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IoT-Based Smart Surveillance System for High-Security Areas

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Abstract: The world we live in today is becoming increasingly less tethered, with many applications depending on wireless signals to ensure safety and security. Proactive security measures can help prevent the loss of property due to actions such as larceny/theft and burglary. An IoT-based smart Surveillance System for High-Security Areas (SS-HSA) has been developed to address this issue effectively. This system utilizes a Gravity Microwave Sensor (GMS), which is highly effective due to its ability to penetrate nonmetallic obstructions. Combining GMS with Arduino UNO is a highly effective technique for detecting suspected objects behind walls. The GMS can also be integrated with the global system for mobile (GSM) communications, making it an IoT-based solution. The SS-HSA system utilizes machine learning AI algorithms operating at a GMS frequency to analyze and calculate accuracy, precision, F1-Scores, and Recall. After a thorough evaluation, it was determined that the Random Forest Classifier achieved an accuracy rate of 95%, while the Gradient Boost Classifier achieved an accuracy rate of 94%. The Naïve Bayes Classifier followed closely behind with a rate of 93%, while the K Nearest Neighbor and Support Vector Machine both achieved an accuracy rate of 96%. Finally, the Decision Tree algorithm outperformed the others in terms of accuracy, presenting a value of 97%. Furthermore, in the studied machine learning AI algorithms, it was observed that the Decision Tree was optimal for SS-HSA.

Keywords: surveillance system for high-security areas; gravity microwave sensor; global system for mobile communications; Arduino UNO; random forest classifier

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1. Introduction

Currently, the popularity of real-time smart monitoring has significantly increased due to the growing demand for security systems for safeguarding property. This is because of the increasing crime rate concerning theft, larceny, burglary, and other offences. In 2021, the Federal Bureau of Investigation (FBI) reported 2,976,659 larceny/theft offenses and 586,564 burglary offenses. Most of these crimes occur in homes and buildings, with larceny/theft and burglary accounting for 60% and 81%, respectively [1], as shown in Figure 1.

Moreover, the rate of crimes committed in vacant houses is increasing daily. In these cases, the owner of a house is unable to receive information on suspected movement near their house [2]. According to the National Incident-Based Reporting System (NIBRS) and the Summary Reporting System (SRS), an effective security system is required to mitigate the loss of property. Proactive security measures can significantly reduce the rate of property loss due to larceny/theft and burglary. The existing security systems framework is based on ultrasonic identifiers, microwave indicators, CCTV, photoelectric finders, infrared locators, etc. The many parts of this framework are very costly, environmentally unfriendly, harmful to the human body, constrained by Line of Sight (LoS) and privacy, and require greater memory capacity and complex circuitry [3]. To address all these issues, an IoT-based smart, cost-effective SS-HSA was developed that utilizes frequency-based identification and alerts the person concerned by generating an SMS message or call through a GSM module [4]. It has been identified through a literature review that frequency-based identification systems are not used of detecting moving or suspected objects behind obstructions. The proposed SS-HSA aims to mitigate property loss rates via the real-time frequency-based identification of moving objects and alerting the individual concerned so that they take necessary actions in a timely manner. The major contribution of the proposed study is given herein.

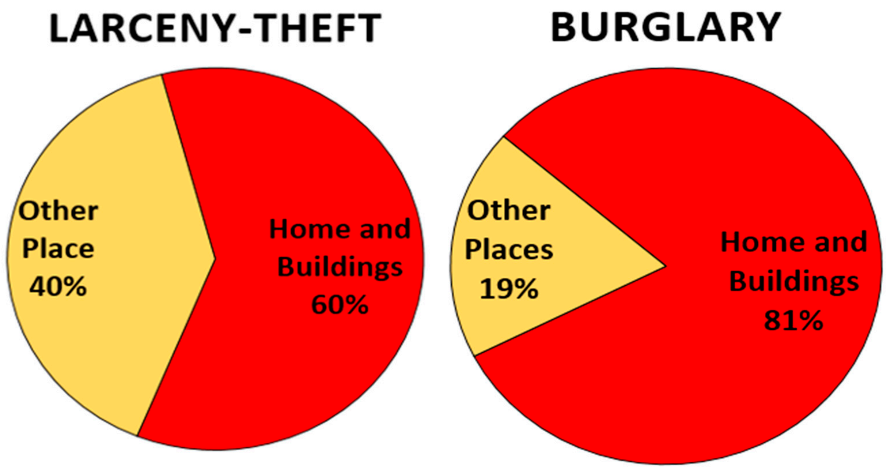


Figure 1. Percentage of crimes reported in homes and buildings.

1.1. Research Motivation

The popularity of the Internet of Things (IoT) has brought revolutionary change in every field of life [3,5–7]. The detection of an object behind a wall or obstruction is an interesting research domain for many applications. Researchers have employed different approaches to detect objects, such as surveillance via camera based on a given vicinity. In these methods, Line-of-Sight (LoS) attributes and other privacy issues, such as people's actions regarding legal problems, must be accounted for. The radio-frequency-signal-based monitoring of moving objects also requires experience working with wireless channels, which is a tricky job that requires a license. Therefore, to overcome the discussed issues, the development of low-cost devices that function using microwave signals is helpful from a human perspective as such devices allow users to see moving objects behind obstructions. To address this issue, in this study, an IoT-based low-cost SS-HSA system was developed based on the principle of microwave signals. The proposed system also generates SMS and call alerts to alert a user upon the detection of an object, allowing them to take necessary actions in a timely manner, ultimately contributing to reducing the chances of crimes such as larceny/theft and burglary. The proposed system employs a GMS module that uses a doppler effect method to accurately detect moving objects using microwave signals. No previous studies have employed this technique to efficiently detect objects behind a wall. The proposed SS-HSA provides a cost-effective solution that can be used to revolutionize human life in different ways such as with respect to home automation, gaming, healthcare, homeland or personal security, rescue services, and law enforcement. In the above-mentioned areas, SS-HAS can play a vital role in assessing any level of threat behind a wall in a hostage situation or rescue mission.

1.2. Contributions of this Study

The SS-HSA provides a cost-effective and efficient solution that resolves issues related to privacy as well as LoS. The major contributions of the proposed system are as follows.

