four modules, as well as the inputs and outputs.

4.3 Sensors Module

Figure 9 illustrates how the LidSonic V2.0 pair of glasses use ultrasonic and Lidar sensors to observe the world. The ultrasonic sound pulse is directed in front of the user as seen on the dotted green line to detect any objects in front of the user. It can also detect obstacles that are transparent, such as glass doors or walls, which Lidar could miss. The Lidar sensor range is represented by dotted blue lines. The Lidar sensor has a range of 10cm to 12 meters. We cover a 60-degree region in front of the user with a servo motor that moves the Lidar sensor, which equates to an area of "m" meters on the floor. This floor area "m" covered by the Lidar sensor for a user of 1.7 meters height would be around 3.5 meters. Note that we ignored that the glasses are at eye level rather than head level. The figure also displays the floor area "n," which is the closest floor area to the user that is not covered by the Lidar sensor since we deactivated it to minimize false alarms triggered by the user's knee while walking. This floor space closest to the user would be around 0.15 meters for a person with 1.7 meters in height. Within this "m" floor space, the LidSonic V2.0 system identifies any obstacles, including descending the stairs, using the Lidar sensor.

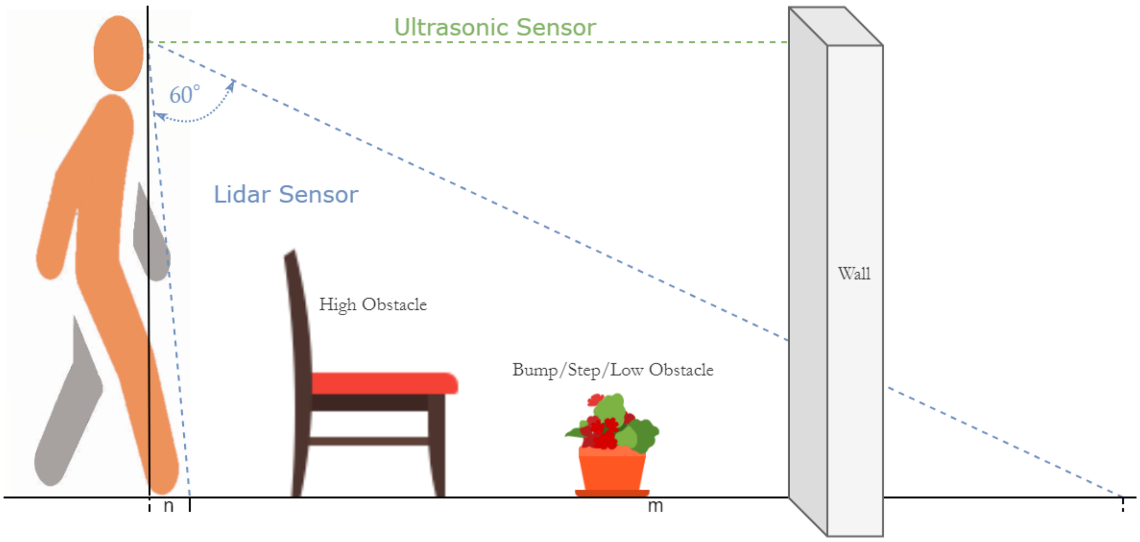

Figure 9. Sensors Coverage.

The flow diagram of the obstacle detection and warning subsystem is shown in Figure 10. The LidSonic V2.0 device uses data from an ultrasonic sensor (UD2O stands for Distance to Object detected by the ultrasonic sensor) and activates a buzzer with a low-frequency warning, LFalert if it falls below a threshold of 0.5. The LidSonic V2.0 device additionally checks the closest point reading from the LiDAR sensor (LD2O is the D2O detected by the LiDAR sensor), and if it is higher than the floor, the LFalert is triggered, signaling that the obstacle might be a high obstacle, a bump, and/or climbing stairs, etc. If it is below the floor, there are obstructions such as falling stairs and/or holes, and a high-frequency alarm HFalert buzzer tone is triggered, the ML Module gives the user Voice input depending on the anticipated obstacle type. MOL is converted from the predicted value (Object Level detected by the ML Module). The buzzer is actuated with LFalert if the predicted value type is an object above the floor; otherwise, the HFalert is triggered. The predicted value is converted to DOL (Object Level detected by the DL Module). If the predicted value type is an object above the floor, the buzzer is activated with LFalert; otherwise, the HFalert is activated. The figure only shows “MOL < Floor”, however, the values of MOL or DOL are used based on the algorithm used.

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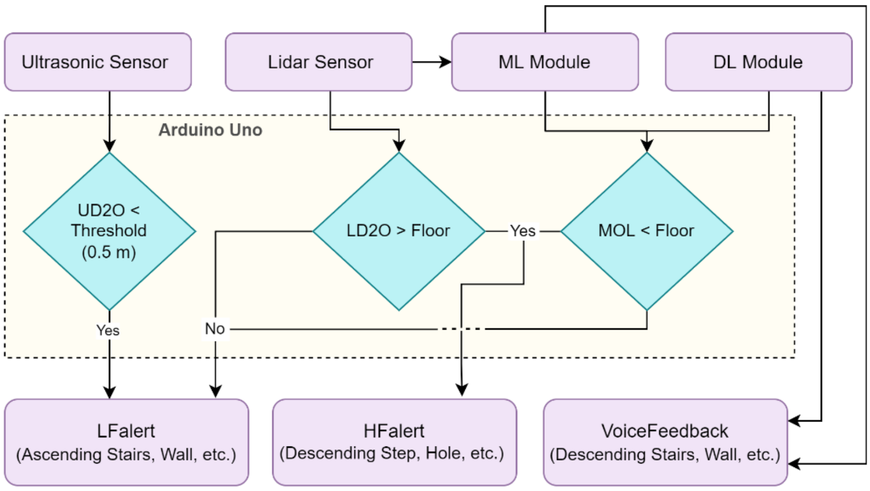

Figure 10 Detection and Warning System.

Algorithm 2 depicts the algorithm for the obstacle detection, warning, and feedback subsystem. It takes ultrasonic data (UD2O), nearby LiDAR distance readings (LD2O), the object level calculated by the machine learning module as inputs (MOL), and the object level calculated by the deep learning module as inputs (DOL). The ObsDetWarnSensors-ModuleSubSystem function analyzes data for detection and generates audio alarms. High-frequency buzzer tones (HFalert), low-frequency buzzer tones (LFalert), and VoiceFeedback are the output alerts. The subsystem calls a logical function that accepts the inputs UD2O, LD2O, and MOL and returns the kind of obstacle (whether the obstacle is an object above the floor level, etc.). No action is required if the output is a floor. If the obstacle returns HighObs, however, it is either a wall or a high obstacle, and so on.

An LFalert instruction is delivered to the buzzer to start the low-frequency tone buzzer. The buzzer parameter HFalert is used to activate the High-frequency tone buzzer if the obstacle is of type LowObs. The goal of selecting a high-frequency tone for low-obstacle outputs is to make low-obstacle outputs possibly more hazardous and destructive than high-obstacle outputs. The high-frequency tone could be more noticeable than the low-frequency tone.

Algorithm 2: Obstacle Detection, Warning, and Feedback

Input: UD2O, LD2O, MOL, DOL
Output: FeedbackType (HFalert, LFalert, VoiceFeedback)
1. **Function** ObsDetWarnSensorsModuleSubSystem ( )
2. Obstacle ← Check (UD2O, LD2O, MOL, DOL)
3. **switch** (Obstacle) **do**
4. **case:** Floor
5. skip;
6. **case:** HighObs
7. Buzzer (LFalert)
8. VoiceModule (VoiceCommands, VoiceFeedback)
9. **case:** LowObs
10. Buzzer (HFalert)
11. VoiceModule (VoiceCommands, VoiceFeedback)
12. **End switch**

4.4 Dataset Module

Machine learning is strongly reliant on data. It is the most important factor that enables algorithm training possible and to have accurate results from the trained models. Our dataset includes a 680-example training set and is formatted as arff files for Weka and CSV files for TensorFlow deep learning. The collection provides distance data obtained from the Lidar equipment by LidSonic V2.0. Table 3 shows the eight classes in the dataset, the kind of obstacles we are dealing with, as well as the number of examples/instances gathered for each.

Table 3 Obstacle Dataset.

Image Class	No. of Instances	Example	Image Class	No. of Instances	Example
Floor	111		Deep Hole	20	
Ascending Stairs	108		High Obstacle	149	
Descending Stairs	89		Ascending-Step/Bump	62	
Wall	87		Descending-Step/Hole	34	

Table 4 shows the preprocessing and feature extraction approaches. PF1 needs to set the LidSonic V2.0 device's upward line scan to the same angle index as the downward scan and end with the class label. PF2 must complete PF1 and then extract just eleven angle readings by dividing the 60 readings by ten plus the last angle distance data (in essence, skipping every five readings assuming that an object does not exist in this gap considering the user is moving and hence this gap is moving too). It also computes the height of the nearest angle to the user, which is the LidSonic V2.0 device's beginning point, as well as the middle angle of the LidSonic V2.0 device's scan, see Figure 12. We need to calculate the distance from the user to the obstacle d2 and the distance from the user to the ground d1 (y-axis) points for both angles once we have the two height calculations, which are the x-axis points. The slope between h1 and h2 can then be calculated. The two heights and the slope are added to the 11-angle distance readings, to create the 14 features dataset DS2. The 60-angle distance readings are the dataset features of DS1.

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Table 4 Preprocessing and Feature Extraction.

