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HeteroSys: Heterogeneous and Collaborative Sensing in the Wild

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***Abstract*—Advances in Internet-of-Things, artificial intelligence, and ubiquitous computing technologies have contributed to building the next generation of context-aware heterogeneous systems with robust interoperability to control and monitor the environmental variables of smart environments. Motivated by this, we propose HeteroSys, an end-to-end multi-functional smart IoT-based system prototype for heterogeneous and collaborative sensing in a smart IoT-based environment. A unique characteristic of *HeteroSys* is that it relies on Home Assistant (HA) to collate heterogeneous sensors (e.g., passive infrared sensors (PIR), reed (door) switches, object tags, wearable wrist-mounted, water leak sensors, and internet protocol cameras), and uses a variety of networking protocols such as Zigbee open standard for mesh networking, WiFi, and Bluetooth Low Energy (BLE) for communication. The reliance on HA (and its broad community support) makes *HeteroSys* ideal for various applications such as object detection, human activity recognition and behavior patterns. We articulated the development phase, integration, testing challenges and evaluation of the *HeteroSys*. We conducted an extensive 24-hour longitudinal data collection from 5 participants performing 6 activities by deploying in an indoor home environment. Our assessment of the acquired dataset reveals that the representations learned using deep learning architecture aid in improving the detection of activities to 83.1% accuracy.**

***Index Terms*—Heterogeneous Sensor Network, Collaborative Sensing, IoT System, Surveillance, Ubiquitous Computing**

I. Introduction

The unfolding of smart wireless IoT sensors and platforms has created a boom in the industrial and academic communities. Due to this, wireless technology protocols are evolving daily, becoming a challenging task to maintain the robustness and scalability of the system. Researchers have recently proposed and developed smart IoT systems across various domains such as healthcare [1], HVAC control system [2], IoT-based transport system [3], etc. One major challenge to developing a smart IoT system is integrating heterogeneous wireless sensors and collaboratively aggregating all the sensing raw data in a local location. The heterogeneous wireless sensor networks (WSN) primarily consist of sensing nodes with different abilities, such as different computing power, operational requirements, and sensing ranges. Also, due to evolving and new sensing technologies, it is formidable for the research and industrial communities to build a robust interoperability system that can be scaled and compatible to integrate multiple wireless sensing modularity into the system. In addition, time desynchronization and data fragmentation are challenges encountered while deploying the IoT-based system in the wild. As a result, collaborative sensing in a heterogeneous environment became one of the primary challenges for the researchers to tackle the interoperability of the smart home system [4].

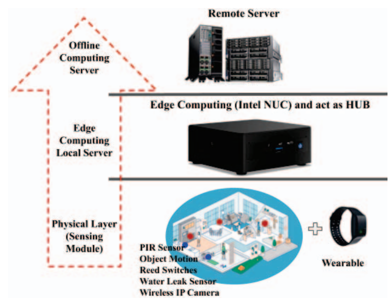

Fig. 1: Hierarchical overview of the *HeteroSys* system

We aim to mitigate the above-mentioned challenges such as data fragmentation, time desynchronization, and seamlessly integrating other sensing modularity into a smart system. We developed a smart-IoT system called *HeteroSys* system that offers better robustness, scalability, and interoperability characteristics compared to state-of-the-art system such as [5]. Figure 1 highlights the hierarchical overview of the proposed *HeteroSys* system. We design the system in a bottom-up architecture where the physical (bottom) layer corresponds to the sensing module, where all the physical sensors and actuators are employed to capture the contextual information, followed by the middle layer, which corresponds to on-site edge computing capability to the system and also enables us to aggregate all the sensed data from heterogeneous WSN. Lastly, the top layer corresponds to the offline computing server where the high computational machine learning experiments can be conducted, and all the sensed data are preserved as a backup.

