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RESEARCH ARTICLE

Obstacle Detection and Warning System for Visually Impaired Using IoT Sensors

SUNNIA IKRAM[1], IMRAN SARWAR BAJWA[2], AMNA IKRAM[3], ISABEL DE LA TORRE DÍEZ[4], CARLOS EDUARDO UC RÍOS[5,6], (Student Member, IEEE), AND ÁNGEL KUC CASTILLA[6,7]

[1]Department of Software Engineering, The Islamia University of Bahawalpur, Bahawalpur 63100, Pakistan
[2]Department of Computer Science, The Islamia University of Bahawalpur, Bahawalpur 63100, Pakistan
[3]Department of Computer Science, The Government Sadiq College Women University at Bahawalpur, Bahawalpur 63100, Pakistan
[4]Department of Signal Theory and Communications and Telematics Engineering, University of Valladolid, Campus Miguel Delibes, 47011 Valladolid, Spain
[5]Department of Project Management, Universidad Europea del Atlántico, PR 00613, Spain
[6]Department of Project Management, Universidad Internacional Iberoamericana, Campeche 24560, Mexico
[7]Department of Project Management, Universidad de La Romana, La Romana 22000, Dominican Republic

Corresponding author: Sunnia Ikram (sunnia.ikram@iub.edu.pk)

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ABSTRACT Ensuring safe and independent mobility for visually impaired individuals requires efficient obstacle detection systems. This study introduces an innovative smart knee glove, integrating machine learning technologies for real-time obstacle detection and alerting. The system is equipped with ultrasonic sensor, PIR sensor and a buzzer, with data processing managed by an Arduino Uno microcontroller. To enhance detection accuracy, multiple machine learning algorithms including Decision Tree (DT), Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Random Forest (RF) and Gaussian Naïve Bayes (GNB) are utilized. A novel Voting Classifier ensemble method is proposed, effectively combining the strengths of these classifiers to maximize performance. Rigorous cross-fold validation ensures robust evaluation under varying conditions. Experimental results demonstrates that the system achieves an impressive 98.34% detection accuracy within a 4-meter range, with high precision, recall and F1 scores. These findings underscore the system's reliability and potential to empower visually impaired users with safer, more autonomous navigation, marking a significant advancement in obstacle detection technologies.

INDEX TERMS Obstacle detection, IoT, sensors, visually impaired, machine learning, android application.

I. INTRODUCTION

According to the WHO reports, it is estimated that there are 285 million visually impaired individuals of all age groups in total [1], [2], [3]. Individuals aged 50 and older constitute 82% of the global visually impaired population. These people require constant support from others and are in need of assistive devices [4]. Recent advancements in obstacle detection technologies, including LiDAR, YOLO and sensor fusion techniques, have shown significant potential for improving navigation and safety for visually impaired individuals. However, such methods often involve high cost and computational complexity, limited their accessibility. This study introduces a novel smart knee glove that leverages IoT and machine learning for real-time obstacle detection and alerts, achieving superior performance metrics. Navigating the world without the benefit of sight is fraught with challenges, particularly in environment filled with obstacles.

Traditional approaches to obstacle detection for the visually impaired have often fallen short in delivering the accuracy, reliability and range required for confident navigation in real-world settings. Key limitation is existing systems include short detection range (often less than 2 meters), sensitivity to environmental factors such as acoustics and reflectivity, and delays in real-time feedback that compromise user safety and autonomy. Additionally, many existing solutions lack the capacity to detect complex or transparent obstacles effectively, making them unsuitable for dynamic environments. These shortcomings emphasize the

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urgent need for innovative solutions optimized for dynamic and unpredictable environments.

The realms of science and engineering have the potential to introduce technical solutions that promote independence and improved navigation and object perception for individuals with visual impairments. Several obstacle detection devices have been created to aid individuals, primarily focusing on camera-based object detection or obstacle identification using various sensors, such as GPS and distance sensors [5]. Sensor-based technologies, integrated with machine learning, hold the promise of creating efficient and empowering devices that help individuals with visual impairments confidently navigate their surroundings [6].

In recent years, many devices have been developed to facilitate mobility of visually impaired individuals such as, band devices for wrists, and sensors in smart caps and smart glasses [7]. Researchers have explored obstacle avoidance and detection using various techniques. Initially, the white can was widely used for obstacle detection due to its simplicity, reliability and cost-effective [8]. However, this method posed challenges in crowded environments, where handling the cane becomes uncomfortable. Moreover, smart shoes could not detect overhead obstacles, and while smart glasses helped, they have their limitations. Many researchers have since proposed solutions leveraging sensor technology [7].

However, existing approaches have notable limitations. First, they often suffer from accuracy issues, including false positives and false negatives which undermine user confidence and increase safety risks. Second, environmental adaptability is a persistent issue, as these systems may struggle to function reliably in noisy, reflective or extreme conditions [9], [10]. Thirdly, they lack real-time feedback mechanisms that integrate seamlessly into users' daily lives, such as voice alerts or vibration cues optimized for individual needs. Lastly, feedback mechanisms like vibrations or auditory cues often lack clarity or are not customized to individual user need, reducing their effectiveness.

The proposed model addresses these deficiencies by integrating advanced sensor technology with robust machine learning algorithms. The system offers extended detection ranges of up to 4 meters, overcoming the short-range limitations of existing designs. Enhanced real-time performance minimizes latency in feedback, providing users with immediate alerts for quicker decision-making. The ensemble model, leveraging DT, SVM, KNN, RF and GNB, ensures reduced false positive and negative, even in dynamic environments. Furthermore, the system is adaptable to detect complex and irregular obstacles, including transparent objects, ensuring user safety in diverse settings.

Incorporate state-of-the-art techniques such as YOLO and SSD for object detection or sensor fusion for enhanced obstacle detection may offer additional benefits. The integration of such methods in future iterations could enable more comprehensive solutions, ensuring adaptability across various environments and conditions. Electromagnetic sensor are also employed in electronic travel aids to assist visually impaired individuals in navigating their surroundings [11]. In a guidance system, ultrasonic sensors are integrated in shoes and stick, paired with algorithms to identify the obstacles and alerts the user [12]. However, these systems have limitations, such as uncomfortable designs, short detection ranges and low efficiency. Many existing systems have achieved accuracy of less than 96%, leaving significant room for improvement.

This paper focuses on developing a smart knee glove-based system that provides an efficient, fully automated obstacle detection solution for visually impaired individuals. The proposed work employs state-of-the-art machine learning algorithms, such as DT, SVM, KNN, RM and GNB along with a Voting Classifier ensemble approach, to enhance detection accuracy and minimize false positive and negatives. The models are rigorously evaluated using cross-validation to ensure reliability and robustness in diverse scenarios, providing a dependable solution for dynamic environments.