Name	Preprocessing and Feature Extraction
PF1	Adjust the upwards line of readings to be the same (angle index) with downwards readings
PF2	PF1 Extract 11 angle reading by dividing the 60 reading by 10 + angle no. 60 Adding three features: Calculates the height of the obstacle of the start angle of the LidSonic V2.0 device (closest angle to the user h1) Calculates the height of obstacle of the middle angle of LidSonic V2.0 device scan (h2) Calculates the slope between h1 and h2

Figure 11 depicts the model for calculating obstacle height. The distance between the LidSonic V2.0 device and the ground is represented by g. The larger triangle's hypotenuse, which is colored blue, is represented by g. The LidSonic V2.0 device's Lidar distance from an obstacle is c. We may compute the height of the object h using the similar triangle law and the value of c. Two triangles that have the same ratio of comparable sides and an identical pair of corresponding angles are called similar triangles.

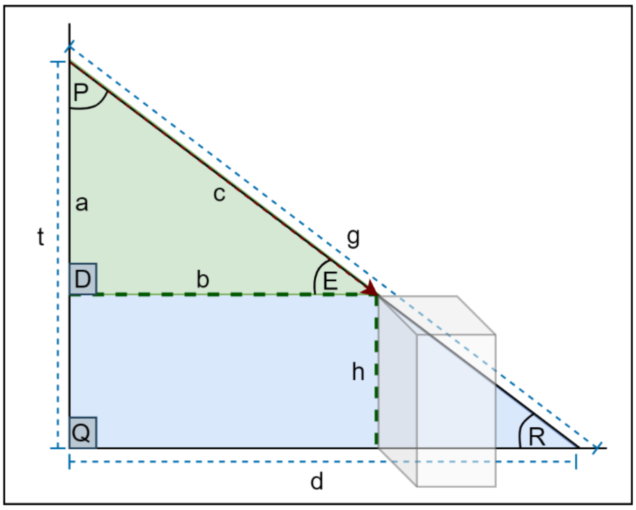

Figure 11. Obstacle Height.

$$In\ \Delta PQR\ and\ PDE,\ \angle DPE\ is\ common\ and\ \angle PDE = \angle PQR\ (corresponding\ angles) \quad (1)$$

$$\Rightarrow\ \Delta PQR \sim \Delta\ PDE\ (PP\ criterion\ for\ similar\ triengles) \quad (2)$$

Hence, from (1) & (2):

$$\Rightarrow \mathrm{PR/PE = PQ/PD} \quad (3)$$

From Equation (3), calculates r as:

$$\mathrm{r = c/g} \quad (4)$$

Then,

$$\mathrm{a = t * r} \quad (5)$$

The height of the obstacle,

$$\mathrm{h = t - a} \quad (6)$$

The horizontal distance from the user to the obstacle is calculated by Equation (7),

$$b = d * r \tag{7}$$

There is a $\cong$ $\pm 3\ cm$ error in computing the height of an object, which we consider insignificant in our case because we do not need the exact height rather than the nature of it (high, low, etc.). The height is calculated and used as a feature in the dataset. We added two height features h1, and h2 because of this computation.

Another crucial parameter we included in our dataset is the slope in Figure 12, between h2 and h1. Since the value of the slope fluctuates depending on the slope of the ground level or the kind of obstacle, especially in the case of stairs, it is a significant factor. Equation (8) calculates the slope as follows:

$$s = \frac{h2 - h1}{b2 - b1} \tag{8}$$

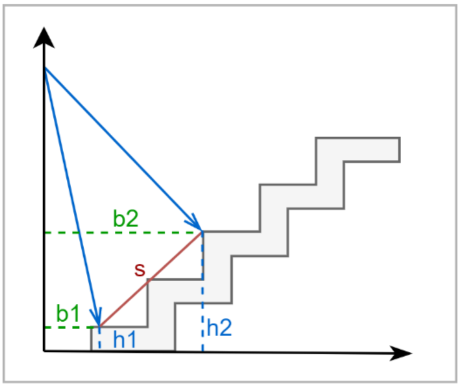

Figure 12. Slop.

We created two types of datasets: one that collects 60 values of features using the Lidar distance of 60 angles we called it DS1. The second dataset DS2 extracts 11 features from the DS1, and three more features have been added: two obstacle heights from two different angles, as well as the slope between these two positions to have a total of 14 features. We constructed 6 train models to be examined, evaluated, and analyzed for optimum utilization. Two different approaches have been investigated: Weka-based machine learning and TensorFlow-based neural networks. We used K* (KStar), Random Committee, and IBk as classifiers in Weka to train 6 machine learning models. For our system, these were the most successful classification methods [39]. The second is a TensorFlow-based deep learning technique that utilizes the two datasets. We constructed two deep learning models for each. Machine and deep learning algorithms are discussed in the next subsection. DS1 labels from a01- a60 and ended with the obstacle class to have a total of 61 features. DS2 has 11 angle labels plus h1, h2, s, and obstacle class.

Table 5 and Table 6 list the two types of datasets we used in our research along with a sample of collected data for each obstacle class. DS1 labels from a01- a60 and ended with the obstacle class to have a total of 61 features. DS2 has 11 angle labels plus h1, h2, s, and obstacle class.

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Table 5. Dataset 1 (D1) Sample.

Obstacle Type	Data
DS1 Labels	a01, a02, a03, a04, a05, a06, a07, a08, a09, a10, a11, a12, a13, a14, a15, a16, a17, a18, a19, a20, a21, a22, a23, a24, a25, a26, a27, a28, a29, a30, a31, a32, a33, a34, a35, a36, a37, a38, a39, a40, a41, a42, a43, a44, a45, a46, a47, a48, a49, a50, a51, a52, a53, a54, a55, a56, a57, a58, a59, a60, Obstacle_class
Floor	309, 305, 301, 295, 288, 285, 274, 266, 264, 260, 259, 253, 249, 243, 240, 229, 227, 211, 215, 214, 211, 208, 208, 205, 205, 197, 193, 191, 187, 186, 180, 176, 172, 169, 167, 172, 173, 172, 171, 169, 168, 167, 166, 165, 164, 163, 161, 161, 159, 158, 33, 25, 24, 23, 23, 26, 29, 120, 154, 157, 0
Ascending Stairs	141, 143, 143, 142, 143, 127, 145, 145, 142, 143, 144, 146, 147, 145, 141, 129, 133, 134, 127, 130, 134, 135, 135, 134, 134, 134, 134, 133, 131, 130, 128, 127, 124, 123, 122, 121, 119, 118, 119, 121, 130, 130, 129, 129, 128, 128, 124, 123, 124, 123, 123, 123, 122, 122, 132, 133, 132, 131, 133, 133, 1
Descending Stairs	696, 740, 841, 834, 575, 372, 380, 396, 608, 659, 654, 614, 546, 353, 343, 386, 389, 385, 382, 374, 359, 356, 355, 354, 350, 342, 336, 321, 308, 305, 303, 299, 296, 268, 264, 264, 262, 264, 263, 261, 254, 190, 189, 201, 215, 217, 211, 211, 209, 207, 208, 208, 206, 200, 154, 186, 186, 186, 185, 183, 2
Wall	49, 52, 46, 46, 46, 50, 51, 50, 52, 49, 53, 52, 50, 50, 55, 54, 57, 55, 55, 57, 58, 56, 57, 58, 62, 62, 62, 63, 65, 64, 66, 66, 69, 70, 78, 80, 83, 83, 84, 86, 88, 93, 95, 96, 102, 111, 123, 126, 118, 120, 120, 120, 122, 125, 129, 141, 152, 152, 152, 152, 3
Deep Hole	638, 643, 646, 650, 654, 659, 654, 661, 669, 663, 666, 668, 669, 672, 638, 631, 628, 630, 592, 588, 589, 592, 577, 554, 555, 532, 531, 531, 530, 528, 523, 520, 495, 494, 490, 487, 485, 482, 480, 476, 472, 450, 441, 443, 446, 438, 434, 434, 434, 436, 436, 430, 429, 427, 426, 423, 422, 422, 422, 421, 4
High-Obstacle	87, 85, 85, 85, 85, 84, 84, 85, 89, 88, 91, 93, 93, 94, 99, 99, 100, 100, 98, 98, 98, 100, 100, 102, 103, 103, 103, 103, 102, 101, 99, 98, 96, 96, 95, 94, 93, 92, 91, 91, 91, 90, 88, 85, 86, 86, 84, 80, 78, 77, 77, 81, 81, 81, 81, 81, 81, 79, 78, 75, 5
Bump	237, 225, 217, 231, 239, 242, 227, 219, 219, 220, 228, 205, 205, 207, 210, 212, 212, 200, 196, 196, 196, 195, 194, 183, 184, 176, 174, 173, 170, 168, 167, 166, 164, 163, 160, 159, 158, 157, 153, 151, 151, 147, 144, 144, 144, 148, 148, 148, 147, 144, 143, 143, 143, 143, 143, 143, 142, 141, 140, 139, 6
Hole	275, 275, 298, 298, 273, 276, 284, 294, 296, 263, 254, 260, 262, 262, 254, 252, 252, 251, 249, 248, 245, 243, 231, 227, 228, 215, 214, 212, 212, 210, 209, 206, 203, 201, 201, 201, 200, 196, 189, 191, 191, 186, 184, 184, 185, 180, 181, 177, 178, 177, 178, 175, 173, 174, 174, 175, 174, 172, 171, 171, 7

Table 6. Dataset 2 (D2) Sample.