Below are the overall contributions of this work:

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1) ***HeteroSys***: develop an end-to-end heterogeneous and collaborative wireless sensor network (WSN). The system comprises passive infrared (PIR), reed switches, vibration (object tags), wearable wrist-mounted, water leak sensors and an IP camera. In addition, all the sensed data is aggregated and stored in a local hub for edge computing capability.
2) **Functional and operational requirements of *HeteroSys* System**: We identify commercial off-the-shelf heterogeneous sensors that can be easily integrated and reduce network complexity. In addition, we focus on eliminating data fragmentation (data stored in multiple sources) and global time desynchronization problems [5], [6].
3) **System Evaluation**: We conduct an extensive data collection drive by deploying the *HeteroSys* system in an indoor home environment. Our in-house longitudinal dataset comprises **5** subjects performing **6** ADLs and IADLs activities for **120** hours. Lastly, to understand the subject's behaviour and actions, we performed human activity recognition (HAR) task on the in-house dataset and obtained **83.1%** accuracy for detecting activities.

II. Motivation Scenarios

HeteroSys's functional paradigm is motivated to integrate heterogeneous wireless sensors to enhance the overall system's interoperability and reliability. Therefore, one of the primary motivations of the study is to develop a flexible and scalable smart IoT system that can scale from one domain to another domain and also enable to seamlessly integrate of new sensing modularity along with IoT protocols. Here we presents two motivating scenarios:

1) **Smart Health Monitoring System:** Studies [7] discuss and demonstrate that the pervasive and wearable sensors can perceive the surrounding contextual information and easily be used to infer individual health and behavior based on the captured information. However, one of the remaining challenges is integrating and aggregating the sensed data in one centralized location to improve the overall system's reliability and operational flexibility. Similarly [5] develop by a smart health system, but one of the system's weaknesses is that the pervasive sensors are proprietary, so all the sensed data is relayed to a third-party cloud server; compared to our proposed *HeteroSys* all the sensed data is relayed and aggregate in the centralized location. Lastly, *HeteroSys* provides an end-to-end heterogeneous and collaborative sensing pipeline that can be seamlessly deployed to other domains.
2) **Indoor/Outdoor Unwarranted Object Presence and Surveillance:** Studies [8], [9] demonstrate that pervasive sensors such as passive infrared (PIR), pressure sensors, etc. can be used for pedestrian counting, pervasive monitoring, surveillance, etc. tasks. In addition, PIR sensors can be effectively deployable during the day or night, whereas other modularity might not be able to detect object presence both day or night. Comprehending the state-of-the-art literature, we conclude that pervasive sensors are feasible and can be deployed effortlessly for indoor and outdoor tasks. So encouraged by this, we propose a *HeteroSys* that can be readily deployed to indoors or outdoors environments. Furthermore, along with object presence, the proposed system, *HeteroSys* can successfully capture other contextual-aware information that might be crucial for other tasks.

III. Related Work

This section reviews and summarize the related work on heterogeneous sensor network. We categorize the related work based on:- *integration of heterogeneous sensors* and *smart system for health monitoring and activity recognition*.

Integration of Heterogeneous Sensors: Integrating wireless sensors from various vendors recently became a very challenging task for researchers to develop an interactive and scalable system. Researchers are trying to bridge the gap by proposing and developing novel wireless integration techniques. Similarly, in [10], the authors propose a long-range (LoRa) based smart home system for remote monitoring of IoT sensors and devices that can be monitored remotely. The system includes sensors (humidity, noise, temperature, gas and dust sensors) and other IoT-enabled appliances. An AI-based data server is designed to control and monitor home appliances, and all the sensed data can be sent periodically to the data center of that server by using the LoRa gateway. Furthermore, in [11], the authors develop an end-to-end IoT monitoring system that effectively collects, analyses and estimates the massive network incoming and outgoing traffic of IoT devices. The proposed IoT system comprises three main components: IoT network traffic monitoring systems, backend based-IoT traffic behavior systems and frontend based-IoT visualization systems. In [12], the authors propose a smart home control system to study and analyze power consumption, human-computer interaction, monitoring of other home appliances, etc. The system comprises four layers: the physical layer (sensors, actuators, video surveillance), the perception layer (embedded gateway), the network layer (server) and the application layer (user interface (panel computer, PC, etc.)).