1.2.1. Decreases Losses in the Event of Larceny/Theft and Burglary

Expanding the number crimes such as theft, larceny, burglary, and other crimes detectable in a home requires an optimal security framework. The most affected areas in this regard are houses and buildings, where larceny/theft and burglary account for 60% and 81% of crimes, respectively. By using GMS with GSM, a proactive security framework can efficiently prevent the loss of property due to larceny/theft and burglary.

1.2.2. Ambient Environment

The operation of GMS is not infected by conditions in the ambient environment, such as sunlight, dust, fog, or any other environmental condition. Noise and dust also do not interfere with its communication. Due to the discussed ambient environmental features, GMS was selected for use in SS-HSA. The previous solutions in this field have not been environmentally friendly.

1.2.3. Cost-Effectiveness

A UWB radar is used to detect the motion of living things as well as life signs such as respiration or heartbeat, but it is very costly. In contrast, GMS is cost-effective, can enable the motion detection of an object, and is suitable for security purposes, specifically the detection of a suspected object behind an obstruction.

1.2.4. Safe for Human Operation

The microwave signals emitted by GSM are not harmful to the human body. In contrast, infrared sensors cause harm because microwaves reflect radiation that is harmful to the human body, especially with respect to the sensory nervous system, which is very sensitive and easily effected by microwave radiation that passively penetrates the human body. The microwaves generated by GMS are not harmful to human organs.

1.2.5. Privacy

Monitoring using a camera privacy poses issues, especially in public places where it is illegal to use a camera to monitor other people. The legal issues regarding the installation of cameras in public places are also restricted by people. In the scenario presented herein, GMS addresses these restrictions, monitoring the movement of suspected persons without falling victim to privacy and legal issues.

1.2.6. Line of Sight

When monitoring suspected objects using CCTV, the LoS and workload of the security framework are strained because extra memory is required to process the images and a huge bandwidth is required during the transmission of video-related packets to the system. Additional costs are also required to store the backup data. Passive InfraRed (PIR) also senses LoS because it works at an angle of 35°. These issues can be resolved via SS-HSA using GMS.

1.3. State of the Art

Researchers' contributions regarding the real-time monitoring of homes and buildings to mitigate the theft, larceny, burglary, and other crimes are illustrated in Table 1. The surveillance system of a camera in a given vicinity requires accounting for the Line-of-Sight (LoS) parameter and other issues such as people's actions regarding legal problems. The electromagnetic spectrum at the 430 to 790 THz band can be used without a license. Then, Visible Light Communication (VLC) band-monitoring systems can address the limitations of RF-based as well as camera-based systems [8], allowing for the detection of the vital signs of moving objects using a single-input–multi-output signal that carries vital signs. Vital signs can be extracted using Multivariate Empirical Mode Decomposition (MEMD) and Fast Furrier Transform [9]. Microwave-based life detection systems are more appropriate in this regard than work on the X-, L-, or S-Bands [6]. Using the forwarded scatter field of electromagnetic signals, fast and accurate computations are performed to extract the vital signs of moving objects. [10]. The microwave scatter signal carries out on an X-band via the use of full 2-D geometry to target the echo signal and extract the vital signs related to the moving object [11]. Low-cost C-band Frequency-Modulated Continuous Wave (FMCW) vital sign processing takes place in three steps for the detection of moving objects [12].

Table 1. Evaluation Tools and Technique used.

Year	Purpose	Evaluation Tool	Utilized Techniques	Performance Matrixes	Datasets
2010	Object Detection	Not explicitly mentioned	Not explicitly mentioned	Not explicitly mentioned	Not explicitly mentioned
2011	Breathing Detection	Not explicitly mentioned	Not explicitly mentioned	Singular value Decomposition	Real-time
2013	Object Detection	Not explicitly mentioned	X-band	Matrix formation	Time gating
2014	Life Detection	Microprocessor	Frequency Domain	X, L, and S-Band	Real-Time
2015	Object Detection	Voltage changes	Not explicitly mentioned	Not explicitly mentioned	Real-Time
2016	Human Detection	Time Domain	Not explicitly mentioned	Through Graphics	Real-Time
2017	Breathing Detection	Microprocessor	Not explicitly mentioned	Simple Matrix	Real-Time
2018	Moving Object Detection	Not explicitly mentioned	KNN, SGD, SVM, NB, DT	Average Accuracy	Real-Time
2018	Motion Detection	Not explicitly mentioned	Frequency	Recording Time	Real-Time
2019	Action Detection	Not explicitly mentioned	CNN	Confusion Matrix	Real-Time
2020	Object Detection	Arduino IDE	Not explicitly mentioned	Not explicitly mentioned	Real-Time
2020	Object Detection	Micro Controller	DT, RFC	Not explicitly mentioned	Real-Time
2020	Human Detection	Calibration	Frequency	Back projection	Real-Time
2021	Object Movement	Matlab and Arduino	Remote Sensing	Not explicitly mentioned	Real-Time
2021	Motion Detection	Microprocessor	NBM, LRM	Confusion Matrix	Real-Time
2021	Motion Detection	RexNeXt-50	CNN	Average and Time	Real-Time
2022	Human Detection	Radar System	Not explicitly mentioned	Signal Clutter Ratio	Real-Time
2023	Object Detection (SS-HSA)	Arduino IDE	RF, BC, SVM, DT, KNN, NB	Precision, Recall, F1-Score, Accuracy	Real-time Gauge

To detect an object behind a wall, one transmitting antenna and five receiver antennas are used to extract signals, which are then stored in a 3-D array and then converted into a 2-D array for further processing [13]. The clutter reduction method of decomposition on the basis of a singular value is used for a variety of data [14]. The ResNeXt network is a transfer learning model that needs fewer epochs and produces a greater accuracy score when compared to a normal convolutional neural network built from scratch [7]. Radar systems developed by employing the method of correlation can determine the distance and velocity variations used to detect the features of moving objects [15]. The residual subspace projection approach is used in a variety of through-wall human being identification scenarios because it has enormous dimensions that can compress sensing approaches. However, a classification system ought to be utilized to identify the state [16]. The phase detection approach is often integrated with the Doppler response method, which extracts vital signs related to respiration [17]. The MUSIC (Multi Signal Classification) algorithm is another approach commonly used in this field. Different percentages of a microwave signal, such as frequency and amplitude, are used to detect living things [18]. Stepped Frequency Continuous Wave (SFCW) radars have become the standard for Ultra-Wide Band radar (UWB) detection. This system uses commercially available components and standard Wi-Fi signals for the detection and path prediction of moving objects. Specifically, it employs channel state information that may be affected by human movement [19].