Obstacle Type	Data
DS2 Labels	a01, a06, a12, a18, a24, a30, a36, a42, a48, a54, a60, h1, h2, s, Obstacle_class
Floor	309, 285, 253, 211, 205, 186, 172, 167, 161, 23, 157, 0.96, 2.42, 0.02, 0
Ascending Stairs	141, 127, 146, 134, 134, 130, 121, 130, 123, 122, 133, 24.21, 47.76, 0.54, 1
Descending Stairs	696, 372, 614, 385, 354, 305, 264, 190, 211, 200, 183, -24.20, -93.90, -0.55, 2
Wall	49, 50, 52, 55, 58, 64, 80, 93, 126, 125, 152, 5.81, 101.19, 19.06, 3
Deep Hole	638, 659, 668, 630, 554, 528, 487, 450, 434, 427, 421, -254.67, -274.42, -0.09, 4
High-Obstacle	87, 84, 93, 100, 102, 101, 94, 90, 80, 81, 75, 80.37, 71.23, -0.23, 5
Bump	236, 264, 221, 209, 182, 173, 162, 152, 148, 141, 139, 18.39, 12.95, -0.08, 6
Hole	275, 276, 260, 251, 227, 210, 201, 186, 177, 174, 171, -12.58, -17.0, -0.05, 7

Algorithm 3 outlines how our system's dataset is created. It takes CSV Header, LDO, and Features as input. Using the Building Dataset function, the CSV header file from CSVHeader is first placed into the new dataset, CSVFile. Data is collected from LDO and saved in a LogFile using the DataCollection method. LDO represents the LiDAR distance

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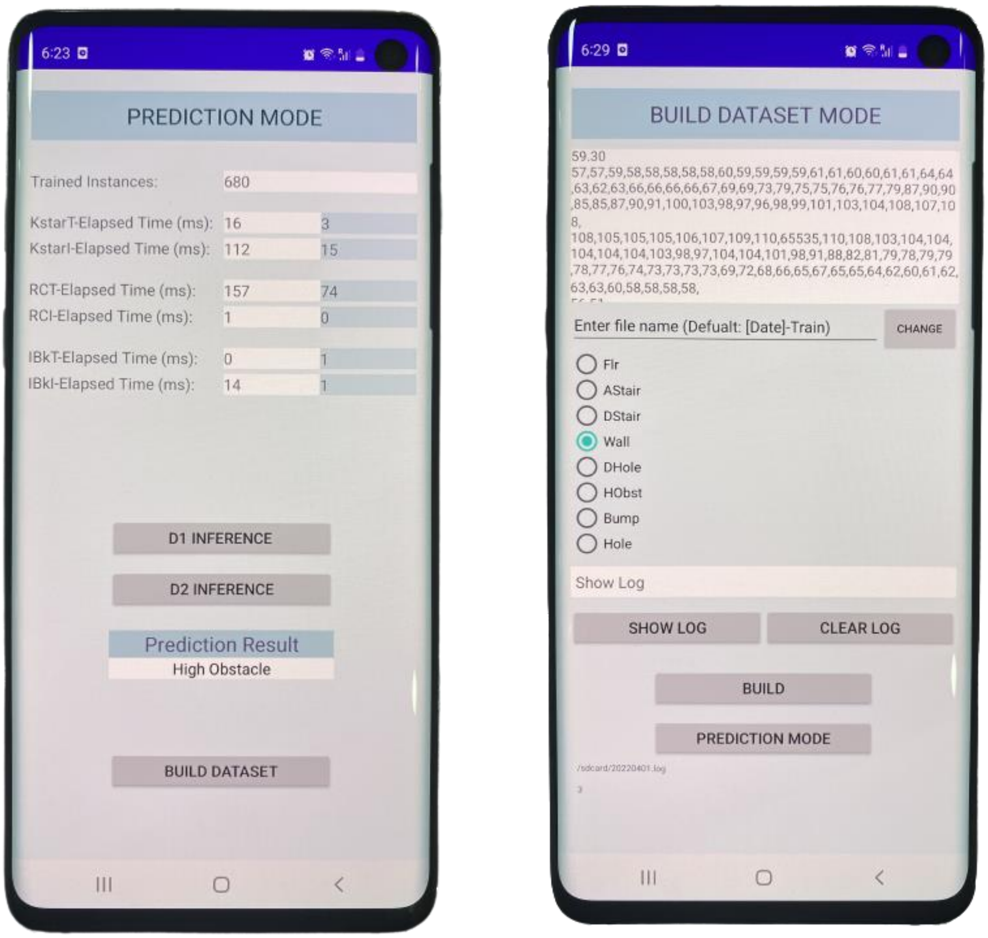
readings, while the loop records the data in the proper format, including saving the LiDAR downwards data in its original order and reversing the order of the LiDAR upward data.

Algorithm 3: DatasetModule: Building Dataset Algorithm

```
Input: Header, LDO
Output: Dataset
    Function: BuildingDataset ( )
        Insert Header into the File
        LogFile ← LDO
        While (not end of LogFile)    // Bluetooth incoming data stored in LogFile
            strLine ← BufferLine      // BufferLine is a line taken from LogFile
            mutualFlag ← true
            While (strLine ! = 0)
                If (mutualFlag)
                    myData ← strLine + Obstacle class
                    Write myData in the File
                    Clear myData
                    mutu-alFlag ← false
                Else
                    Store numbers of strLine into an array called strarr
                    For (x = (strarr.length) - 1; x >= 0; x--)
                        reverseStr ← reverseStr + strarr[x] + ","
                    End For
                    myData ← myData + reverseStr + Obstacle class
                    Write myData in the File
                    Clear my-Data and reverseStr
                End If
            End While
        End While
```

Figure 13 depicts the LidSonic V2.0 Smartphone app's user interface for building the dataset. The LiDAR sensor sends data to the mobile app through Bluetooth, which it saves in a file named LogFile. On the left-hand side is the prediction mode in which the user hears the verbal feedback of the recognized hazard. In addition, it shows some of the evaluation measurements that are conducted on the three classifiers. For example, KstarT-Elapsed Time (ms) shows the time in milliseconds that is taken to build the Kstar classifier (we provide more details regarding the classifiers in the next subsection) for the DS1 dataset in the white box and the DS2 dataset in the blue box. KstarI-Elapsed Time (ms) shows the inference time taken to predict an object for datasets DS1 and DS2 respectively. When the D1 INFERENCE button is pressed evaluation measurement on DS1 is presented in the white boxes for each classifier, while the D2 INFERENCE button shows the results conducted on DS2.

The LogFile data is displayed in the figure's right-hand mobile app view. The real number ultrasonic sensor measurement is shown in the first line. We will look into it further in future work to determine whether it is worthwhile to include it as a feature. The ultrasonic measurements were not included in the dataset for this study. The LiDAR sensor's downward and upward 60-degree readings are represented by the first two lines, which include 60 comma-separated numbers. The LiDAR sensor is linked to a servo that rotates in one-degree increments downwards and upwards, capturing the distance to the object at each degree position. The 60-degree downward and upward measurements are taken in this manner. Each line of data basically provides 60 distance measurements from the user's eye to the object, each with a distinct line of sight angle. Every two lines of 60-degree downward and upward measures are followed by a real number and so on.



(a) (b)

Figure 13. LidSonic V2.0 App **(a)** Prediction Mode **(b)** Build Dataset Mode.

4.5 Machine & Deep Learning Module

We tested multiple types of models on different types of datasets to see which one performed the best. Algorithm 4 shows how to preprocess data and extract features. The inputs are Dataset, LIndex1, and LIndex2. This is the way we preprocess and extract features from the dataset the variation between the Arff file (for WEKA) and CSV file (for TensorFlow) based on the file format. To begin, we should proceed to the locations where the dataset's data begins. The SelectedFeatures function extracts from 60 values, 11 data values for each line. CalculateHight function takes the two pointing locations of the Lidar sensor LIndex1 and LIndex2 to acquire their heights yielding Hight[1] and Hight[2]. The two numbers are then sent to the CalculateSlope function to determine the slope, finally, incorporating the findings into the file.

Algorithm 4: PreProFXModuleDL: Preprocessing and Feature Extraction

```
Input: Dataset, LIndex1, LIndex2
Output: Dataset
1.  Go to the first instance
2.  While (not end of File)
3.      strLine ← BufferLine    // BufferLine is a line taken from the Dataset
4.      While (strLine ! = 0)
5.          SData[1, …, 11] ← SelectedFeatures()
6.          Hight[1], Hight[2] ← CalculateHight(LIndex1,LIndex2) // Equation 4, 5, 6
7.          Slope ← CalculateSlope(Hight[1], Hight[2]) // Equation 7, 8
8.          DataLine ← AddFeatures(SData[], Hight[], Slope)
9.          Write DataLine in the File
10.         Clear DataLine
11.     EndWhile
12. EndWhile
```

Algorithm 5 and Algorithm 6 provide high-level algorithms for the machine and deep learning modules. A detailed explanation is presented in Sections 4.5.1 and 4.5.2.

Algorithm 5: Machine learning Module

```
Input: Dataset, PrFx
Output: MOL, VoiceCommands
1.  If (PrFx)
2.      Dataset ← PreProFXModuleML(Dataset)
3.  End If
4.  MLModel ← Train (Dataset)
5.  [MOL, VoiceCommands] ← Inference (MLModel)
```

Algorithm 6: Deep Learning Module

```
Input: Dataset, PrFx
Output: DOL, VoiceCommands
1.  If (PrFx)
2.      Dataset ← PreProFXModuleDL(DLDataset)
3.  End If
4.  DLModel ← Train (Dataset)
5.  [DOL, VoiceCommands] ← Inference (DLModel)
```

The prediction mode may be used in three distinct ways to aid visually impaired users: prediction button, throw gesture, or voice instruction. To utilize Voice instruction, double-tap the screen to access the Speech-to-Text API, then speak "Prediction Mode" on the command line. The prediction mode is accessed by flinging the screen.