Sensors in this work detect objects within a range of 0-4 meters and provide detailed information about the surroundings. To overcome the limited detection range of previous works, knee gloves are introduced, maximizing coverage and ensuring accurate obstacle detection. Experimental results demonstrate that the system achieves a detection accuracy of 98.34% within a 4-meter range, surpassing prior systems and offering improved mobility and independence to visually impaired individuals.

RQ1: How Machine learning can be used to detect obstacles and their distance for visually impaired with acceptable accuracy?

RQ2: How to optimize the real-time computation time for detecting obstacles and their distance?

The paper aims to address these research questions by integrating ultrasonic and PIR sensors to detect obstacle types, distances and motion. A buzzer provides auditory alerts, warning users of obstacles, particularly in critical situations. Future work can expand on this model to assist individuals who are both visually impaired and deaf, further enhancing their usability and impact.

The paper is structured in the following manner:

In Section I, the related work in the field of obstacle detection and the techniques utilized are presented. Section II provides an overview of the proposed model's framework, including preprocessing techniques and text-to-speech (TTS) audio processing. Section III outlines the implementation details, highlighting the hardware components used in the model and their configuration. Section IV presents the experimental results, including performance testing and a discussion of the outcomes achieved through the proposed approach. Finally, Section V provides a comparison of accuracy and concludes the study, summarizing its findings and identifying.

II. RELATED WORK

Through a comprehensive analysis of existing research, valuable insights into the progression and status of obstacle detection systems for visually impaired individuals have been uncovered. Table 1 provides a detailed overview of previous studies, presenting key findings and corresponding references.

Obstacle detection is essential for autonomous driving, improving safety and reducing accidents. While CNN-based models dominate the field, they often overlook the differences between image channels and struggle with multi-scale detection due to the limitations of single-scale feature extraction. The Multi-Scale Squeeze and Extraction (MSMSE) model addresses these issues by integrating a channel attention mechanism and multi-scale feature fusion. This enhances feature differentiation and robustness, capturing both global and local details. Experimental results show that MSMSE outperforms model like Vision Transformer (ViT), making it a promising solution for real-world applications [13].

Wearable sensor technology has also made strides with insole devices that monitor human activity, gait patterns, and pressure distribution using low-power sensors and IoT devices. These smart soles, equipped with accelerometers with gyros, allow seamless integration in everyday environments. A sensor data-collection module paired with an ANN-based classification model has been developed for gait analysis, including detecting in-toeing and out-toeing. Experimental validation has proven the system's effectiveness in gait pattern classification [14].

Previous research compared the interpretation of visual and tactile stimuli in terms of reaction time and consistency. A study on tactile stimuli and its impact on reaction time for obstacle detection in real-world traffic scenarios found that visual stimuli produce faster responses than tactile stimuli. However, tactile stimuli, like point or column vibrations were more consistent and quicker to recognize than wave patterns. This highlights the potential of haptic feedback devices, such as a haptic vest, in minimizing cognitive load and aiding obstacle detection for the visually impaired. These findings emphasizes the potential of a haptic vest as a low cognitive load device, particularly for localization tasks in early warning systems for obstacle detection in real-world traffic scenarios [15].

In [16], the authors addressed the challenges of safe path planning for autonomous mobility in the face of multi-modal perception uncertainties. They tackled this issue by addressing various sensor inputs, which result in distinct Gaussian process-regulated certainties, referred to as multi-modal perception uncertainties. To manage this, they applied a Bayesian inference algorithm that merges these uncertainties into a single unified uncertainty, which is then transformed into a dynamic task map. This risk map is used as input for a safe path planner, enabling secure navigation into a dynamic task map. This risk map is used as input for a safe path planner, enabling secure navigation for autonomous vehicles. The algorithm's effectiveness and practicality were confirmed through experiments conducted on an autonomous golf cart testbed.

In [17] with visual impairments face numerous challenges in daily life, both in outdoor and indoor navigation. Traditional walking sticks often fall short in addressing many of these issues. To assist visually impaired individuals, a smart stick has been developed. This stick is enhanced with ultrasonic sensor, a buzzer and a vibration motor for obstacle detection, providing safety alerts. The smart stick also integrates GPS and GSM modules for locating the user during emergencies and features RF wireless home automation control. In previous work [18], the focus was on fire detection. Single-sensor systems often struggle to differentiate between actual fires and false alarms, such as those triggered by cigarette smoke. To overcome this, the system combines three sensors to improve detection accuracy. An AI-based fuzzy logic algorithm processes sensor data, ensuring accurate fire detection and enabling intelligent decision-making with feature-rich alerts and hardware control.

In another work of obstacle detection for visually impaired, the creation of two perception modules designed for individuals with visual impairments. The initial module introduces a resilient YOLO- based neural network model, capable of recognizing America, European, Mexican and Colombian banknote denominations, achieving a detection performance exceeding 97% across all denominations. The second module features an effective obstacle detection algorithm relying on stereo nation, intended to avert collisions during walking. Rigorous performance tests and simulations were conducted for each module, affirming their precision and effectiveness in assisting visually impaired individuals with the specified perception tasks [19].

Consequently, visually impaired individuals still required a lightweight, cost-effective solution with the wide-range detection capabilities. Existing solutions are limited by short detection ranges, bulky designs and moderate efficiency, leaving significant room for improvement. To address the current needs of visually impaired users, this paper introduces a smart and intelligent wearable device in the form of knee gloves. The primary objectives of this device are to enhance detection and warning capabilities while improving accuracy in identifying moving objects within the user's environment. Additionally, this proposed model contributes to system security, helping mitigate model failure and safeguarding the real-time database against unauthorized access, manipulation and misuse.

III. MATERIAL AND METHODS

The proposed method aims to assess the performance and dependability of machine learning techniques for real-time obstacle detection, specially designed to assist visually impaired individuals. The model utilizes various sensors for accurate object detection and employs machine learning algorithms to minimize false positive and false negative. These techniques not only improve the precision of obsta-

TABLE 1. State of the art in obstacle detection for visually impaired individuals.