Smart IoT systems for Health Monitoring and Human Activity: The emergence of wireless pervasive and wearable sensors enables us to build a contextual-aware system that can help every individual's daily life. CASAS [13] is a smart home in a box designed to estimate and recognize individual behavioral patterns in an indoor environment. CASAS comprises three layers of operations- the physical layer (integrating sensors and actuators) followed by middleware (communication bridge between the layers) and the software layer (activity recognition, activity recovery, and user behavior). In [14], the authors develop two smart home IoT systems using Bluetooth low energy (BLE) sensor nodes to collect and monitor heating, ventilation and air conditioning (HVAC) raw data from wireless sensors. Then the sense data is dispatched to a Wi-Fi

TABLE I: Summary of pervasive sensors for *HeteroSys* system components

Pervasive Sensors	Properties	Unit Cost
PIR Motion Sensor	Max. Detection Angle = 170°	$ 24.99
Reed Switch	Max. Detection Distance = 22 mm	$ 17.99
Vibration (Object tag) Sensor	Sensitivity threshold wide = 1.5 in and thick = 0.4 in	$ 19.99
Water Leak Sensor	Sensitivity threshold ≈ 0.5mm	$ 18.99

gateway hub, raspberry pi 3B, which also communicates with other wireless devices in the local network. Finally, in [15], the authors propose a health monitoring system for older adults. The application mainly focuses on estimating and detecting stress and blood pressure of older adults by integrating with a voice-based indoor location detection system. The system comprises three major components: edge computation, cloud computation and user interaction. Lastly, we underline a few limitations of state-of-the-art smart-IoT sensing systems and potential challenges.

A. Challenges and Limitations

We discuss and enumerate the challenges and shortcomings faced during the smart IoT sensing system development. Here are a few challenges listed below:

1) ***Scalability and Generalizability characteristics***: Integrating multiple heterogeneous sensors is one of the critical challenges to address. Similarly, in SenseBox [5], the sensors are not integrated, prevailing problems such as data fragmentation and time desynchronization.
2) ***Synchronize and Centralized Data Storage***: Time Synchronized data is a predominant requirement for deploying any pervasive sensing system to store the sensed data in a centralized data hub.
3) ***Lossy network connectivity***: In the development phase, network reliability and connectivity are crucial aspects for better durability of smart home systems.
4) ***Functional and operational requirements***: The feasibility test to optimize the overall cost of functional and operational requirements capturing rich contextual information between the subjects and environment.

IV. Overview of the HeteroSys

Motivating from the key challenges and limitations discussed in section III-A, one of the primary design goals of *HeteroSys* is the aggregation of data in one local hub device to eliminate data fragmentation and desynchronization problems. To resolve this issue, *HeteroSys* directs all data flow from the sensors through the hub to the offline server as needed for machine learning inference and data redundancy/backup. Thus, we can sync all data with one reference local hub device clock, which is, in turn, synchronized with an internet reference time service using network time protocol. We discuss the sensors utilized to develop the *HeteroSys* system in detail, shown in Fig. 2 and Table I.

1) **Wearable Empatica E4 Sensor**: The wearable sensor would ideally have a design closer to a comfortable wristwatch than a traditional large, hard plastic sensor, since this would be a more familiar form factor to the older study populations; this may increase participant retention and compliance.
2) **PIR Sensor**: The sensor must have a sufficient field of view (FOV) to detect inhabitants in any part of the room it is placed in the corner this suggests a minimum effective FOV of 90 degrees, with an optimal FOV closer to 180 degrees allowing for placement along the edges of rooms instead of just in corners similarly shown in [9].
3) **Reed Sensor**: The reed sensor does not have any notable requirements since the switching mechanism itself is a simple electromechanical switch which is inherently binary state, with no further computation necessary.
4) **Vibration (Object Tag) Sensor**: Since the other pervasive sensors are by their nature only binary state, we accepted binary state object tag motion sensors as a viable alternate to other triaxial object tag motion sensors. These sensors must be small and light enough to adhere to household objects (including trash can, dust pan, etc.) [5] without impairing their functionality.
5) **Wireless IP Camera**: Capturing all the activities occurring in the environment is one of vital components of the *HeteroSys* system which requires relatively high resolution and frame rate. However higher resolutions and frame rates increase data storage, cost, and power consumption substantially and thus, we determined a rough estimate of 1440p resolution (2560 x 1440 pixels) and 10 frames per second frame rate to be a workable.
6) **Hub**: The intel NUC housed with Intel Core i7-1165G7 Processor (12M Cache, from 2.4 GHz base up to 4.70 GHz, four cores (8 threads), 16GB RAM and 1TB NVMe SSD. The Hub was employed to aggregate and relay all the sensed data from the wireless heterogeneous sensors and to provides edge computing capability.