4.5.1 Machine Learning Models (WEKA)

WEKA, a java-based open source program that contains a collection of machine learning algorithms for data mining applications [143], was employed to train the dataset with three classifiers that are carefully selected from detailed experiments provided in our previous works and provide the best results, KStar, IBk, and Random Committee classifiers [39].

KStar Algorithm

KStar is an instance-based classifier, which means that the class of a test instance is decided by the class of related training examples, as defined by some similarity function. It utilizes an entropy-based distance function, which sets it apart from other instance-based learners. Instance-based learners use a dataset of pre-classified examples to categorize an instance. The essential hypothesis is that comparable instances are classified similarly. The issue is determining how to define the terms "similar instance" and "similar class". The distance function, which defines how similar two examples are, and the classification function, which describes how instance similarity creates a final classification for the new instance, are the related components of an instance-based learner. The KStar algorithm employs an entropic measure, which is based on the chance of randomly selecting among all conceivable transformations to turn one instance into another. It is particularly helpful to use entropy as a metric for instance distance, and information theory aids in determining the distance between the instances [144]. The distance between instances determines the complexity of a transition from one instance to another. This is accomplished in two stages. To begin, a limited set of transformations is created that transfers one instance to another. Then, using the program, convert one instance from x to y in a limited sequence of transformations that begins at x and ends at y.

Instance-Based Learner (IBk) Algorithm

An ideal description is the principal output of IBk algorithms (or concept). This is a function that maps instances to categories: it returns a classification for an instance chosen from the instance space, which is the anticipated value for the instance's category attribute. A collection of stored examples and, maybe, some information about their historical performances during classifying are included in an instance-based concept description (e.g., their number of correct and incorrect classification predictions). After each training instance is handled, this list of instances may vary. IBk algorithms, on the other hand, do not generate extensive idea descriptions. Instead, the IBk algorithm's chosen similarity and classification functions determine concept descriptions based on the current collection of stored instances. Two of the three sections of the framework that describes all IBk algorithms are these functions: 1. The Similarity Function determines how similar a training instance x is to the concept description's examples. Similarities are given numerical values. 2. Classification Function: This function takes the results of the similarity function and the classification performance records of the instances in the concept description and uses them to classify them. It leads to an x classification. 3. Updater for Concept Descriptions: This program maintains track of the results of classification and decides which instances should be included in the concept description. Include '*I*' inputs, the similarity outcomes, the classifying results, and a current concept description are all inputs. It results in an updated concept description. Unlike most other supervised learning approaches, IBk algorithms do not create explicit abstractions, such as decision trees or rules. When cases are provided, most learning methods produce generalizations from them and utilize simple matching processes to classify subsequent instances. At presentation time, this includes the objective of the generalizations. Because IBk algorithms do not store explicit generalizations, they do less work at presentation time. However, when they are supplied with more cases for classification, their workload increases as they compute the similarities of their previously saved instances with the newly presented instance. This eliminates the need for IBk algorithms to keep rigid generalizations in concept descriptions, which may cost a lot to update to account for prediction errors [145].

Random Committee Algorithm

The Random Committee algorithm is an ensemble of randomizable base classifiers that may be built using this class. A distinct, random number seed is used to build each base classifier (but based on the same data). The final prediction is an arithmetic mean of the predictions made by each of the base classifiers [146].

Figure 14 shows the model procedure using Weka and TensorFlow frameworks. The data is obtained from the LidSonic V2.0 gadget via its sensors and labeled by the user. Next, from the preprocessing and extraction module, we produced two datasets, DS1 and DS2. Then, these datasets are trained using three machine-learning methods IBk, Random Committee, and KStar in the Machine Learning Obstacle Recognition Module. In the evaluation and visualization module, six Weka models were evaluated using three classifiers

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and two datasets. We used 10-fold cross-validation to evaluate the training datasets. Weka runs the learning algorithm eleven times in 10-fold cross-validation, once for each fold of the cross-validation and once more on the complete dataset. Each fit is done on a training set made up of 90% of the entire training set chosen at random, with the remaining 10% utilized as a hold-out set for validation. The deployment may be done in a variety of ways, and we have chosen the optimal deployment method on the basis of the performance and analysis of each classifier.

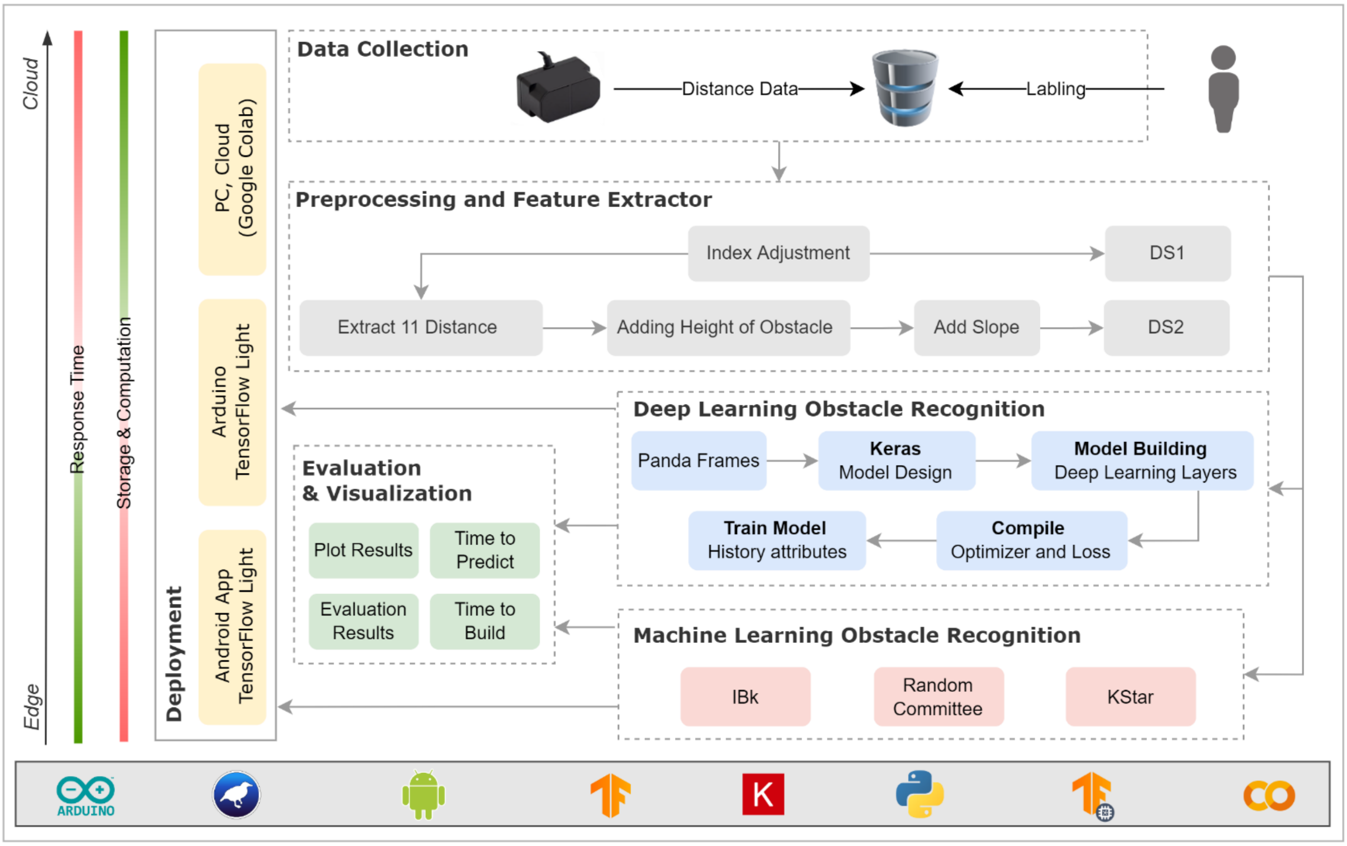

Figure 14. Machine and Deep Learning Modules.

The train model building time was evaluated on a Samsung Galaxy S8 mobile; see Figure 15. The mobile has 4GB RAM, Exynos 8895 (10 nm) – EMEA shipset, and Octa-core (4x2.3 GHz Mongoose M2 & 4x1.7 GHz Cortex-A53) – EMEA CPU. In the results section, the results are fully clarified.

Model	Galaxy S8
Platform	Android
Memory	4GB RAM
Shipset	Exynos 8895 (10 nm) – EMEA
CPU	Octa-core (4x2.3 GHz Mongoose M2 & 4x1.7 GHz Cortex-A53) – EMEA

Figure 15. Samsung Galaxy S8 Specification.

4.5.2 Deep Learning Models: TensorFlow

The model procedure of the TensorFlow framework is depicted in Figure 14. The user labels the data that is acquired from the LidSonic V2.0 device via its sensors. After that, we created two datasets, DS1, and DS2 (these are the same datasets that are used for the machine learning models). We build two models TModel1 and TModel2 to evaluate the

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two datasets we constructed. The deep models used are Convolutional neural networks (CNNs). In the Evaluation and visualization module, the models are evaluated and the results were plotted and analyzed.