Citation	Sensors	Tasks	Features	Techniques	Goals	Knowledge source	Results
[13]	Camera and IoT	Multi-scale feature fusion	Squeeze and excitation network	CNN	Classify obstacles in front of vehicle.	Deep learning	Significant advantages.
[14]	Pressure sensor, gyroscope, accelerometer, smart shoes	Gait pattern analysis	correlation, mean, standard deviation, kurtosis, crest factor, skewness	Random forest, SVM, KNN, logistic regression	Feature analysis	Machine learning algorithms	89% Accuracy
[15]	Visual stimuli and tactile stimuli	Comparing time and consistency of interpreting visual	Point, column, wave	Reaction time measurement for interpreting stimuli	Assess the suitability and evaluate the effectiveness	Comparative analysis of reaction time	Reaction times to visual were shorter than the tactile stimuli
[16]	Multimodal sensors	Obstacle detection, avoidance and navigation	Resolution and space clearing	Assistive technology	Pre diagnose	Image based	Upto the mark
[17]	Smart stick, ultrasonic sensor, moisture sensor, Arduino microcontroller, buzzers, vibration motor, RF remote.	Obstacle height, Water and mud detection	Actual, measured distance, Hypotenuse	Pythagoras theorem	Pre diagnose	Data mining and machine learning	Not given
[18]	Temperature, humidity, flame and smoke sensor	Fire Detection, warning system	CR-Temp (◦C) CR-Humidity (%) CR-Smoke (ppm)	Fuzzy logic	Monitor system activities	Machine learning algorithm	100%
[19]	Real-sense stereo camera	Collision detection, banknote recognition	Point cloud calculation	YOLO algorithm	3D region classification	Data mining and Deep learning	97%

cle detection but also ensure robustness by adapting to dynamic environments and providing real-time feedback to users.

A. HARDWARE IMPLEMENTATION

This Obstacle detection model is used on knee gloves, provides an efficient way of detecting obstacles on the road and even inside the house in a cost-effective manner. Previously many techniques were used for this purpose like detection through camera, detection through ultrasonic sensor and with the buzzer beep. In this proposed Obstacle detection smart knee glove, we have used another feature of detecting motion of obstacle by using PIR sensor. Detection of moving objects helps the person in making decisions. This Obstacle detection model is based on latest technologies such as data mining, IOT and android system [20]. Data collected from the real time environment is in the form of raw data. Data should be pre-processed for the better accuracy of the Obstacle detection model [21]. In Figure 1, the external architecture of the smart knee glove obstacle detection model is illustrated. This architecture utilizes ultrasonic and PIR sensors, a Buzzer connected with Arduino uno data collected from Arduino is transmitted to firebase cloud via Wi-Fi device. Firebase servers send data to mobile applications for Text-to-speech (TTS) audio production, consisting of several key components.

The Figure 1 above shows the architecture of the smart knee glove obstacle detection model. This architecture utilizing ultrasonic and PIR sensors, a Buzzer connected with Arduino uno data collected from Arduino is transmitted to firebase cloud via Wi-Fi device. Firebase servers send data to mobile application for Text-to-speech (TTS) audio production, consists of several key components:

1) ULTRASONIC SENSOR

The obstacle detection sensor that is used in this model measures both the distance and echo when the object is detected. Here are some details about how this hardware works. It features four pins, including VCC, GND, Trigger (output pin), and echo (input pin). The sensor emits a signal, much like a bat spreading sound waves, and then listens for the echoes of nearby obstacles. It operates on a similar principle to ultrasonic sensor. The transmitted signal interacts with objects, and their reflections are received by the sensor, allowing it to measure the distance to the object. This device is commonly employed in obstacle detection projects to ascertain the presence of obstacles and their respective distances. In a setup, both these sensors and buzzer are connected to an Arduino board to collect data, which is particularly useful for visually impaired individuals in identifying and navigating around obstacles [22].

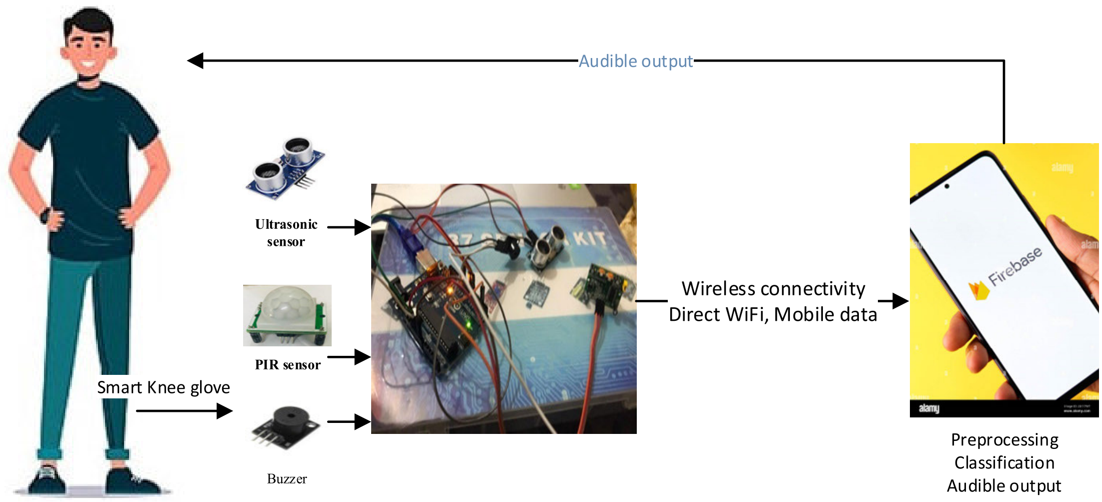

FIGURE 1. External architecture of the obstacle detection model.

Distance can be measured as:

$$D = (S \times T)/2, \tag{1}$$

where,

- D is the distance between the user and the obstacle.
- S is the speed of sound is in meters per second.
- Time T is calculated by dividing distance with speed of echo in micro per second.

2) PIR SENSOR

PIR stands for Passive Infrared Sensor. This sensor is employed to detect motion in its vicinity. It is commonly used with LED lighting systems, with the PIR sensor as the input and the LED light serving as the output device. The sensor features three pins: VCC, GND and central output pin. PIR sensors are termed "passive" because they don't emit any energy for detection purposes. Instead, they rely on detecting energy emitted by other objects, including humans and animals. The core principle behind PIR sensors is that objects with an internal temperature of approximately 0 degree Celsius emit heat energy in the form of infrared radiation [23]. It's essential to note that these infrared emissions are invisible to the human eye, and PIR sensors are specifically designed to detect these emissions. Their maximum detection range extends up to 7 meters.

3) ARDUINO UNO R3

Microcontrollers are compact computing units integrated into this model to process data efficiently. These devices can execute small software programs while consuming minimal power, making them suitable for battery-powered applications. Arduino, a well-known company specializing in microcontroller platforms, providing versatile circuit boards for seamless integration. Among the various Arduino boards, the Arduino uno stands out as an affordable and reliable option, utilized in this smart system for its efficiency and simplicity.

4) WI-FI MODULE OF OBSTACLE DETECTION MODEL

Wi-Fi module is likely related to communication and data transmission. This module connects to a Wi-Fi network, allowing the obstacle detection model to communicate with other devices or as central server.