V. Integration of Wireless pervasive and Wearable Sensors

This section summarizes and discusses the methods adopted to integrate all the wireless pervasive and wearable sensors with the hub by employing a home assistant operating system. Fig. 5 highlights the network nomenclature of heterogeneous sensors connected wirelessly to the local hub.

1) **Wearable Empatica E4 Sensor**: After careful consideration, we decided to remain using the Empatica E4 wearable for *HeteroSys*. Out of the 25 devices surveyed, the Empatica E4 was the only device which allowed access to live-streamed blood volume pulse (BVP), accelerometer (ACC), electrodermal activity (EDA), heart rate (HR) data in a wristwatch-like form factor. The E4 unit uses bluetooth low energy (BLE) to stream live data to a specific model of BLE USB dongle. In addition, Empatica maintains a streaming server program which can connect to E4 devices through this USB dongle and allows clients to connect to itself through UTF-8-encoded transmission control protocol (TCP) socket with

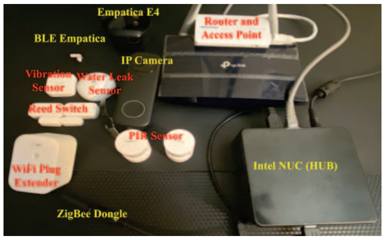

Fig. 2: Overview of *HeteroSys* system components

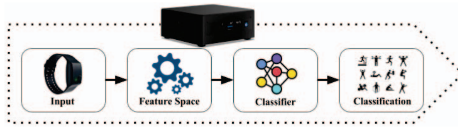

Fig. 3: Overall pipeline of activity recognition module on the Hub

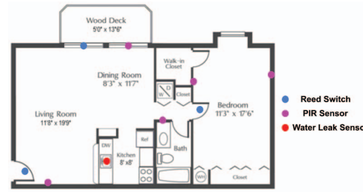

Fig. 4: Pervasive sensors floor layout

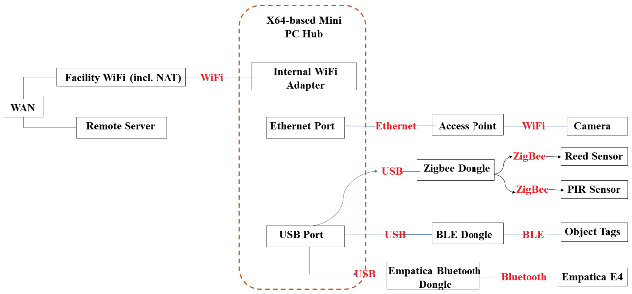

Fig. 5: Network flow of the *HeteroSys* system

messages terminated (by the specification) with two-character Windows-style newlines carriage return/line feed (CRLF) [16]. This socket connection allows the client to discover nearby E4 devices, connect to one, subscribe to different data streams, and receive the requested streamed data.
Unfortunately, this software is proprietary and only available for Windows. As such, the method determined best for streaming data from the E4 data is to run the E4 streaming server inside of a Windows virtual machine (VM) running through quick emulator using the kernel-based virtual machine inside of a Docker container, with the TCP port exposed from the VM. The Docker container runs a custom Python client script for the streaming server, which connects to Home Assistant through a representational state transfer (REST) exposed port and a home assistant RESTful API [17]. The Docker container will then be packaged as an add-on for the HA.

2) **PIR, Reed and Vibration (Object tag) Sensors**: The pervasive sensors, after identifying Zigbee as the preferred wireless communication protocol for these sensors, we decided to use the same protocol for all the pervasive sensors to simplify the hub setup. The sensors are easily integrated with the hub due to the highly user-friendly interface of the home assistant.
3) **Home Assistant Configuration**: Using the InfluxDB integration for HA connects to the InfluxDB mentioned above add-on to store all home assistant entity state changes in the local InfluxDB instance. Using an edge data replication feature introduced in InfluxDB version 2.2, this state change data can be synchronized on write with the study server, which can be queried as needed. InfluxDB helps us to maintain the synchronized database for all the incoming sensed data.