The datasets were divided into three sections: training, validation, and testing; see Table 7. The validation set is used to evaluate the loss and any metrics during model fitting, however, the model is not fitted using this data. In the deployment phase, we put the module into production so that users can make predictions with it. TensorFlow has great capabilities and gives a variety of choices to deploy the models to choose among; TensorFlow Serving, TensorFlow Light (TinyML), and more. TensorFlow Serving: is a TensorFlow library that enables to serve models through HTTP/REST or gRPC/Protocol Buffers. TensorFlow Serving is a model deployment strategy for machine learning and deep learning models are flexible and high-performing. TensorFlow Serving makes it simple to deploy models. TensorFlow Lite is a lightweight TensorFlow solution for mobile and embedded devices that focuses on running machine learning (mostly deep learning) algorithms directly on edge devices such as Android and iOS, as well as embedded systems such as Arduino Uno. Tiny machine learning is a branch of machine learning microcontrollers and mobile phones. Because most of these devices are low-powered, the algorithms must be carefully tuned to operate on them. TinyML has become one of the fastest developing subjects in deep learning due to the requirement to perform machine learning directly on edge devices and the ease that comes with it. The smartphone or Arduino Uno microprocessor, in our scenario, is an edge device that employs the final output of machine learning algorithms. Many operators run machine learning models on more capable devices and then send the results to edge devices; this method is starting to change because of the emergence of TinyML.

Table 7. TensorFlow Train Model Shapes.

Dataset	TModel1	TModel2
Training features shape	(435, 60)	(435, 14)
Validation features shape	(109, 60)	(109, 14)
Test features shape	(136, 60)	(136, 14)

The datasets are split according to Table 7. During the training phase, the test set is ignored, and it is only utilized at the end to assess how well the model generalizes to new data. This is especially essential with unbalanced datasets when the absence of training data poses a considerable risk of overfitting.

ReLU

The model has been fine-tuned with layers to increase its accuracy and precision. We employed three layers for the Deep Neural Network, in addition to the input and output layers as shown in Table 8 for DS1, and Table 9 for DS2, and applied the Rectified Linear Unit activation function (ReLU).

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Table 8. TModel1 Summary.

Model: "sequential_16"

Layer (type)	Output Shape	Param #
flatten_16 (Flatten)	(None, 60)	0
dense_74 (Dense)	(None, 60)	3660
dense_75 (Dense)	(None, 120)	7320
dense_76 (Dense)	(None, 60)	7260
dense_77 (Dense)	(None, 60)	3660
dense_78 (Dense)	(None, 30)	1830
dense_79 (Dense)	(None, 8)	248

Total params: 23,978
Trainable params: 23,978
Non-trainable params: 0

Table 9. TModel2 Summary.

Model: "sequential_2"

Layer (type)	Output Shape	Param #
flatten_2 (Flatten)	(None, 14)	0
dense_8 (Dense)	(None, 140)	2100
dense_9 (Dense)	(None, 64)	9024
dense_10 (Dense)	(None, 30)	1950
dense_11 (Dense)	(None, 8)	248

Total params: 13,322
Trainable params: 13,322
Non-trainable params: 0

Softmax Regression

Since we have a multi-class dataset, we employed Softmax regression. Softmax regression (also known as multinomial logistic regression) is a generalization of logistic regression for dealing with several classes. As a result, the softmax function does two tasks: First, it converts all of the scores to probabilities. Then, the total probability equals 1. The sigmoid function is used for the same problem in the Binary Logistic classifier to classify two classes. The softmax function is little more than a generalized sigmoid function.

Cost Function

We must create a cost function for which the softmax probability and one-hot encoded target vector must be compared for similarity. For this, we employ the conception of Cross-Entropy. Cross-entropy is a distance computation function that uses the softmax function's estimated probability and the one-hot-encoding matrix to determine the distance. The distance values for the correct target classes is less, while the distance values for the incorrect target classes is bigger. Passing an input through the model and comparing predictions to ground-truth labels is how a neural network is trained. A loss function is used to make this comparison. Categorical cross-entropy loss is the loss function of choice in multiclass classification issues. It does, however, necessitate one-hot encoding of the labels. Sparse categorical cross-entropy loss may be a useful option in this instance. The loss function does the same type of loss as categorical cross-entropy loss but on integer targets rather than one-hot encoded targets. This eliminates the categorical step that is so prevalent in TensorFlow/Keras models. In artificial neural networks, the softmax function is employed in a variety of multiclass classification algorithms. The outcome of K's unique linear functions is used as the input to multinomial logistic regression and linear discriminant analysis, and the predicted probability is calculated by equation (9):

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$$P(y = j|x) = \frac{e^{x^T w_j}}{\sum_{k=1}^{K} e^{x^T w_k}} \quad (9)$$

with j'th class given x sample vector and w weighting vector.

Adam Optimizer

Next, we employed adam as an optimizer. Adam comes from the phrase "adaptive moment estimation". Adam is an optimization algorithm that may be used to update network weights iteratively based on training data instead of the traditional stochastic gradient descent procedure. The following advantages of employing Adam on non-convex optimization problems: Implementation is simple. Effective in terms of computation. There are not that many memory demands. The gradients are invariant to diagonal rescaling. It is ideally suited to issues with a lot of data and/or parameters. It is a great option for non-stationary objectives. It is suitable for gradients that are exceedingly noisy or sparse. Finally, Hyper-parameters are easy to read and usually do not require much adjustment. Adam is a stochastic gradient descent extension that combines the benefits of two earlier extensions, Adaptive Gradient Algorithm (AdaGrad) and Root Mean Square Propagation (RMSProp). Adam is a popular deep learning method since it produces good results swiftly. The results were plotted and reviewed during the evaluation and visualization phase. The model configuration of the experiments is shown in Table 10.

Table 10 Deep Learning Model Configurations.

Specifications	Value
Number of hidden layers – Tmodel1	5
Number of hidden layers – Tmodel2	3
Activation function - hidden layers	Relu
Activation function - output layer	Softmax
Loss function categorical	Sparse_categorical_crossentropy
Optimizer	Adam
Epochs	200

4.6 Voice Module

A multiplicity of Application Programming Interfaces (APIs) are now accessible for a variety of activities that formerly required significant programming effort from developers. When working with audio file data, the job gets a bit more challenging. As a result, we relied on Google's speech-to-text engine [147], which can transcribe any audio while maintaining context and language. The API supports up to 120 languages. Other functionalities include voice command and control, call center audio transcription, real-time streaming, pre-recorded audio processing, and others. The Google Speech-to-Text tool can successfully translate written text into grammatically and contextually relevant speech using a range of natural voices. The Google Text-to-Speech API enables developers to interact with customers through speech user interfaces in devices and applications, as well as customize communication depending on voice and language preferences.

The Voice Module, for example, allows the user to generate the dataset and transition between different development and operation phases using voice commands. To begin the process of producing a dataset, the user types the command "Train." The system then asks the user "what is the obstacle class," in order to classify the incoming data. The user specifies the obstacle, such as "Wall." The system then requests that the user to "Specify the dataset file name." Finally, the user enters the file name audibly.

5. Performance Evaluation

We now analyse the performance of the LidSonic V2.0 system: Section 5.1 discusses the performance using the machine learning models and Section 5.2 discusses the system performance using the deep learning models.

5.1 *Machine Learning-Based Performance*

There are a few metrics defined in the Weka software that can be computed by the model and are useful for measuring performance. Accuracy is defined as the percentage of properly classified instances. Precision is defined as the percentage of expected positives that were correctly classified. Table 11 displays the accuracy and precision of the 6 machine learning models adopting three classifiers to construct models from two datasets DS1 and DS2.

Table 11 Evaluations of Machine Learning Models.

Trained Model	Dataset	No. of Features	Classifier	Precision	Accuracy
IBk-DS1	DS1	60	IBk	94.0	93.68
RC-DS1	DS1	60	Random Committee	94.7	94.56
KStar-DS1	DS1	60	KStar	95.6	95.44
IBk-DS2	DS2	14	IBk	95.2	95
RC-DS2	DS2	14	Random Committee	95.2	95.15
KStar-DS2	DS2	14	KStar	94.1	93.82

The results are depicted in Figure 16. The results indicate that using DS2 with Random Committee and IBk classifiers increases accuracy to (95%) and (95.15%), respectively, with equal precision results of (95.2%). The KStar classifier, on the other hand, has greater accuracy (95.44 %) and precision (95.6 %) when utilizing DS1.

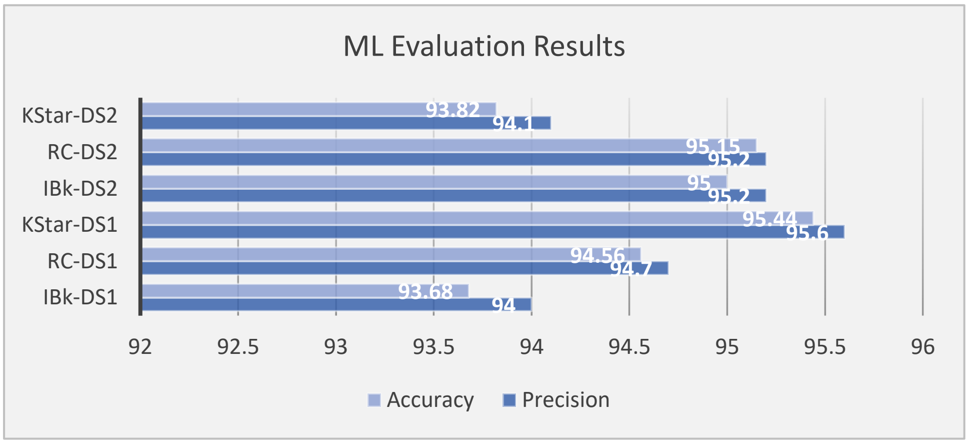


Figure 16. Weka Classifiers Evaluation Results.