5) ANDROID APPLICATION FOR OBSTACLE DETECTION MODEL

The smartphone module of the warning system is used to transmit data from hardware to the server. Wi-Fi modules transmit data from the server to Firebase cloud for visualization, analysis and classification of dataset through Wi-Fi. After processing this dataset transmit to the android app for the user. Text to speech feature is to send voice messages to the user.

Figure 2 depicts the flowchart of an obstacle detection model utilizing ultrasonic and PIR sensor, buzzer and Arduino Uno, and a mobile application for Text-to-Speech audio.

The flowchart of the proposed model using ultrasonic and PIR sensors, buzzer and Arduino Uno, and a mobile application for Text-to-Speech audio can be broken down into steps. Below is the description of the process.

1) Start: indicate the start of the system.
2) Initialize hardware and sensors.
3) Check for obstacle is there any obstacle detected.
4) Analyse obstacle, if detected check distance and whether the object is static or moving.
5) Determine location and position of the obstacle.
6) Update the user's navigation path.
7) Notify the user about the detected obstacle via audio.
8) If IoT is integrated, send data to the Firebase server for monitoring.
9) Return to check obstacle again.

In Figure 3, the process of transmitting the real-time dataset to Firebase is illustrated. Real-time data transmitted

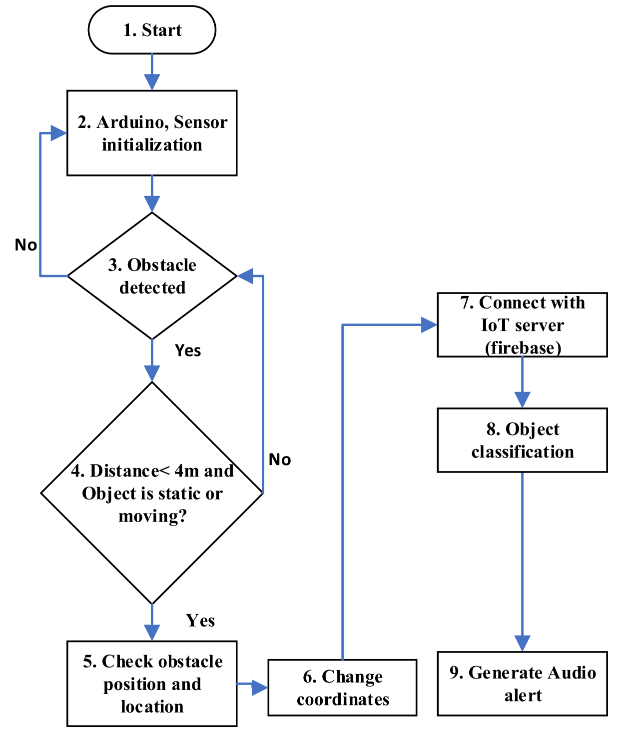

FIGURE 2. Flowchart for obstacle detection model.

to the firebase, making it available to a mobile application. Firebase has been configured by enabling to the Realtime Database. Firebase added to sensor device's software. Then run the code for the collection of data from sensors. Formatted the data appropriately for Firebase, as JSON object. Firebase SDK is used on sensor device to establish a connection to firebase. The data is transmitted to Realtime database module. During transmission secure authentication and authorization mechanisms is monitored.

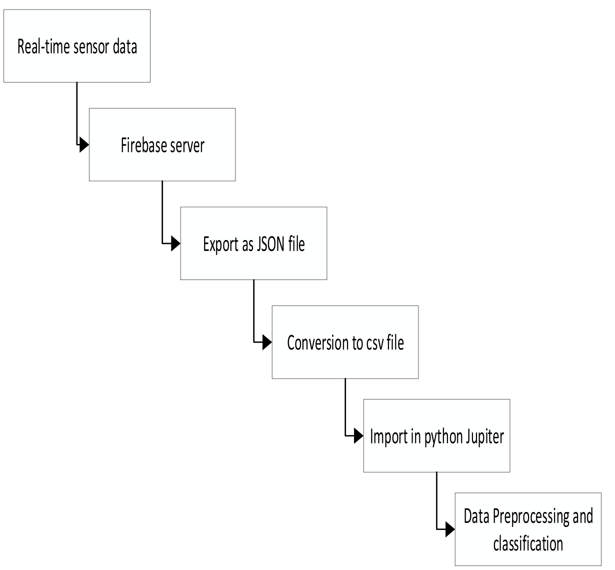

FIGURE 3. Data transmission process of Obstacle detection model.

The Firebase has been configured by enabling the Realtime Database as shown in Figure 3. The firebase was added to the sensor device's software. Then run the code for the collection of data from sensors. Formatted the data appropriately for Firebase, as JSON object. Firebase SDK is used on sensor devices to establish a connection to firebase. The data is transmitted to the Realtime database module. During transmission secure authentication and authorization mechanisms is monitored. Firebase security rules applied to restrict access to the sensor data and ensure that only authorized users and devices can read or write data. Mobile application is developed using development framework in English language. Firebase is integrated with the mobile app by adding the Firebase SDK for the target platform. Used Firebase SDK function in the mobile app to read data from the Firebase Realtime Database. Subscribe to the data changes to receive updates in real-time.

Process the received sensor data and display it within the mobile application's user interface. This may involve visualizing data or triggering alerts based on sensor readings. Implemented user authentication within the mobile app to ensure that only authorized users can access the sensor data. We have also implemented error handling mechanisms in both the sensor device and the mobile application to manage connectivity issues or unexpected data discrepancies.

6) USED ALGORITHM FOR OBSTACLE DETECTION MODEL

After data collection the algorithm used in this model is discussed below, Table 2 presents the machine learning classifier algorithms utilized in the study, after connecting with firebase dataset has been pre-processed, split into test train and classified by using machine learning classifiers.

After data collection the algorithm used in this model is discussed below

TABLE 2. Machine learning classifier algorithm.

Algorithm MLC //Machine Learning Classifier

1. Set Wi-Fi/ Bluetooth-connection
2. **if** Wi-Fi/Bluetooth status = connected **then**
3. Call - Firebase-database
4. **if** Connection == connected **then**
5. dataset_file = Read pd. read_csv _ Firebase-database
6. dataset_file = Call Normalize (dataset)
7. X_train, X_test, y_train, y_test = train_test_split (X, y, random state=2, test size=0.25)
8. dataset_file = Apply Base Classifiers (train data)
9. text synthesis-audio voice signal
10. **end if**
11. **end if**

Accurate and timely detection is a critical aspect of this model. Errors in parameter measurement could result in accidents or other adverse outcomes. To address this, the proposed real-time obstacle detection system aims to enhance safety by minimizing such risks. Its notification mechanism intelligently informs visually impaired users about their immediate surroundings, helping them avoid collisions.