Motion in a picture is estimated using a statistical-based model. Where in location is linked to the variance of moving objects. Object detection uses recursion via a Kalman filter to detect an object in a moving image [20]. Naive Bayes and Logistic Regression have been investigated in this regard. The end-to-end system described here allows mm wave radar to be classified in addition to range detection [21]. The 3D images provided by the (RF) are understandable according to human nature, addressing issues such as geometric and semantic perception tasks or classification and pose estimation addressed by supervised learning. Data gathered via RF are tested with the help of trained optical images taken on the other side of a wall. The algorithm is based on the nearest neighbor or neural network, using a CNN-based algorithm as well as pose estimation in thick material. However, some limitations related to shape classification and the filtering of the unwanted signal from original signals also exist, which can be nullified or addressed [22]. Utilizing deep learning techniques for categorization will steer research in a new path because radar signals carry important information on items hidden behind an obstruction. This study employs a convolutional neural network (CNN) and wall-penetrating radar waves to classify human postures behind walls. The suggested methodology yields amazing and effective outcomes [23].

The initial stage of intelligent video surveillance is the most important process of moving object detection, which entails differentiating the motion of foreground objects from a background model. The objective is to accurately segment and classify the moving objects, distinguishing them from other regions in an image. Enhancements have been achieved through the integration of background subtraction and deep convolutional neural network algorithms for moving object detection and categorizing irregular falling activity. This monitoring process employs rank polling to ensure accuracy and reliability [24]. The incorporation of context awareness in the algorithm leads to notable improvements in energy consumption, execution cost, network utilization, delay, and fairness. These findings confirm the efficacy of leveraging context-aware information for optimizing network performance. Autonomous management is employed to collect contexts in the monitor–analysis–plan–execution loop for all offloading processes. The simulation results relating to this approach demonstrate the superiority of the method compared to local computing and offloading without considering context-aware algorithms with respect to various metrics, including energy consumption, execution cost, network usage, delay, and fairness [25]. The early detection of fire is crucial for preventing loss of life and minimizing financial costs. Smoke and gas sensing plays a vital role in this regard. The main objective in this regard is to design an affordable and user-friendly system capable of operating in three distinct modes: gas and fire leakage detection as well as temperature monitoring. The related study aims to expedite the identification and characterization of fire incidents by equipping each node with multiple sensors for collecting temperature, smoke, and fire-flickering data. In the event of fire detection, an automatic notification is sent to a designated officer via email. By implementing this system, the project enables faster response times and improved fire incident management [26]. The collection of constituent models under consideration encompasses a wide range of time series, providing predictions through linear or nonlinear approaches. Additionally, the evaluation of data points based on the Bayesian Information Criterion (BIC) enables the smoothing of certain observed data points, as necessary.

Ultimately, the optimal model is determined using the BIC method. The obtained results validate the effectiveness of our prediction models, as they consistently outperform all other mentioned prediction models across all evaluation metrics. Based on the experimental results obtained from the CoMon project dataset, it has been observed that the proposed approach consistently achieves superior accuracy when compared to other ensemble prediction algorithms. These findings highlight the effectiveness and competitiveness of our approach in accurately predicting outcomes and outperforming alternative methods within the context of the CoMon project [27]. The domain of through-wall radar imaging and detection is witnessing substantial growth, but a major challenge lies in dealing with strong clutter that often masks a target's presence, thereby hampering accurate detection. In this research paper, a novel algorithm is introduced to address clutter reduction and target downrange correction in through-wall monostatic radar imaging. The algorithm involves organizing the received radar signals into a matrix and subsequently dividing this matrix into frames for further processing [28].

The Doppler method is often combined with other techniques that are helpful to determine the presence of living things; therefore, it is used in medical fields and rescue operations where debris has buried humans during an earthquake, explosion, or other disaster. Therefore, it is not suitable for a security framework due to its complexity. To overcome the above-discussed issues, low-cost devices that work on microwave signals are helpful from the human perspective with respect to seeing moving or suspected objects behind obstructions. These low-cost devices can be used to revolutionize human life in terms of, e.g., home automation, gaming, healthcare, rescue services, and law enforcement. In the above-mentioned areas, low-cost devices play a vital role in assessing any level of threat behind a wall in hostage situations or rescue missions. SS-HSA focuses on issues related to homeland or personal security from theft, larceny, burglary, and illegal activities performed in or near houses. For this purpose, GMS is selected because Infrared sensor (IR) ultrasound sensor radar module thermal cameras and localization sensors are affected by adverse weather conditions such as heavy rain, fog, dust, snow, and temperature fluctuations, whereas GMS is not affected in such scenarios. GMS technology has emerged as the preferred choice for many applications. It has a strong penetrative ability and range resolution capacity with respect to obstructions. It has a detection distance from 2 to 16 m and a continuously adjustable range resolution that helps to differentiate multiple objects. GMS operates at a baseband up to 10.525 GHz, granting it a strong capacity not only for penetrating nonmetallic walls but also detecting a suspected object behind a wall. In this way, using GMS, in conjunction with Arduino UNO and GSM, is helpful for taking proactive measures in real-time to prevent crimes such as thefts, robbery, burglary, and other occurring in houses. Arduino UNO is an open-source microcontroller board. A schematic of the proposed SS-HSA is shown in Figure 2.

1.4. Remaining Work

The remaining work regarding SS-HSA is organized into three sections. Section 1 describes the methodology behind SS-HSA. Section 2 describes the experiments and results of this work. Section 3 presents the conclusions and directions for future work.