Figure 17 plots the model training times for the top three classifiers. The highest time spent building the classification model using DS1 in general compared with the time spent building the classifiers using DS2. Using DS1, the highest time to build was by RC (299 ms), followed by KStar (42 ms), and IBk (1 ms). For DS2, the highest time to build was by RC (128 ms), followed by KStar (11 ms), then IBk (1 ms). While RC classifier has the longest time to build its model, it has the shortest time to predict an object see Figure 18.

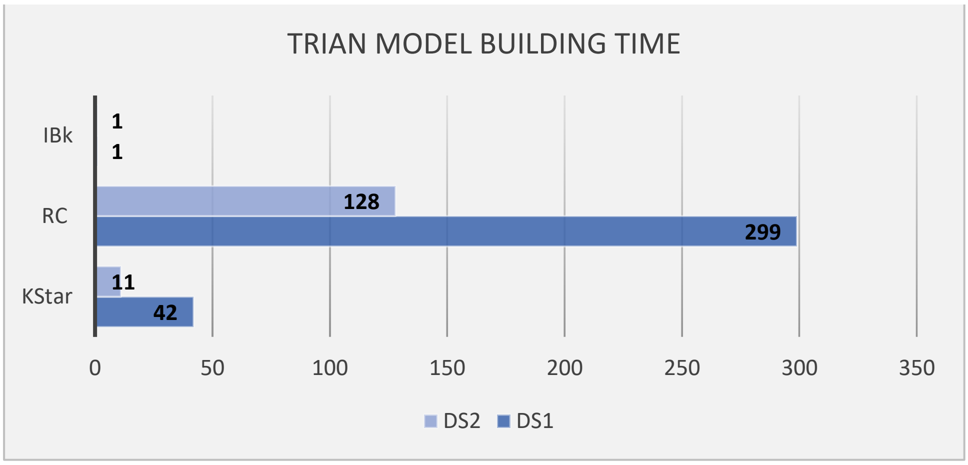
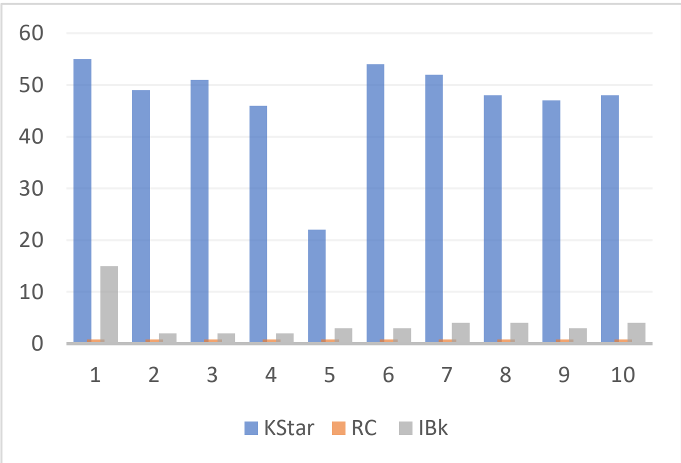
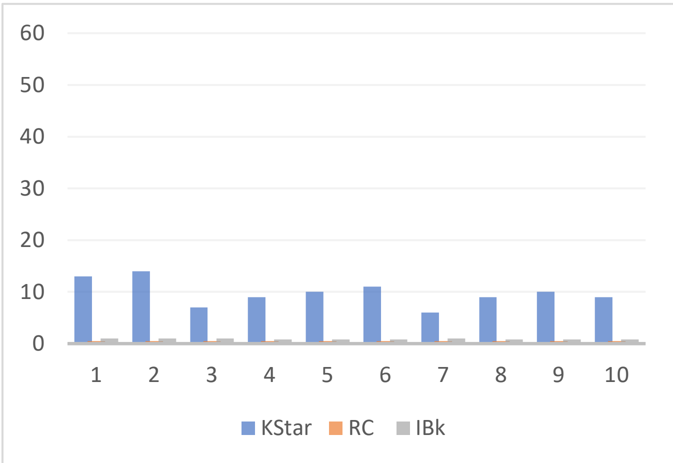


Figure 17. Time to Build a Model for each Classifier.

Figure 18 plots the model inference times for the top three classifiers. For both the DS1 and DS2 test samples, we construct 10 test predictions and time each classifier to produce the outcome. The time it takes KStar to forecast an object varies between 22 and 55 milliseconds when using DS1 test samples, and between 9 and 13 milliseconds when using DS2 test samples. IBk classifier, on the other hand, has faster times than KStar, with an average of 4-5 milliseconds for DS1 test samples and 0-1 milliseconds for DS2 test samples. Random Committee takes a substantial amount of time to develop its training model, it predicts test samples in less than 1 millisecond for both DS1 and DS2 test samples.



(**a**)



(**b**)

Figure 18. Classifiers Inference Elapsed Time in Milliseconds on **(a)** DS1 Test Samples **(b)** DS2 Test Samples.

It is worth mentioning that IBk and KStar algorithms trained models generated faster than Random Committee algorithm see Figure 17. Random Committee takes 299 milliseconds to create its trained model using DS1, whereas DS2 takes 128 milliseconds. KStar additionally requires a long time to construct its training model, taking 42 ms for DS1 and 11 ms for DS2. On the other hand, for both DS1 and DS2, IBk classifier builds the trained model in 1 ms. As a consequence, we suggest the IBk classifier above the Random Committee and KStar classifiers for mobile adaption, embedded microprocessors, and/or large datasets. Although there is a modest accuracy trade-off, the IBk classifier delivers a significant decrease in mobile computing and battery usage.

When taking a design of a system architecture that takes advantage of fog or cloud in the training phase, we suggest KStar classifier - especially with a larger training dataset

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to be trained in the layers of fog or cloud, because it can exploit its computation processing powers and return results for the edge level. For RC classifier it can be trained in the higher layers (cloud or fog) and the constructed model then can transfer to the edge, because its prediction time is the least among the three classifiers.

Figure 19 depicts the confusion matrix with the best training model score, which was obtained using the KStar classification method on the D1 dataset. Figure 20 shows the confusion matrix of Random Committee classifiers trained on DS2. Figure 21 shows the confusion matrix for IBk classifier. Because these are the top three highest performing classifiers from our past study, we have chosen these three to exhibit their confusion matrices. The abbreviations used in the figures are listed in Table 12.

Table 12. Class Abbreviation.

Class	Abbreviation	Class	Abbreviation
Floor	F	Deep Hole	DH
Ascending Stairs	AS	High Obstacle	HO
Descending Stairs	DS	Ascending Step	ASt
Wall	W	Descending Step	DSt

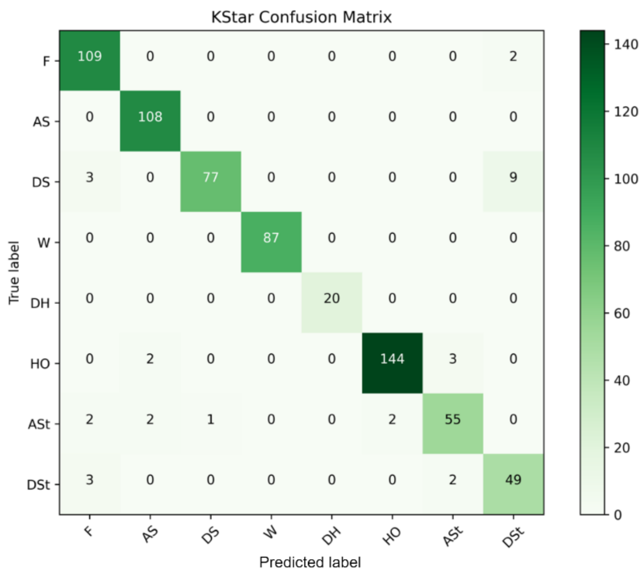

Figure 19. KStar Confusion Matrix using DS1.

Figure 19 plots the confusion metrix for the KStar classifier. The number of true positives is for the Floor class (109), followed by Ascending Stairs (108), Descending Stairs (77), Wall (87), Deep Hole (20), High Obstacle (144), Ascending Step (55), and Descending Step (49). The total number of wrong predictions for the classes are Floor (2), Ascending Stairs (0), Descending Stairs (3), Wall (0), Deep Hole (0), High Obstacle (5), Ascending Step (7), and Descending Step (5). Obviously, the number of wrong predictions should be considered relative to the total number of instances. It is possible that the higher number of wrong predictions for some classes is due to the low number of instances for the data objects for those classes. Note also that the Floor was misclassified two times as Descending Step. Descending Stairs are misclassified 3 times as Floor, and 9 times as Descending Step. High Obstacle class is misclassified 2 times as Ascending Stairs, and 3 times as Ascending Step. Ascending Step was misclassified 2 times as Floor, 2 times as Ascending Stairs, 1 time as Descending Stairs, and 2 times as High Obstacle. Descending Step was misclassified 3 times as Floor, and 2 times as Ascending Step. On the other hand, Ascending Stairs, Wall, and Deep Hole classes have no misclassified results.