VI. Challenges and Potential Solutions

This section discusses and enumerates the challenges and shortcomings faced during the development of the *HeteroSys*. We also highlight some potential solutions to these challenges. Here are a few challenges listed below:

1) Empatica E4 real-time data streaming software runs on Windows, whereas home assistant is a Linux-based OS. Another shortcoming with Empatica E4 is that all the live-streaming procedure has much inconsistency throughout the documentation.
2) Scalability, connectivity, complexity, etc. challenges associated with REST sensor integration.
3) InfluxDB version not supporting edge data replication feature in the current version home assistant InfluxDB.

In order to resolve the challenges mentioned above, we enumerate potential solutions to the above challenges.

1) To overcome Empatica E4 real-time data streaming software, we are developing an add-on (docker image) for home assistant, which uses the Wine compatibility layer to run the proprietary windows streaming software on an x64-based Linux host OS (home assistant). However, if the compatibility issues persist, it will still virtualize a complete instance of Windows inside the host OS. However, the compatibility layer is much more efficient than full virtualization. In addition, we are developing software, an object-oriented asynchronous Python client library, using asyncio to mitigate the challenges faced for the real-time data streaming task. It is still in the developing and testing phase and planning to release as FOSS with full test code coverage.
2) The setup with the REST sensor integration for home assistant can be simplified and improved by bundling the Python client script with the necessary home assistant integration boilerplate directly, as opposed to using the more limited REST sensor integration. This would also allow for a local push configuration that updates the

TABLE II: Hyper-parameters of CNN-based classification model

Hyper-parameters	Values
No. of maximum convolution layers	2
No. of filters in convolution layers	32, 64
Convolution filter dimension	3x1,1x1
No. of maximum fully connected layers	3
No. of neurons in fully connected layers	96, 128, 6
Batch size	16
Dropout rate	0.35
Learning rate	0.0003
Max number of epochs	64

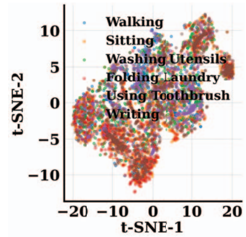

Fig. 6: Raw feature representation of high-level activities

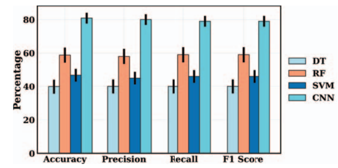

Fig. 7: Classification Accuracy

home assistant immediately when new data is available instead of after a polling delay.

3) In order to resolve the issue mentioned above with the add-on InfluxDB version not supporting edge data replication, developing a new add-on is necessary, which runs the new database. However, InfluxDB is open-source and already has a Docker image, so the add-on should not be challenging to create. Alternatively, since the add-on is also open-source, upgrading the InfluxDB version the add-on uses is also an option.

VII. System Evaluation: Activity Recognition

This section extensively evaluates the proposed smart IoT-based system by deploying it in an indoor home environment. Subsequently, using the enriched in-house dataset, we conduct *context-aware activity recognition task* to comprehend the subject's behaviours' and actions' while capturing the interaction between the subjects and *HeteroSys*. For the context-aware activity recognition task, we concentrate on high-level activities (sitting, walking, etc.) instead of low-level actions such as personalized and contextual information (indoor-positioning, time, user, etc.), similarly, discuss in CAPHAR [18]. This is because we hypothesize that prior knowledge from pervasive sensors about the interaction between subjects and the environment is comprehended. Furthermore, the motivation employs high-level activities to demonstrate that one can detect the temporal actions captured across subjects. Lastly, we used Emaptica-E4, attached to the subject's dominant hand, to capture temporal signals while performing the activities.

Additionally, our in-house dataset comprises synchronized pervasive and wearable sensors by deploying *5*, *3* and *1* PIR, reed switches and water leak pervasive sensors, respectively and *1* Empatica-E4 in the indoor environment layout shown in figure 4. We. We deploy *HeteroSys* for **120 hours** and collect dataset from **5** subjects performing **6** ADLs and IADLs activities: *sitting, walking, washing utensils, folding laundry, using toothbrush and writing*. Furthermore, Empatica-E4 records the movement (through accelerometry; 32 Hz sampling frequency), Electro-Dermal Activity (EDA), skin temperature, and heart-rate variability. Lastly, we enumerate the data preprocessing, experiment strategy and results.