B. RESULTS AND DISCUSSION

1) PRE-PROCESSING STEPS USED IN OBSTACLE DETECTION MODEL

Pre-processing plays a crucial role in preparing sensor data for obstacle detection using ultrasonic and PIR sensors. The input data was collected by connecting the sensing devices, and missing, null and NaN values in the dataset were addressed through a robust pre-processing pipeline, including imputation and normalization techniques.

Steps followed to pre-process the data are given next.

- **Data Collection**: Gathered data from the ultrasonic sensor (distance measurements) and the PIR sensor (motion detection) as they continuously monitor the environment.
- **Data Cleaning**: Removed noisy or erratic data points to enhance the data quality and accuracy. Calibrate the sensor data to account for any inaccuracies, such as variations in sensor readings due to environmental conditions.
- **Synchronization**: Ensured that the data from the Ultrasonic and PIR sensors are synchronized in time to correlate motion events with the corresponding distance measurements.
- **Normalization**: Data has been normalized to ensure that values from both sensors are on a consistent scale, preventing one type of data from dominating the analysis.

These pre-processing steps optimized the sensor data for analysis and classification, enabled the obstacle detection model to accurately identify obstacles, their distances and the presence of motion, enhancing the safety and mobility of users.

2) DECISION SUPPORT RULES

Obstacle detection model used decision support rules to analyze the dataset. 5 machine learning algorithms are used to analyze the data from the input and output is concluded on the bases of rule set provided during dataset. Our Obstacle detection model used some decision rules given in table are designed by observing the ranges of the obstacle detection (distance, echo, time and motion). Table 3 displays the Decision rules applied on the dataset.

TABLE 3. Decision support rule.

Motion detection	Echo	Distance	Classes	Labels
High	108in	0 - 0.5	0	Collision
High	109in	0.5 – 1.0	1	Alarming
High	110in	1.0 – 2.0	2	Warning
High	472in	2.0 – 3.0	3	Danger
Low	2in	3.0 – 4.0	4	Normal

Decision rules are applied on the dataset, user will be notified with collision if the obstacle came closer between 0 to 0.5 meters, if the obstacle is 1 meter away user will be notified with alarming, 1 to 2 meters away obstacle gives the message of warning and at the distance of 3 to 4 meters he is in normal situation. The detection range or the sensors are from 0 to 4 mm. The values are taken on Arduino application. The total number of instances used is 240. After testing the model with laptop, we made an android app to get the data of sensor on the mobile app.

Distance, echo and motion detection are used as parameters or other sensors. If the motion is detected it will count as High and if the motion is not detected it is counted as Low [24]. There are many applications used previously for classification e.g. Ningbo Long used CNN for image classification to monitor the surroundings [25]. In all the previous work done on obstacle detection, many other techniques used for classification.

3) TESTING SCENARIO OF OBSTACLE DETECTION MODEL

Experiments were conducted under various conditions to evaluate the performance of the proposed model:

The model was tested on a road sensor to detect obstacles efficiently during the user's walk using a wearable knee glove. The system demonstrated a high level of accuracy in identifying common obstacles such as uneven surfaces, stationary objects and moving vehicles, ensuring real-time adaptability for navigation. The user relies on the wearable smart knee glove obstacle detection model equipped with ultrasonic and passive infrared (PIR) sensors, a buzzer and a microcontroller to ensure a safe journey. During walk ultrasonic sensor constantly emitting high-frequency sound waves and measuring the time it takes for them to bounce back after hitting obstacles. A PIR sensor is positioned on the front of the device, monitoring user's surroundings for the presence of living beings through changes in thermal radiation. An audible alert system in the device, which can emit different patterns of beeps to communicate information about obstacles or hazards. The brain of the system, processing data from the sensors and controlling the buzzer to provide real-time feedback to the user.

4) TEST CASE 1 IN STANDARD ROAD CONDITIONS

The user is on his way to the grocery store on the street. As they step out of their house and onto the sidewalk, the obstacle detection system is activated. Ultrasonic sensor detects obstacles like lamp posts, trash cans, and pedestrians walking in the vicinity. The microcontroller passes this data and emits a series of quick, non-intrusive beeps to signal that there are objects at varying distances. PIR sensors constantly scan the presence of people around the user. When the person detects a nearby buzzer may emit a distinctive beep pattern, signaling the presence of a person in their proximity. Table 4 illustrates the real-time experiment conducted during a walk, where the model observed the real-time environment for 25 minutes.

During the walk the model observed the real-time environment for 25 minutes. The ultrasonic sensor provides

TABLE 4. Test case in standard road condition.

Echo	Distance	Motion detection
123in	1205cm	0
123in	1205cm	0
123in	1205cm	0
2in	5cm	1
2in	5cm	1
108in	277cm	1
108in	277cm	0
108in	277cm	0
110in	281cm	0
110in	281cm	0
110in	281cm	0
110in	281cm	0
108in	277cm	0
108in	277cm	0
108in	277cm	1
108in	277cm	1
109in	278cm	1
109in	278cm	1
109in	278cm	1
109in	280cm	1
109in	280cm	1
108in	277cm	1
107in	274cm	0
105cm	250cm	0
2in	5cm	0
2in	5cm	0

continuous values corresponding to the distance, echo and time it measures within its specified range. These values are in centimeters. PIR sensor provides binary output. They either output a "High" signal (1) when motion or presence is detected within their range or a "Low" signal (0) when there is no motion. PIR sensor provides continuous value during the test. We have tested the traffic user detects in his surroundings for extremely fast speed bikes or cars, model gave alert to save him with the buzzer and the other sensors. Intensity of the buzzer and ultrasonic sensor increases as the obstacle comes closer.

5) TEST CASE 2 IN COMPLEX ENVIRONMENTS (RAINING AND WET CONDITION)

To assess the robustness of the model, additional experiments were carried out in environments with varying obstacle detection, including crowded streets, construction zones and narrow pathways in rainy weather. The multi-sensor fusion approach significantly improved obstacle detection accuracy and resilience, even in cluttered and unpredictable settings. Although the system performed well overall, some challenges in identifying transparent obstacles, such as puddles, were observed which highlight areas for further refinement. Table 5 shows the values of the dataset acquired from experiment 2.

TABLE 5. Test case in low-light environment.