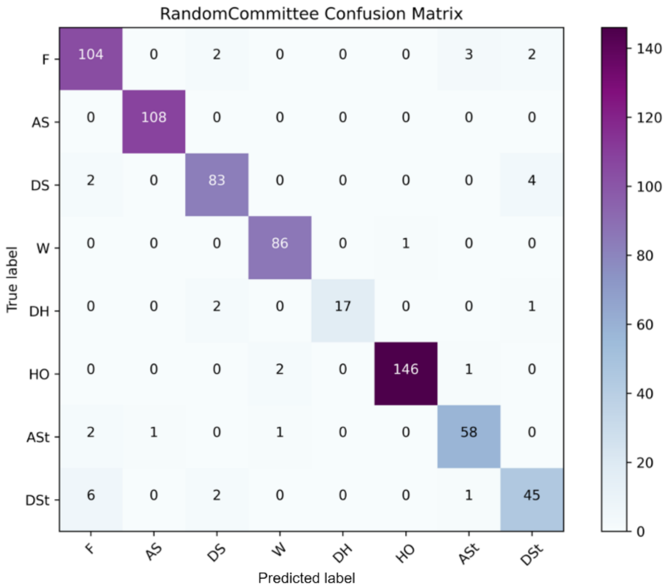

Figure 20. Random Committee Confusion Matrix using DS2.

Figure 20 plots the confusion matrix for the Random Committee (RC) classifier. The highest number of true positives are for the High Obstacle (146) and Ascending Stairs (108) classes, followed by Floor (104), Wall (86), Descending Stairs (83), Ascending Step (58), Descending Step (45), and Deep Hole (17). The total number of wrong predictions for the classes are Floor (7), Ascending Stairs (0), Descending Stairs (6), Wall (1), Deep Hole (3), High Obstacle (3), Ascending Step (4), and Descending Step (9). Note that Floor was misclassified 2 times as Descending Stairs, 3 times as Ascending Step, and 2 times as Descending Step. Descending Stairs were misclassified 2 times as Floor, and 4 times as Descending Step. The Wall class is misclassified 1 time as High Obstacle. Deep Hole was misclassified 2 times as Descending Stairs, and 1 time as Descending Step. The High Obstacle class was misclassified 2 times as Wall, and 1 time as Ascending Step. Ascending Step was misclassified 2 times as Floor, 1 time as Ascending Stairs, and 1 time as Wall. Descending Step was misclassified 6 times as Floor, 2 times as Descending Stairs, and 1 time as Ascending Step. Ascending Stairs have no misclassifications.

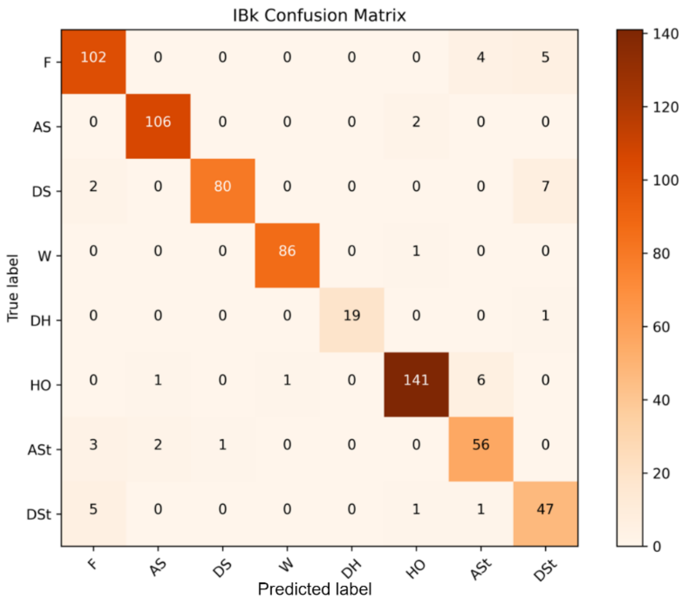

Figure 21. IBk Confusion Matrix using DS2.

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Figure 21 plots the confusion matrix for the IBk classifier. The highest number of true positives are for the High Obstacle (141) and Ascending Stairs (106) classes, followed by Floor (102), Wall (86), Descending Stairs (80), Ascending Step (56), Descending Step (47), and Deep Hole (19). The total number of misclassifications for the classes were: Floor (9), Ascending Stairs (2), Descending Stairs (9), Wall (1), Deep Hole (1), High Obstacle (8), Ascending Step (6), and Descending Step (7). The larger number of incorrect predictions for some classes is likely due to the low number of instances for the data objects for those classes, as we have seen with the KStar classifier. Note that Floor was misclassified 4 times as Ascending Step S, and 5 times as Descending Step. Ascending Stairs were misclassified 2 times as High Obstacles. The Descending Stairs class was misclassified 2 times as Floor, and 7 times as Descending Step. The Wall class was misclassified 1 time as High Object and zero times as any other class. Deep Hole was misclassified 1 time as Descending Step and zero times as any other class. The High Obstacle class was misclassified 1 time as Ascending Stairs, 1 time as Wall, and 6 times Ascending Step. Ascending Step was misclassified 3 times as Floor, 2 times as Ascending stairs, and 1 time as Descending Stairs. Descending Step was misclassified 5 times as Floor, 1 time as High Obstacle, and 1 time as Ascending Step. Wall and Deep Hole have the least number of misclassifications.

5.2 *Deep Learning-Based Performance*

Observing the performance of neural networks and deep learning models over time during training helps give us knowledge about them. Keras is a Python framework that encapsulates the more technical TensorFlow backends and provides a clear interface for generating deep learning models. We used Keras in Python to evaluate and display the performance of deep learning models over time during training to measure accuracy and loss. Note that the deep learning models were trained and executed on a laptop device. Future work will attempt to implement deep learning models in the mobile phone and other edge devices using TFLite as in our other strands of work [148]. Table 13 summarizes the findings.

Table 13. TensorFlow Model Evaluation.

Trained Model	Dataset	Features	Model Accuracy	Test Accuracy	Model Loss	Test loss
TModel1	D1	60	88.05	76.32	0.3374	0.7190
TModel2	D2	14	98.01	96.49	0.0883	0.3672

TModel1 and TModel2 accuracy and loss results were plotted throughout each epoch and are presented in Figure 22 and Figure 23 respectively. Using different datasets, we can see the large differences in performance. The TModel2 trained model, which is used on DS2, has a 98.01 percent training accuracy and a model loss of 0. 0883 percent. The model accuracy on the test dataset was 96.49 and the test model loss was 0.3672. The model accuracy of TModel1 is 88.05 and loss of 0.3374. The test model accuracy is 76.32 and loss of 0.7190.

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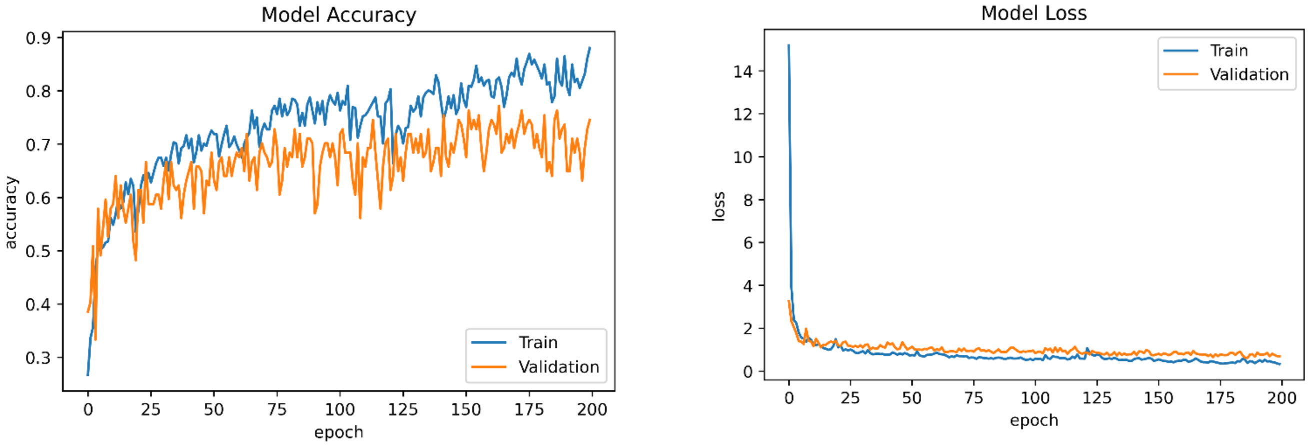
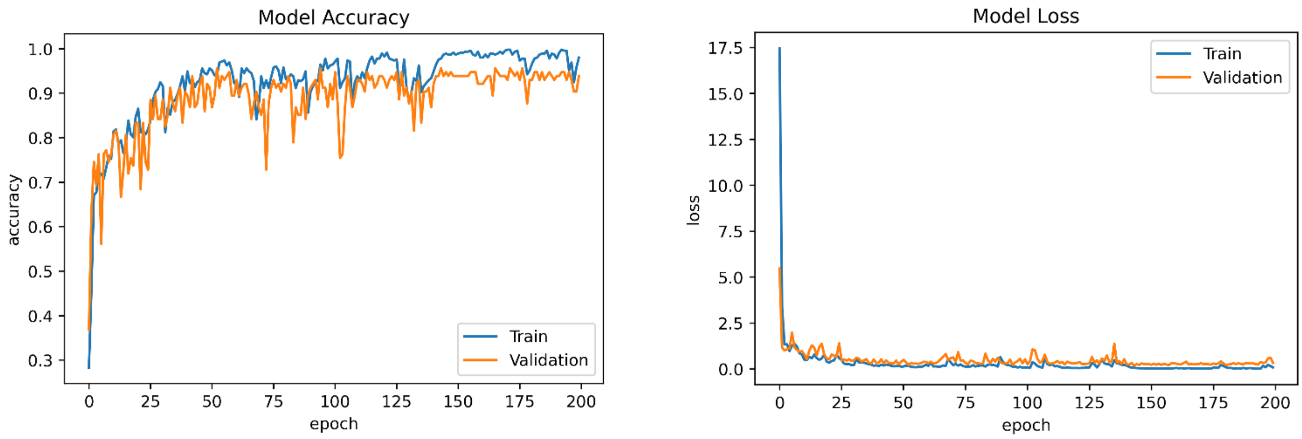