- **Data Preprocessing**: For this study, we employ the temporal signals from the wearable sensor *accelerometry* data as our input to capture the unique movements. First, the raw data acquired is preprocessed using a median filter to eliminate the data's noise because most body-worn wearable sensors are vulnerable to noise, such as motion artifacts. Next, we employ the sliding windowing technique on the filtered signals as it is extensively utilized to remove the motion or device artifacts from the dataset. We employed a sliding windowing with 50% overlap with a window size of 0.50 sec at a sampling rate of 32 Hz. Within each window, we employed the majority voting for data labelling for each window segment. We showcase the feature representation of preprocessed raw signals shown in Fig. 6. Finally, we record the data collection session using IP cameras as the ground truth to assign the labels to the activities.
- **Experiment Setup**: We utilize four evaluation metrics: ***Accuracy***, ***Recall***, ***Precision*** and ***F1-Score*** and split the dataset into *60-20-20%* as training, validation and testing sets, respectively. The validation set is used to fine-tune the hyperparameters and also the validation and test datasets were not utilized during the training phase. All the codes for data preprocessing and deep learning mechanisms is implemented with python and PyTorch libraries. The experiment is conducted on the hub, the overall pipeline shown in Fig. 3.
- **Results and Discussion**: We apply several machine learning (ML) algorithms with 10-fold cross validation over the in-house dataset. Different parameters for the ML algorithms are fine-tunned to achieve the maximum accuracy. The applied traditional ML algorithms are- Random Forest (RF), Decision Tree (DT) and Support Vector Machine (SVM). In addition to the traditional machine learning algorithms, we also experimented with a simple deep learning architecture for the classification task and have seen substantial increase of **22%** in the classification accuracy shown in Fig. 7. We obtain the proposed CNNs-based deep architecture through several grid search among various hyper-parameters shown in table II. The increase of accuracy is realizable as the convolutional neural network (CNNs) provides the advantage of feature engineering and enable us to learn the embedding space efficiently compared to the traditional ML algorithms. We notice the CNNs-based classification

network obtained F1-score of **82.5%** and outperform all the shallow learning algorithms. We notice CNNs-based classification network relatively took less time with total parameters of **22,726**. Furthermore, this experiment demonstrates the system's end-to-end characteristic, aiding us in aggregating all the sensed data to a centralized location and performing detection of high-level activities.

VIII. Conclusion

This work showcases an end-to-end heterogeneous and collaborative sensing IoT-based system, *HeteroSys* that will enable us to integrate multiple sensors and aggregate all the sensed data into the hub. First, we highlight and discuss the different problem scenarios where the *HeteroSys*system can be effortlessly scaled and deployed to the real-world domain. Secondly, we enumerate the operational and functional requirements of the *HeteroSys* system to be deployed in the wild, followed by methodologies to integrate all the heterogeneous sensors concurrently to the hub. We also enumerate the challenges and potential solutions faced during our development phase. Furthermore, we evaluated the proposed *HeteroSys* by deploying in an indoor home environment and collected **6** ADLs and IADLs from **5** subjects for **120** hours. We developed CNNs-based architecture for the high-level classification task and obtained **83.1%** accuracy. Lastly, we summarize our study with potential future work.

IX. Future Work

We highlight the potential future work and showcase that the proposed *HeteroSys* system can be scaled to different domains by enhancing the existing prototype's operational and functional attributes and employing low-level pervasive sensor data information to comprehend subjects' behavior. Furthermore, as the technologies evolve, we must include futuristic aspects in the proposed IoT-based system.

1) One of the future aspects is to include a WiFi [19] channel state information (CSI)-based approach for the indoor localization system instead of depending on passive infrared sensor (PIR) point measurement data.
2) We would like to integrate more depth-informative data-driven sensors, such as infrared cameras, radars, LiDARs, etc., with the *HeteroSys* system to build a data enrichment platform.
3) In future, we would like to integrate *HeteroSys* system with Matter [20] to build a more sophisticated and reliable IoT-based system for heterogeneous sensors.
4) We envision integrating the proposed IoT-based system with robot platforms such as Amazon Astro, ROSbots 2.0, etc. to build a better human and machine interaction platform and enhancing the robot's performance with the more incoming flow of contextual-aware information from the other sensors.

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