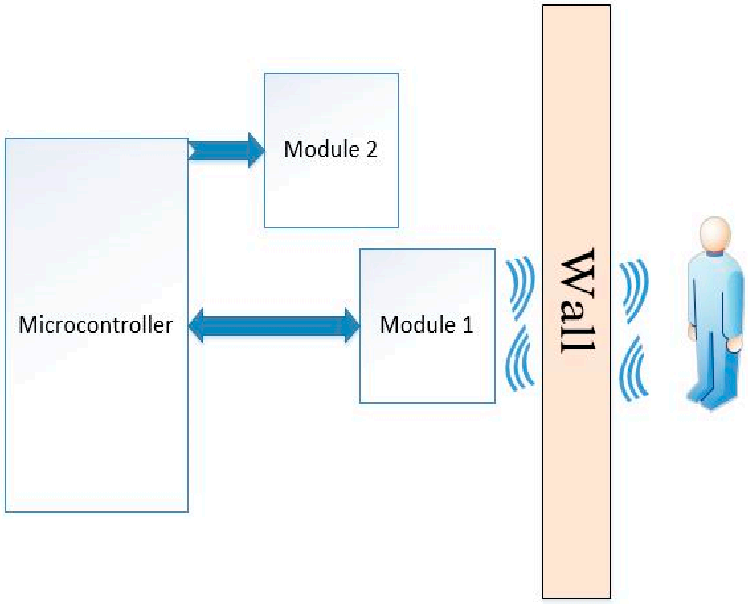


Figure 2. Real-time SS-HSA.

2. Materials and Methods

The methodology behind SS-HSA is categorized into three main sections. The initial section provides a detailed explanation of how SS-HSA operates. The second section highlights the hardware features and specifications that are employed in SS-HSA. The final section delves into the application of machine learning techniques to evaluate the precision and authenticity of SS-HSA. SS-HSA is composed of six modules. The initial module is GMS, followed by Arduino UNO, GSM, and an end-user device, such as a cellular phone or similar device. The fifth and sixth modules concern the construction of an XLSX file that contains data on detected moving objects and testing their accuracy using machine learning algorithms. The block diagram of SS-HSA is shown in Figure 3.

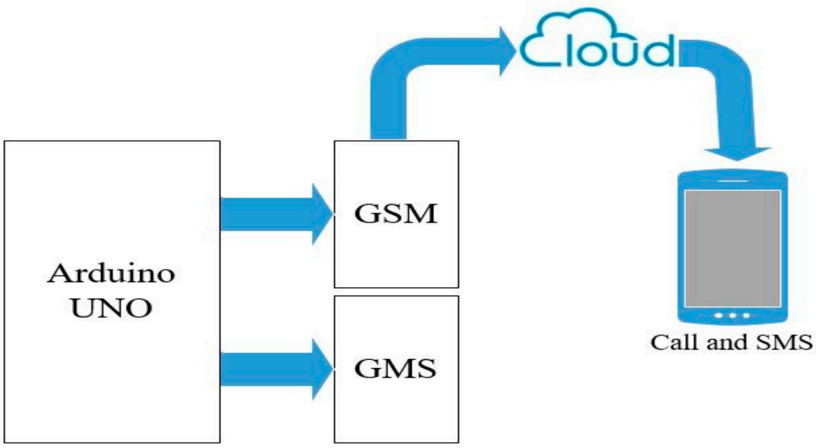


Figure 3. Block diagram of the SS-HSA.

The SS-HSA was constructed in three phases: a setup phase, a detection-of-suspected-object phase, and a notification-of-a-user-in-real-time phase, the latter of which is carried out through a GSM call and SMS generated on the end-user's device. In the first phase, 5 V is supplied to activate Arduino UNO. In the second phase, the GMS module begins detecting an object. If it finds an object, sends a notification signal to Arduino UNO that an object has been detected. In the third phase, Arduino UNO coordinates with the GSM module and instructs it to send SMS and call alerts to the end user via their mobile device.

In this way, it is possible to take necessary action upon the detection of a suspected object, which, ultimately, contributes to mitigating the loss of property as shown in Figure 4.

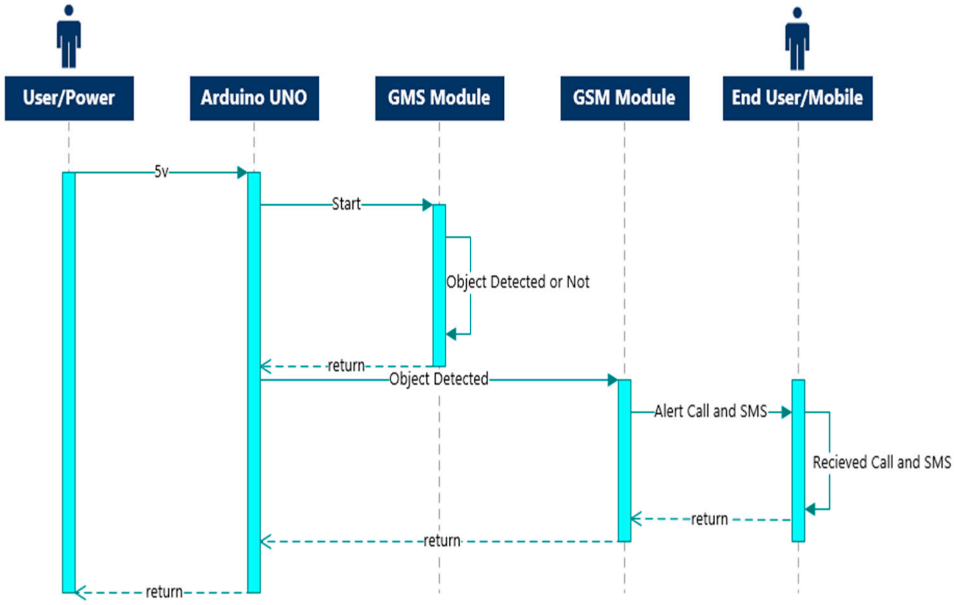


Figure 4. Sequence Diagram of SS-HSA.

2.1. The Interface and Description of SS-HSA

The presented interface and description of SS-HSA consist of three modules. The first one is GMS, which continuously senses a suspected object behind an obstruction. The transmitted signal is received in analog form after being reflected by the suspected object, converted via GMS into a digital form, and then transferred to Arduino UNO. Arduino UNO is a microcontroller that simultaneously controls GMS and GSM according to a given program via input/output pins. Arduino UNO pin2 is used to connect the GMS module with Arduino UNO, while pins 6 and 7 are used to connect the GSM module. Arduino UNO receives a digital signal from GMS and instructs the GSM module to generate SMS and call alerts. Furthermore, Arduino UNO uses the analogRead () function to read the sensed data and then the GSM module's AT commands to transfer the data to a server. The GSM is an IoT-based device. It is used to transfer calls and generate SMS messages on mobile phones using a cloud network. Unboxing of SS-HSA is to be done in the four steps, carefully remove the packing and wood, lift from box it with care to avoid any damage and inspect its components to make sure everything is included and in good condition as shown in Figure 5.