Echo	Distance	Motion detection
108in	272cm	1
108in	272cm	1
108in	273cm	1
472in	273cm	1
472in	273cm	1
472in	275cm	1
108in	275cm	0
109in	275cm	0
109in	281cm	0
110in	281cm	0
110in	281cm	0
110in	281cm	0
108in	270cm	0
108in	5cm	0
108in	5cm	0
108in	265cm	1
109in	270cm	1
109in	270cm	1
109in	270cm	1
109in	280cm	1
109in	280cm	1
2in	277cm	1
107in	274cm	0
105in	250cm	0
472in	4cm	0
472in	4cm	0

To evaluate the performance of an obstacle detection model, chairs, sofa other home-hold equipment have been detected by ultrasonic and PIR sensor. PIR gives the output 1 as High as it faces person by detecting temperature. For the other things it detects as 0 "Low". Smart phones relate to Wi-Fi devices to pair the sensor data is shown on the mobile screen.

6) CLASSIFICATION RESULTS OF OBSTACLE DETECTION MODEL

The results indicate that the inclusion of multi-sensor fusion and ensemble machine learning techniques enables the model to handle diverse environmental conditions effectively. While preprocessing addressed the sensitivity of sensors to missing or noisy data, ongoing refinement is essential to further improve detection under extreme and dynamic scenarios. The experiments conducted in complex environments and under low-light conditions emphasize the robustness and adaptability of the proposed system, making it a promising solution for real-world applications, particularly for visually impaired users.

Base classifiers were used to perform the classification of the obstacle detection model. Ensemble technique used on multiple base classifiers to improve overall predictive performance. This method helped to leverage the wisdom of the crowd, harnessing the strengths of individual classifiers while mitigating their weaknesses. The use of ensemble technique proves a powerful strategy for enhancing model robustness and generalization. Model is trained with five classifiers. The Average mean of Precision for trained objects is 0.95. The Average F1-score for trained objects is 0.95. The basic threshold of obstacles is set to 4mm. If the sensor detected the obstacle and the distance measured goes below the threshold, it is classified that the user and the obstacle is to be alarmed about that. Otherwise, another condition is satisfied about the obstacle and its information is conveyed. Performance analysis is shown in the chart.

7) CROSS-FOLD VALIDATION RESULTS OF OBSTACLE DETECTION MODEL BY USING COMPLEX DYNAMIC DATASET

To evaluate the robustness and adaptability of the proposed model, additional testing was conducted under two challenging conditions: *complex dynamic scenarios* and *low-light conditions*. These scenarios mimic real-world challenges to assess the performance of various classifiers utilized in the system. The following results highlight the accuracy of classifiers in these environments and provide insights into their behavior under adverse conditions.

Cross-validation is used to evaluate the performance of machine learning models. In a 5-fold cross-validation, the dataset of outdoor environment is divided into five equal "Folds" [24]. The model is trained and evaluated five times, with a different fold serving as the test set in each iteration, while the other four folds are used for training. This process helps assess the model's performance on multiple test sets, reducing the risk of overfitting or random variations. It utilizes the entire dataset for both training and testing, maximizing the data usage. This process helped in identifying potential issues like data imbalance and model variance. In Table 6, the results of the cross-validation experiment are presented.

For each of the 5 iterations, we have used four out of five folds for training the obstacle detection model. This forms the training dataset for the current iteration. The remaining one-fold served as the test set for current iteration. Accuracy, precision, recall and F1 score are calculated to measure the performance of the model. This method proves to be very useful across different scenarios and datasets.

TABLE 6. Results for five-fold cross-validation or complex environment dataset.

DT	RF	SVM	KNN	GNB
0.91	0.94	0.91	0.94	0.91
0.88	0.94	0.88	0.91	0.88
0.94	1.00	0.97	0.97	0.91
1.00	0.97	0.97	0.97	0.83
1.00	1.00	0.97	1.00	0.88

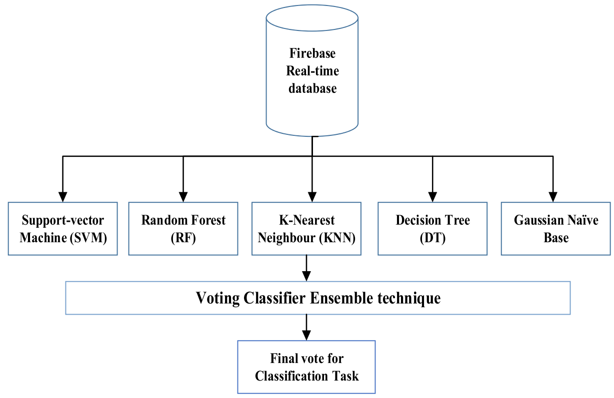

FIGURE 4. Machine learning classifiers are used in obstacle detection models.

Figure 4 shows the classification of an obstacle detection system. Five machine learning algorithms are used to check the accuracy of the model. Support Vector Machine, K-Nearest Neighbor, Decision tree, Random Forest and Gaussian-naïve base algorithms are used for the classification and Gradient booting ensemble technique is applied on the results of algorithms to vote the final classification result. In real time scenarios with higher dimensions, parameters of sensors are used as feature vectors. In this contrast distance, motion detection and echo are feature vectors for the classifiers to exploit the frequency diversity among the flow.

The following equations represent measurement for our used classifiers.

$$Accuracy = \frac{TP + TN}{FP + FN + TP + TN}, \tag{2}$$

$$Recall = \frac{TP}{(TP + FN)}, \tag{3}$$

$$Precision = \frac{TP}{(TP + FP)}, \tag{4}$$

$$Fmeasure = 2 \times (\frac{\boldsymbol{Recall \times Precision}}{(\boldsymbol{Recall + Precision})}, \tag{5}$$

We have used these equations in our model to calculate the accuracy of our models. TP represents true positive predicted instances and TN represents true negative; FP represents false positive of predicted instances whereas FN is the false negative of predicted instances.

The training data, including both validated and unused portions, is merged to construct the detection model. This process utilizes parameters derived from k-fold validation,

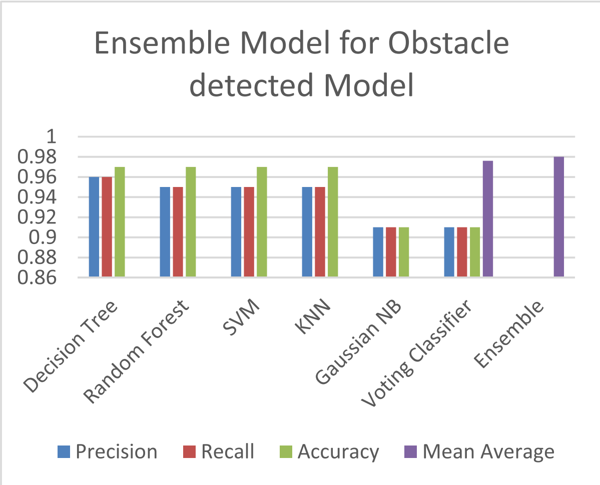

FIGURE 5. Accuracy comparison of base classifiers by using complex dynamic environment dataset.

as illustrated in Figure 5. The resulting model is saved for further applications. During the testing phase, the unused data is combined to create a feature vector that serves as input for the detection model [25]. The detection model, developed during training, predicts the class corresponding to the given input values. 20% of data was used for the testing and 80% data was used for the training purpose of the model. Ensemble technique is applied on the base classifiers achieved 98% accuracy.