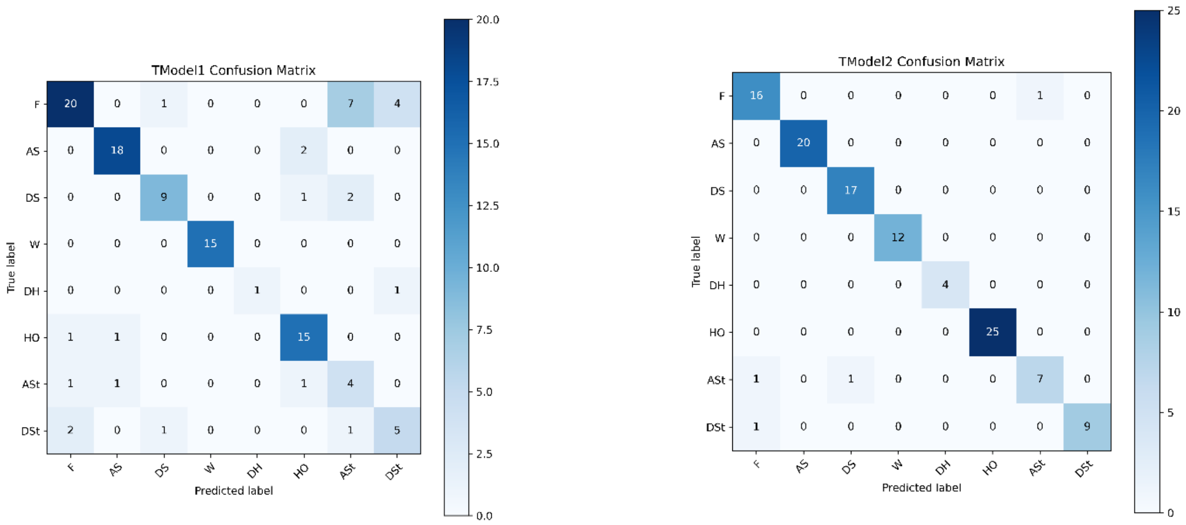
(**a**) (**b**)

Figure 22. Deep Learning Evaluation Using DS1 **(a)** TModel1 Accuracy **(b)** TModel1 Loss.



(**a**) (**b**)

Figure 23. Deep Learning Evaluation Using DS2 **(a)** TModel2 Accuracy **(b)** TModel2 Loss.



(**a**) (**b**)

Figure 24. Deep Learning Confusion Matrix on Test Dataset **(a)** TModel1 **(b)** TModel2.

Figure 24 plots the confusion matrices for the TModel1 and TModel2 deep learning models on a test dataset that has not been seen by the trained model. For TModel1 highest number of true positives are for the Floor (20) and Ascending Stairs (18), followed by Wall and High Obstacle (15), Descending Stairs (9), Descending Step (5), Ascending Step (4), and Deep Hole (1). The total number of wrong predictions for the classes are Floor (13), Ascending Stairs (2), Descending Stairs (3), Deep Hole (1), High Obstacle (2), Ascending Step (3), and Descending Step (4). Wall has been classified correctly. The Floor was misclassified 1 time as Descending Stairs, 7 times as Ascending Step, and 4 times as Descending Step. Ascending Step was misclassified 2 times as High Obstacle. Descending Stairs has been misclassified 1 time as High Obstacle and 2 times as Ascending Step. Deep Hole has 1 misclassification as Descending Step. High Obstacle was 1 time misclassified as Floor, and 1 time as Ascending Stairs. Ascending Step was misclassified 1 time as Floor, 1 time as Ascending Stairs, and 1 time as High Obstacle. Descending Step was misclassified 2 times as Floor, 1 time as Descending Stairs, and 1 time as Ascending Step.

For TModel2 highest number of true positives are for the High Obstacle (25) and Ascending Stairs (20) classes, followed by Descending Stairs (17), Wall (12), Descending Step (9), Ascending Step (7), and Deep Hole (4). The total number of wrong predictions for the classes are Floor (1), Ascending Step (2), and Descending Step (1). Note that the Floor was misclassified 1 time as Ascending Stairs. Ascending Step was misclassified 1 time as Floor, and 1 time as Descending Stairs. Descending Step was misclassified 1 time as Floor. Ascending Stairs, Descending Stairs, Wall, Deep Hole, and High Obstacle have no misclassifications.

6. Conclusions

Over a billion people around the world are disabled, among them, 253 million are visually impaired or blind, and this number is greatly increasing due to ageing, chronic diseases, poor environment, and health. Despite many proposals, the current devices and systems lack maturity and do not completely fulfill user requirements and satisfaction. Increased research activity in this field is required to encourage the development, commercialization, and widespread acceptance of low-cost and affordable assistive technologies for visual impairments and other disabilities.

In this paper, we developed the LidSonic V2.0 system by leveraging a comprehensive understanding of the state-of-the-art requirements and solutions involving assistive technologies for the visually impaired, through a detailed literature review and a survey. The system is based on a novel approach of using a combination of a LiDAR with a servo motor and an ultrasonic sensor to collect data and predict objects using machine and deep learning for environment perception and navigation. We implemented this approach into a pair of smart glasses called LidSonic V2.0 to identify obstacles for the visually impaired. The LidSonic system consists of an Arduino Uno edge computing device integrated into the smart glasses and a smartphone app that transmits data via Bluetooth. Arduino gathers data, operates the sensors on smart glasses, detects obstacles using simple data processing, and provides buzzer feedback to visually impaired users. The smartphone application collects data from Arduino, detects and classifies items in the spatial environment, and gives spoken feedback to the user on the detected objects. LidSonic uses far less processing time and energy than image processing-based glasses to classify obstacles using simple LiDAR data using a few integer measurements. We comprehensively describe the proposed system's hardware and software design, construct their prototype implementations, and test them in real-world environments.

The deep learning model TModel2 over the DS2 dataset provided the overall best accuracy results at 96.49%. The second-best accuracy was provided by the KStar classifier at 95.44% and precision at 95.6%. The IBk and RC classifiers provided the same precision at 95.2% and similar accuracy results at 95.15% and 95%, respectively, using the DS2 dataset. Note that the IBk classifier was seen to be relatively independent of the size of the datasets. This could be because both the datasets are numeric and the difference in their sizes is small. It took 1ms to train both D2 and D1 datasets and these were the fastest training time results overall. The IBk classifier also provided the second fastest prediction time with 0.8ms and hence we recommend it to use it at the edge for training and prediction. As for the KStar classifier, the training time is influenced by the size of the training dataset. It took 11ms to train KStar with the DS2 dataset and 42ms to train it with the larger DS1 dataset. Moreover, the KStar classifier took much longer times for prediction, between 22ms to 55ms, compared to the other classifiers in our experiments. Hence, we proposed using the KStar classifier at the fog or cloud layers.

Using the open platforms WEKA and TensorFlow, the entire LidSonic system is built with affordable off-the-shelf sensors and a microcontroller board costing less than $80. Essentially, we provide the design of inexpensive, miniature, green devices that can be built into, or mounted on, any pair of glasses or even a wheelchair to help the visually impaired. Our approach affords faster inference and decision-making using relatively low energy with smaller data sizes. Smaller data sizes are also beneficial in communications, such as those between the sensor and processing device, or in the case of fog and cloud computing, because they require less bandwidth and energy, and can be transferred in relatively shorter periods of time. Moreover, our approach does not require a white cane, and therefore, it allows handsfree operation.

We evaluated the proposed system from multiple perspectives. For instance, we proposed based on the results to use the Random Committee classifier at the edge for prediction due to its faster prediction time, however, it needs to be trained at the fog or cloud layers because it requires larger resources. In this respect, we plan to extend and integrate this work with other strands of our work on big data analytics and edge, fog, and cloud computing [148–151]. For example, we plan to experiment with different machine learning and deep learning methods at the edge, fog, and cloud layers, their performance, applicability of the use of edge, fog, and cloud computing for smart glasses, and new applications for the integration of smart glasses with cloud, fog, and edge layers. Another direction of our research is green and explainable AI [152,153] and we would also explore the expandability of the LidSonic system. We also plan to test the glasses with different visually impaired and blind people.

We conclude this paper with the note that the technologies developed in this paper are of high potential and are expected to open new directions for the design of smart glasses and other solutions for the visually impaired using open software tools and off-the-shelf hardware.

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Data Availability Statement: The Dataset developed in this work can be provided on request.

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Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this paper.

ETA	Electronic Travel Aids
ToF	Time-of-flight
RNA	Robotic Navigation Aid
ALVU	Array of Lidars and Vibrotactile Units
BLE	Bluetooth Low Energy
SDK	Software Development Kit
RGB-D	RGB-Depth
CNN	Convolutional Neural Networks
RFID	Radio-Frequency Identification Reader
HRTFs	Head-Related Transfer Functions
GPS	Global Positioning System
MSER	Maximally Stable External Region
SWT	Stroke Width Transform

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