2.2. Operational Mechnaism of SS-HSA

The operational mechanism of Arduino UNO is divided into three phases. The initial phase is the "setup", where a burn code is deployed to the system along with the mobile number of the relevant person. If there are no errors, a physical connection is established. The next phase is the "detection" phase, which involves detecting the suspected object and turning on its specific pin to inform Arduino UNO of the successful detection of an object. Once the suspected object is detected, Arduino UNO transmits the information about it to the relevant user through GSM. The third phase, also referred to as the "repetition" phase, involves continuously executing the program in a loop to detect suspected objects for a specific duration. Arduino UNO is connected to both GMS and GSM modules simultaneously, operating as an IoT base powered by 5 V. GMS is placed in the designated area to detect suspected objects continuously, even behind walls. It sends sensing data to Arduino UNO via its data port; then, Arduino UNO processes the data to detect any suspected objects. When Arduino UNO successfully identifies a suspected object, it triggers a message to GSM via ports 7 and 8 for IoT purposes. GSM operates as an IoT device and notifies the concerned entity via call and SMS to take reactive measures accordingly as shown in Figure 6.

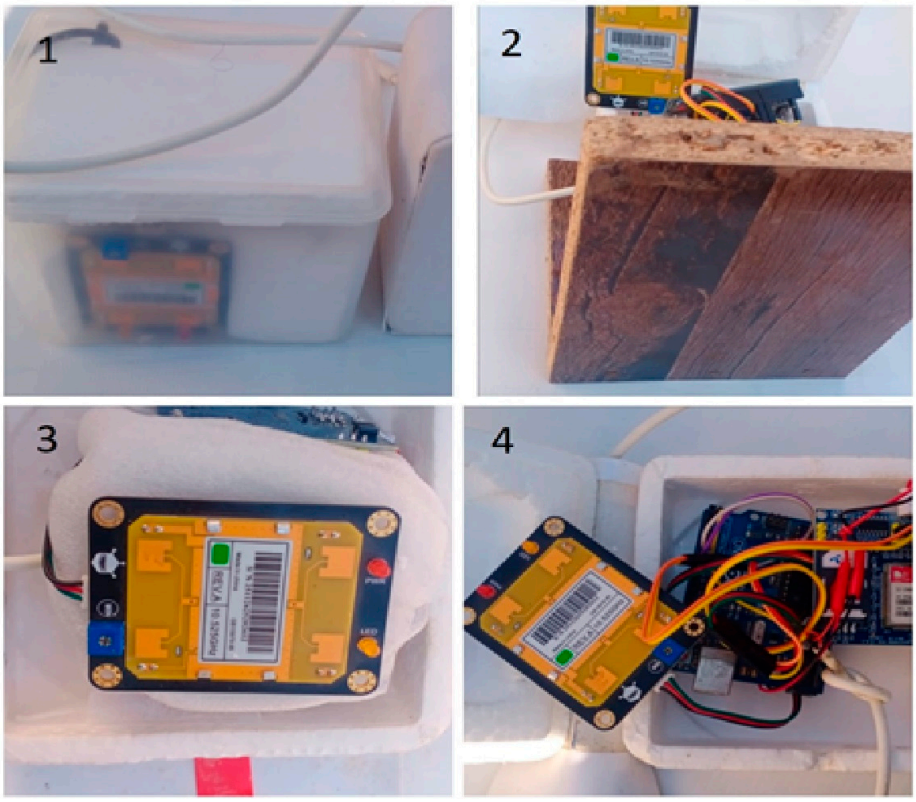


Figure 5. Physical interface.

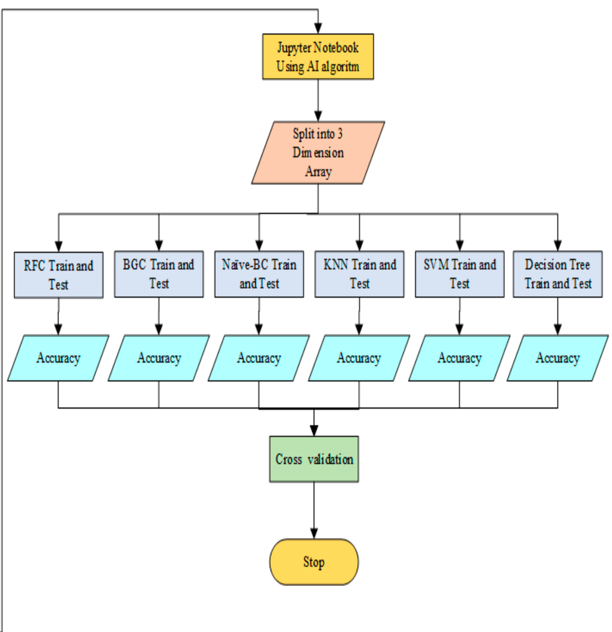


Figure 6. Data flow.

During the third phase, validity and accuracy are tested using machine learning models. At this stage, Arduino UNO constructs an XLSX file that contains processed data related to object detection, including whether or not an object is in motion. This XLSX file is then imported into Jupiter Notebook, where its validity is tested using various AI algorithms as shown in Figure 6.

2.3. Hardware Components Used SS-HSA

Arduino UNO is an open-source, programmable microcontroller that is cost-effective and portable. GMS is also cost-effective and can be used to monitor moving objects, even behind obstructions, without being affected by ambient environmental factors. In addition, it can send real-time alerts via calls or SMS using GSM, making it an IoT-based system.

2.3.1. Gravity Microwave Sensor v2.0

A gravity microwave sensor is based on a microwave signal that can penetrate a dielectric material and detect moving objects easily. Microwaves are also very sensitive to changes associated with boundary interfaces that detect minute variations in the shape and dimension of a moving object. The scattered signals contain information on phase and magnitude. The attenuation information is also used to determine the structure of the moving object. Using the detection of moving objects via microwaves, the GMS can track the location of a moving object behind an obstruction, which can also assist in the search process after a disaster, allowing the search-and-evaluation process to be carried out efficiently.

2.3.2. Global System for Mobile (GSM) SIM900A

GSM is used to communicate with mobile-based systems because mobile systems are widely used. GSM uses less power and is cost-effective. Its installation is very simple, with a small footprint of $24 \times 24 \times 3$ mm. The GSM is digital cellular and open-source technology that plays a vital role in making any system IoT-based. The frequency used to send data and transmit voices is the 900/1800 MHz band. This corresponds to the GSM and GPRS dual-band. For communication purposes, different techniques are used, such as frequency division multiple access and others, while the GSM uses time division multiple access to communicate with a mobile system. The GSM overcomes the use of bandwidth by digitizing and reducing the size of data.