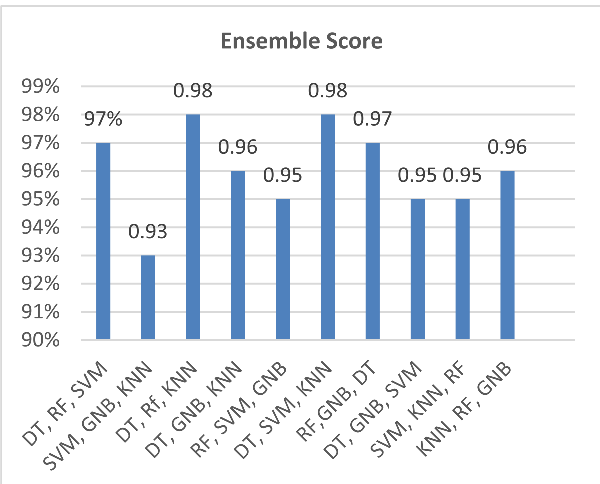

FIGURE 6. Ensemble comparisons of base classifiers.

Figure 6 shows the results of Ensemble Comparisons. Accuracy is checked with every 3 pair of classifiers to improve the model accuracy. Every 3 classifiers gave the ensemble results between 95% to 97%. Decision Tree, Random Forest and SVM gave accuracy of 97%. SVM, Gaussian and KNN gave accuracy of 93%. Each classifier has a comparison with the other 2 to vote the results of the model. 11 pairs are used to apply ensemble technique to improve accuracy, and all the pairs gave accuracy between 93% to 97% which means this Obstacle detection model is working perfectly. In Table 7, the comparative analysis of the proposed model is illustrated. It has been differentiated with some techniques used in existing work.

8) PERFORMANCE IN LOW-LIGHT CONDITIONS

The following results highlight the accuracies of classifiers in low-light conditions.

TABLE 7. Accuracies of classifiers in low-light conditions.

Classifier	Test 1	Test 2	Test 3	Test 4	Test 5	Average Accuracy
DT	0.91	0.88	0.94	1.00	1.00	0.946
RF	0.94	0.94	1.00	0.97	1.00	0.97
SVM	0.91	0.88	0.97	0.97	0.97	0.94
KNN	0.94	0.91	0.97	0.97	1.00	0.958
GNB	0.91	0.88	0.91	0.83	0.88	0.882

Under low-light conditions, the RF classifier again outperformed others, achieving the highest average accuracy of 91%, while DT and KNN also demonstrate reasonable robustness with accuracies of 87.8% and 88.2%, respectively as shown in Table 8. GNB struggled significantly in these scenarios and low-light conditions. These results demonstrate that while the proposed model achieved 98.34% accuracy overall, its robustness in challenging environments varies across classifiers. RF consistently exhibits superior performance in both complex dynamic scenarios and low-light conditions, suggesting it is a more reliable choice for real-world applications. Enhancements to other classifiers may improve their adaptability to diverse conditions, making the system more versatile and robust.

Table 9 shows the comparison of the proposed ensemble model with existing approaches demonstrated its superior performance across key metrics such as accuracy, precision and recall. The results underline the effectiveness of integrating ensemble techniques and cross-validation strategies for obstacle detection, especially in challenging real-time scenarios. In addition, the proposed model addresses the limitations of existing techniques, such as their reduced adaptability to complex environments and reliance on specific datasets, by incorporating a more generalized and scalable approach. This ensures higher reliability and precision in applications like obstacle detection for visually impaired users or dynamic vehicular environments.

IV. DISCUSSION

Obstacle detection for visually impaired individuals using machine learning holds great promise and has been significant advancements in recent years. This technology has improved the independence, mobility and safety of visually impaired individuals in real-time environments. By integrating advanced sensor technology and machine learning algorithms, the proposed systems offer not only enhanced situational awareness but also a novel contribution of real-time detection and personal adaptability, which addresses critical gaps identified in existing solutions.

TABLE 8. Comparison analysis of complex dynamic environment with existing system.

Model	Accuracy	Precision	Recall	Detection Range	Environment
OW-YOLO, [27]	77.9%	78%	77%	5 meters	Normal lightweight
YOLO-OD, [28]	30%	30%	30%	Feature Weighting Block	Publicly available dataset
Optical flow-based detection, [29]	75%	75%	75%	Visual information	Mid-Air collision avoidance
YOLOv5, [30]	85%	85%	85%	2D positional information	Real-world train operation
Proposed model (Ensemble)	98.34	0.97	0.97	4 meters	Complex, dynamic environment

This system assists users in navigating their surroundings while ensuring a more dependable experience through real-time alerts and guidance. Unlike prior systems, our model incorporates multi-sensor data fusion and ensemble machine learning techniques to improve accuracy and resilience across diverse environmental conditions. The choice of the model depends on factors such as cost, effectiveness and specific user needs. Real-time feedback remains one of the most significant advantages of machine learning systems, enabling users to make quick decisions and avoid obstacles. However, challenges such as false negative or positive and limitations in detecting transparent objects or water pools, persist and require further attention. In this regard, the proposed system addresses the sensitivity issue by integrating multiple sensors, yet further refinement is essential to tackle more complex real-world scenarios. Enhancing the model's ability to address these challenges is crucial for increasing user trust and safety. Moreover, incorporating security mechanisms for user data and system integrity sets this work apart, ensuring both privacy and robustness in deployment.

The model can be customized according to the requirements of the user, and its predictions can be further improved. Incorporating user-centered design principles, adaptive algorithms and robust testing in dynamic environments can lead to solutions that effectively bridge existing gaps and ensure consistent reliability in diverse settings. This approach establishes a foundation for next-generation systems that align with the evolving needs for visually impaired individuals, paving the way for more accessible, reliable and secure technologies. By leveraging these advancements, technology can profoundly enhance the independence, confidence and quality of life of visually impaired individuals.

V. CONCLUSION

The development of an obstacle detection and alert system using machine learning has demonstrated its potential to significantly enhance the mobility and independence of visually impaired individuals. By leveraging advanced sensor technologies, real-time processing capabilities and machine learning models, the proposed system provides accurate and reliable obstacle detection within a 4-meter range, achieving a classification accuracy of 98,34%. Despite its effectiveness, certain limitations, such as range constraints, sensor sensitivities and challenges in dynamic environments, highlight areas requiring further exploration. Addressing these gaps through advancements like longer-range sensors, adaptive algorithms and enhanced real-world testing will pave the way for broader applications.

The integration of user-centered design principles, customizable features and continuous innovation ensures the system's adaptability to individual needs, making it a valuable tool for improving the quality of life of visually impaired users. This study establishes a strong foundation for future research and development in assistive technologies, emphasizing the importance of robust, real-time solutions that cater to diverse and complex environments. By addressing current limitations and incorporating emerging technologies, this work offers a pathway to creating more inclusive and empowering solutions that bridge critical accessibility gaps for visually impaired individuals.

VI. LIMITATIONS AND FUTURE WORK

While this obstacle detection and alert system shows promising results with 98.34% classification accuracy and effective detection within a 4-meter range, several limitations are noteworthy.

A. RANGE CONSTRAINTS

The system has a detection range of only 4 meters which may not be sufficient for high speed and outdoor environments where the obstacles to be detected are at larger distances. Such a limitation might limit its applicability in open areas or in conditions which require fast reaction rates.

B. SENSOR DEPENDENCIES

Another limitation that arises from the use of ultrasonic and PIR sensors will be the capability of the system to comprehend all sorts of barriers. Real-time detection of an object may be affected by the sensitivity of the sensors and thus, the option like the ultrasonic sensors may be less precise when used on items that are narrow or have irregular cross-sections.

1) ENVIRONMENTAL SENSITIVITY

The environment affects performance by factors such as noisy environments while PIR sensors are sensitive to temperature changes making the system less versatile in different conditions.

2) MODEL COMPLEXITY AND PROCESSING POWER

The model involved in the ensemble approach is generally a large one: even more so when there are multiple classifiers involved such as DT, SVM, KNN, RF and GNB- the number of performances might not be optimized and adequate which may limit the apt implementation of the model. Especially on devices with low computational power such as the Arduino Uno. Such an integration may require using more computationally efficient algorithms or even new dedicated hardware for real-time processing under such conditions.

3) REAL-WORLD TESTING

Cross Validation gives good estimates of the performance but real-world testing in different environments is restricted. The model could be less accurate in complex, dynamic environments, for example in the city or indoors where more testing is required.

4) USER-SPECIFIC ADAPTATIONS

The proposed system does not fully take into consideration the rate at which different users walk or their movement pattern thereby affecting the system's real time performance and usability. The options for adaptation to the user's needs and preferences might enhance the accessibility of the site.

In future work, improvements like the use of longer-range sensors, the use of adaptive algorithms and more extensive real-world testing could help refine the system and expand its usefulness in a wide variety of situations.

DATA AVAILABILITY

The primary data used to support the findings of this study is available and will be provided on request.

CONFLICTS OF INTEREST

The authors have disclosed no potential conflicts of interest concerning the authorship and/or publication of this article.

AUTHORS' CONTRIBUTIONS

Sunnia Ikram contributed to the methodology, data coding, data validity, and writing. Imran Sarwar Bajwa contributed to writing articles and supervision. Amna Ikram contributed to data collection and verification. Isabel De La Torre-Díez contributed to Sensor Connectivity. Carlos Eduardo Uc Ríos has data validity. Ángel Gabriel Kuc Castilla has worked on performance validation.

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SUNNIA IKRAM received the M.S. degree in computer science from The University of Lahore. She is currently a Lecturer with the Department of Software Engineering, The Islamia University of Bahawalpur, Pakistan. As a dedicated educator and a researcher, she continues to push the boundaries of AI-driven solutions, integrating computer vision, pattern recognition, and real-time sensor data processing into practical applications. She has made significant contributions to the field of the IoT, artificial intelligence, and sensor fusion technology. She is a distinguished academic and a researcher specializing in computer networks, the Internet of Things (IoT), and deep learning applications.

IMRAN SARWAR BAJWA received the Ph.D. degree in computer science from the University of Birmingham, U.K. He has more than 19 years of teaching and research experience in various universities in Pakistan, Portugal, and U.K. He is currently a Full Professor at the Department of Computer Science, The Islamia University of Bahawalpur (IUB). He is the author/editor of 12 books published by IEEE, Springer, and IGI Global. He has more than 200 articles and 3100 citations in Google Scholar. In addition, he has more than 138 articles in Scopus and 1700 citations of the work in Scopus. His Google H-index is 30 and Scopus H-index is 22. His personal impact factor is more than 150. His current research interests include intelligent systems, the IoT, and data analytics. He has been an associate editor and a guest editor of various IEEE and Elsevier journals.

AMNA IKRAM received the B.S. and M.S. degrees in computer science from The Islamia University of Bahawalpur, Pakistan, in 2006 and 2016, respectively, where she is currently pursuing the Ph.D. degree in computer science. She is also a Senior Lecturer with the Department of Computer Science and Information Technology, The Government Sadiq College Women University, Bahawalpur, Pakistan. Her research interest includes cropping yield maximization using AI-driven decision-based methodologies.

ISABEL DE LA TORRE DÍEZ is currently a Professor with the Department of Signal Theory and Communications and Telematic Engineering, University of Valladolid, Spain, where she is also the Leader of the GTe Research Group. Her research interests include the design, development, and evaluation of telemedicine applications, services, and systems, e-health, m-health, electronic health records (EHRs), EHRs standards, biosensors, cloud and fog computing, data mining, quality of service (QoS), and quality of experience (QoE) applied to the health field.

CARLOS EDUARDO UC RÍOS (Student Member, IEEE) was born in Campeche, Mexico, in 1974. He received the B.Sc. degree in electronic and communications engineering from the University of Campeche, Mexico, in 1998, and the M.Sc. degree in electrical engineering from CINVESTAV-IPN, Mexico, in 2001. In 2000, he was with the University of Carmen, Mexico. In 2001, he joined the University of Campeche as a Lecturer. He is currently working with the Department of Project Management, Universidad Internacional Iberoamericana, Arecibo, Puerto Rico, USA. His research interests include cellular systems dimensioning and quality-of-service provisioning.

ÁNGEL KUC CASTILLA was born in Campeche, Mexico. He received the Ph.D. degree in engineering, with a specialization in marine and coastal engineering from the National Autonomous University of Mexico. He is currently with the Department of Engineering and Projects, Universidad Internacional Iberoamericana, Mexico. In addition, he is also with several esteemed institutions, including the International University Foundation of Colombia, Bogotá, Colombia, and the University of La Romana, La Romana, Dominican Republic. He is a Professor and a Researcher in the field of coastal engineering. His work focuses on the development of innovative solutions for the sustainable management of marine and coastal ecosystems. He has published numerous articles in top-tier journals. His research has been funded by prestigious organizations, such as the National Science Foundation and Mexican Council for Science and Technology.