2.3.3. Arduino UNO

The Arduino UNO ATmega328P is an open-source and programmable hardware device that is used in many projects for a variety of purposes. It is suitable for SS-HSA because it is cost-effective, easy to handle, and flexible. It contains Integrated Development Environment (IDE) that is used to develop a computer program that is integrated into its physical circuit board. A regular USB link is used to develop a program on Arduino UNO. There are three different methods to supply power: using an AC-to-DC converter, using a battery, and, the most widely adopted, plugging in a USB cable. For SS-HSA, the last strategy was chosen for the power supply. Its input voltage limit is six to twenty volts, but a range of seven to twelve volts is recommended, and it operates on five volts efficiently.

2.4. Classification Model

Six machine learning algorithms were employed to test the validity and accuracy of SS-HSA. These algorithms are Random Forest Classifier, Booster Classifier, Naive Bayes Classifier, KNN Classifier, SVM Classifier, and the Decision Tree.

2.5. Time Complexity of Proposed Solution

The length of an input determines how long it takes an algorithm to run, which is known as time complexity. This measure determines how long it takes for each code statement in an algorithm to execute. One frequently considers the worst-case time complexity scenario, which is the highest amount of time needed for inputs of a particular size, because an algorithm's running time may vary across several inputs of the same size. The average-case complexity, which measures the average amount of time spent on inputs of a given size and is less common and typically expressed explicitly (because there are only a finite number of possible inputs of a given size), was reasonable for application in this case. Time complexity is often expressed in both scenarios as a function of the input size. Since the exact computation of this function is typically challenging, and the running time for small inputs typically has little bearing, attention is usually focused on the complexity's behavior as the input size grows, that is, the complexity's asymptotic behavior. Consequently, Big O notation is frequently used to indicate time complexity [29]. The data flow of SS-HSA is shown in Figure 6, which describes the complete process of execution from start to finish. There are n number of statements that will be executed repeatedly depending upon the supply of voltage, which is required to trigger functional mode. Additionally, k time period is required to execute each statement. Therefore, the time complexity of the proposed SS-HSA is O (n $\times$ k), indicating that is linear in nature.

3. Results

3.1. Data and Information

During the experiment, the dataset was acquired in different places because Arduino UNO is not affected by the ambient environment. When it was used in a home, 1600 executions were performed. When it was used in a garage, 1200 executions were performed, while when it was used at a shopping center, 1150 trials were conducted. However, when it was used in governmental buildings, especially police stations, 1000 experiments were performed. Hence, the total number of records collected is 4950.

3.1.1. Frequency

The GMS produces an analog frequency, which remains in an analog form even after bouncing off a potential target. The GMS converts the analog signals into digital format and makes a decision regarding whether an object has been detected; afterward, the information is forwarded to Arduino UNO for further processing.

3.1.2. Decision

The GMS employs a Doppler Effect technique to determine whether or not a detected object is a potential target. This decision is based on the phase shift of the frequency component. Additionally, Arduino UNO is also used in the process. When the GMS successfully detects an object, the signal is converted into a numeric form, namely, 1, whereas when no object is detected, a numeric value of 0 is assigned.

3.2. Output of SS-HSA Concerning Frequency

The original XLSX file generated data constructed by the Arduino UNO that received a signal from the GMS; these data indicate whether the suspected object was successfully detected against the reflected frequency as shown in Table 2.

3.3. IoT-Based Generated Call and SMS

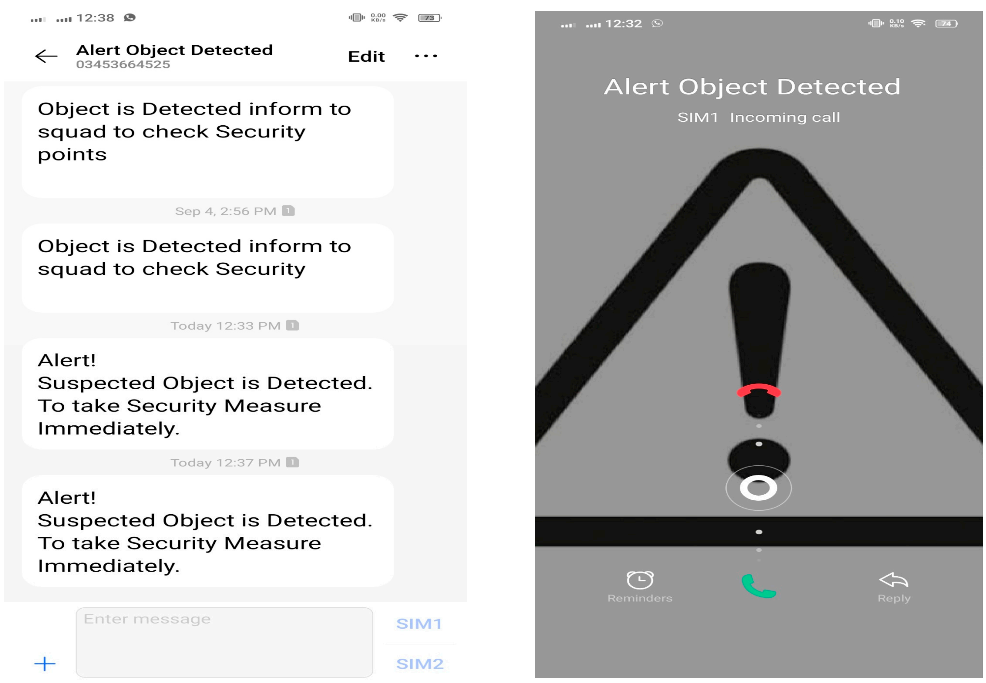
The SS-HSA monitors home security in real-time and notifies the end-user to take proactive action against a suspected intruder. Arduino UNO is simultaneously connected with GMS and GSM to generate real-time notifications in order to inform the concerned entity via a message and a call when an object is detected.

3.4. Alert SMS and Call

The SS-HSA to monitor the home security in real time as well as notify the concerned person to take proactive action against the suspected object. The Arduino UNO simultaneously connected with GMS and GSM to generate real-time notification to inform the concerned entity via message as well as call when the object is detected as shown in Figure 7.

Table 2. The output of SS-HSA concerning frequency.

Date	Time	Frequency	Decision
2 February 2023	11:15:10	0	Object Not Detected
2 February 2023	11:15:11	0	Object Not Detected
2 February 2023	11:15:12	2	Object Detected
2 February 2023	11:15:13	0	Object Not Detected
2 February 2023	11:15:14	2	Object Detected
2 February 2023	11:15:15	0	Object Not Detected
2 February 2023	11:15:16	19	Object Detected
2 February 2023	11:15:17	9	Object Detected
2 February 2023	11:15:18	7	Object Detected
2 February 2023	11:15:19	1	Object Not Detected
2 February 2023	11:15:20	3	Object Detected
2 February 2023	11:15:21	0	Object Not Detected
2 February 2023	11:15:22	5	Object Detected
2 February 2023	11:15:23	0	Object Not Detected
2 February 2023	11:15:24	0	Object Not Detected
2 February 2023	11:15:25	1	Object Not Detected
2 February 2023	11:15:26	4	Object Detected
2 February 2023	11:15:27	1	Object Not Detected
2 February 2023	11:15:28	0	Object Not Detected
2 February 2023	11:15:29	0	Object Not Detected
2 February 2023	11:15:30	2	Object Detected
2 February 2023	11:15:31	0	Object Not Detected
2 February 2023	11:15:32	2	Object Detected
2 February 2023	11:15:33	2	Object Detected
2 February 2023	11:15:34	0	Object Not Detected



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

Figure 7. SMS alert: (**a**); call alert: (**b**).

3.5. Output into Binary Form

After representing the output concerning frequency in Section 3.2, it is necessary to convert the output decision into binary so that it can be in a form that is acceptable to machine learning algorithms to enable further classification. Therefore, the information regarding the detection or absence of an object in string form is converted into binary form (consisting of 0s and 1s) in the XLSX file. Furthermore, this file is imported into Jupiter Notebook so that may be applied to the machine learning algorithms. The validity and accuracy comparisons between Random Forest Classifier, Booster Classifier, Naive Bayes Classifier, KNN-Classifier, SVM-Classifier, and Decision Tree algorithm are also presented herein as shown in Figures 8 and 9, and Tables 3 and 4.

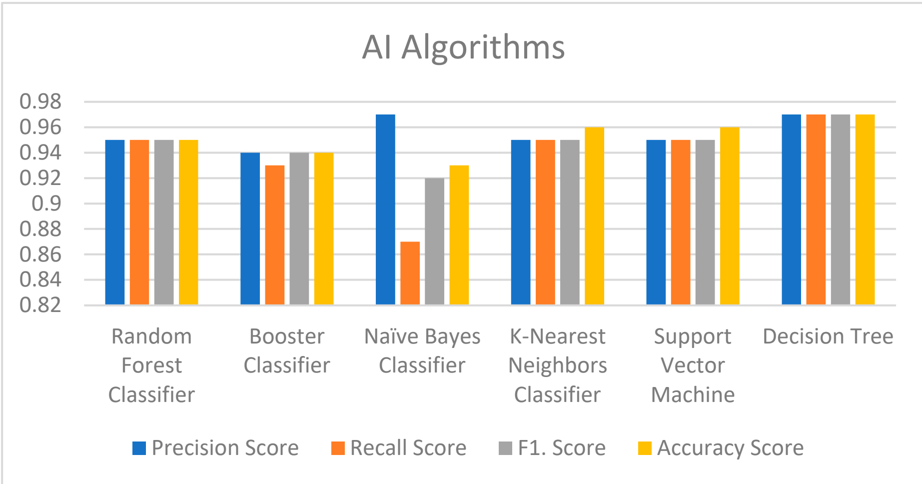


Figure 8. Evaluation measures for AI algorithms.

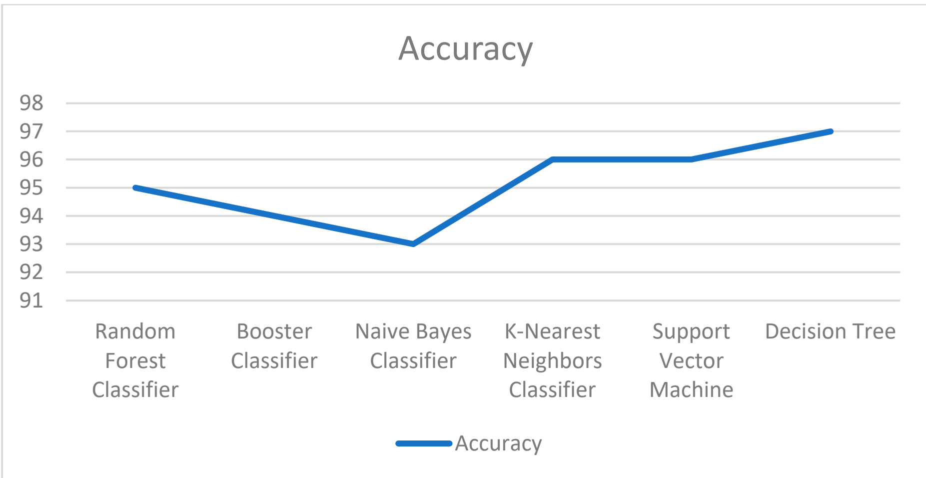


Figure 9. Accuracy of AI algorithms.

Table 3. Algorithms with scores.

Sr.No	AI Model	Precision Score	Recall Score	F1. Score	Accuracy Score
1	Random Forest Classifier	0.95	0.95	0.95	0.95
2	Booster Classifier	0.94	0.93	0.94	0.94
3	Naïve Bayes Classifier	0.97	0.87	0.92	0.93
4	K-Nearest Neighbors Classifier	0.95	0.95	0.95	0.96
5	Support Vector Machine	0.95	0.95	0.95	0.96
6	Decision Tree	0.97	0.97	0.97	0.97

Table 4. Algorithms with accuracy scores.

Name of Algorithm	Train and Test Data Ratio	Accuracy
Random Forest Classifier	30% in training and 70% for testing	95%
Booster Classifier	30% in training and 70% for testing	94%
Naive Bayes Classifier	30% in training and 70% for testing	93%
K-Nearest Neighbors Classifier	30% in training and 70% for testing	96%
Support Vector Machine	30% in training and 70% for testing	96%
Decision Tree	30% in training and 70% for testing	97%

3.6. Confusion Matrix

A confusion matrix is a 2×2 matrix that is used to evaluate the performance of a model with respect to distinguishing between two classes. The matrix consists of four outcomes: true positive, true negative, false positive, and false negative. A true outcome indicates a correct prediction, while false indicates an incorrect prediction. The true and false outcomes in a confusion matrix are further categorized into positive and negative values, leading to four quadrants. These quadrants are false negative (FN), true negative (TN), true positive (TP), and false positive (FP). The four attributes (FN, TN, TP, and FP) in a confusion matrix can be used to measure the performance and reliability of a model. These attributes are also used to calculate other evaluation metrics, such as recall, precision, accuracy, and F1 score. In precision scores, false positives and false negatives have a key role.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Using the recall score, the actual positive value can be chosen from among all the positive outcomes, which will help to identify a good model that only selects positive examples. A lower recall score means the system is unable to identify the correct or suitable examples.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Precision and recall contradict each other during the performance evaluation of the classifier model. The F1 score plays a role in balancing recall and precision, but the F1 score is not a perfect solution. The F1 score is a reciprocal of recall and precision used to evaluate performance despite the limitations of precision and recall score.

$$\text{F1} - \text{Score} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}}$$

The accuracy score is used to attempt to balance a performance evaluation when the F1 score does not perform well regarding precision and accuracy.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

3.7. Receiver Operating Characteristic (ROC)

The ROC is a graphical curve that identifies and discloses the characteristics of a binary classifier system. It also illustrates the performance of classification models. When two models are compared, the true positive rate (TPR) and false positive rate (FPR) play a role in measuring the ROC curve.

3.8. ROC Plot Decision between Tree and KNN and between Random Forest and Naïve Bayes

There are two solid lines: the orange solid line indicates the propagation of the Random Forest and the Decision Tree, and the green solid line shows the propagation of Naive Bayes and the KNN algorithm. The blue dashed line shows the random prediction or diagonal indication. The area above the diagonal line and under the orange and solid green lines indicates the Area Under Curve (AUC), which evaluates the strength or performance of the Random Forest and Naïve Bayes as well as the Decision Tree and K-Nearest Neighbor algorithms, respectively. If the covered area above the diagonal and solid curve is smaller, this indicates poorer performance of the model, while a larger area between the dashed curve and solid line indicates better performance of the model. The FPR and TPR play a role in calculating this area. The TPR propagates along the y-axis, while the TNR propagates along the x-axis, as shown in the following Figures 10 and 11.

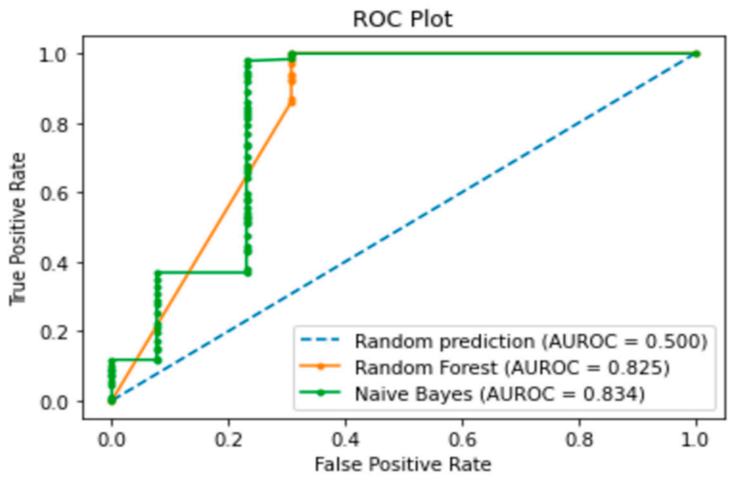


Figure 10. ROC plot: Random Forest and Nave Bayes.

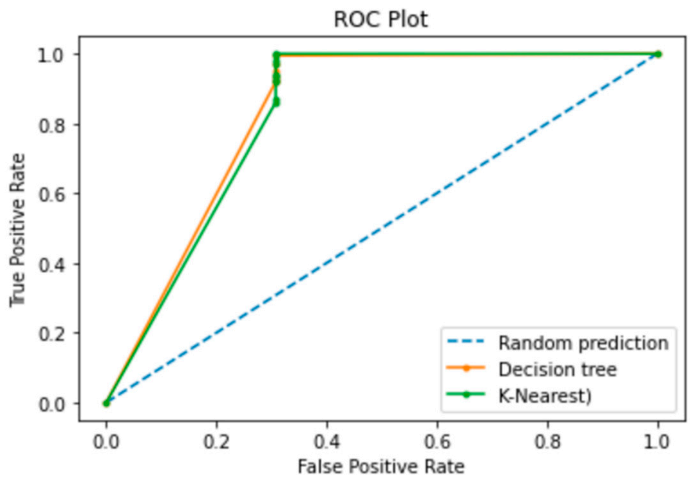


Figure 11. ROC plot: Decision Tree and KNN.

3.9. Execution Time of Proposed Solution

In Table 5, the execution time illustrates the amount of time required to execute the total number of instructions. The proposed SS-HSA was tested in different scenarios to detect objects and alert users via SMS and call in case of a detection. There are n statements in the proposed SS-HSA module, and each statement in the code requires k time to execute. Moreover, a delay of 2000 ms is used between each iteration. We have tested the model in different situations, and a period equal to n multiplied by k is the amount of execution time required.

Table 5. Execution time required.

Scenario	Location	Time Required (Second)
1	Home	3.00
2	Garage	3.50
3	Office	3.15

4. Conclusions

The features of SS-HSA, such as the manageability and usability of GMS, Arduino UNO, and GSM, all allow for the model's simple operation. It presents scalability with respect to monitoring or sensing security threats. The microwave detection model assured availability in any circumstances. The SS-HSA has a strategy concerning reactive and proactive security measures, and latency, as well as throughput, can be achieved in SS-HSA. SS-HSA uses GSM to communicate with mobile-based systems because such systems are widely used, allowing this model to function as an IoT-based system that can notify a concerned entity in real-time.

Future work will enhance the SS-HSA by implementing all its decisions using fuzzy logic via cloud computing and notifying the user to take action in real-time.

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