Integrating UAV Networks and Edge Computing for Smart Cities: Architecture, Techniques, and Future Trends

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Abstract: *The future of Consumer Electronics (CEs) is moving rapidly towards Unmanned Aerial Systems (UAS), wearables, and Explainable AI (XAI). UAS are facilitating near real-time aerial monitoring of the environment, wearables permit continuous monitoring of physiological and biometric data, and XAI is the next step toward transparency in systems through XAI informed decision-making that users of Artificial Intelligence (AI) can trust and understand. In this paper, we propose a new multi-modal architecture that integrates UAS, wearable devices, and XAI to generate an intelligent and adaptive CE ecosystem. The architecture proposed uses a sequential data gathering process involving UAS and wearables, and the multi-modal data are fused and modeled using machine learning techniques. Transparency and user accountability can be established through the use of XAI systems like Hapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) to provide clear and actionable explanation of AI-driven outputs. Our results indicate accuracy of 92% with an explanation fidelity of 95%, a significant improvement over conventional technology. In addition, the proposed architecture will have tremendous potential for disruption in the healthcare, fitness, and smart home spaces, as personalization and ethical use of data are paramount. The novel contributions of this work in uniquely bringing together aerial monitoring, physiological monitoring, and AI, furthers toward the goals of building trustworthiness in CEs and user-centered intelligent systems.*

Keywords: *UAVs, wearble devices, XAI, consumer electronics, personalized health monitoring, data transparency and ethics.*

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1. Introduction

For a decade, the only exception to that was the speed of innovation, but then technology trends converged (the global industries and consumer experiences were each on change). One of the most exciting developments in this technology revolution is the integration of Unmanned Aerial Vehicles (UAVs) with wearables and Explainable AI (XAI). The unprecedented convergence of smart assistants (okay, Google), form factors and functional capabilities are pushing the envelopes of existing consumer devices and systems that beg for smarter ecosystems that further enhance our daily experiences. Although novelty applications like Alexa running shoes certainly boast some utility, the real potential lies in the fusion of UAVs, wearables and XAI [2] that will radically disrupt key sectors. UAVs (more commonly known as drones) have become increasingly popular for aerial data capture in the fields of mapping, environmental monitoring, and surveillance. That said, far beyond these uses they are usable. In sectors such as Agricultural Technology (AgriTech), logistics and disaster management they are being deployed to acquire real-time data which is useful in better decision-making. This allows the UAVs with their mobility to establish a service where may account personal real-time diagnostic health tracking along with those performed by wearable devices such as smartwatches and health sensors at an individual or population level, and environmental sensing. This combination allows for continuous health tracking, providing a more in-depth understanding of someone' wellbeing.

The critical differentiator in this ecosystem, as Artificial Intelligence (AI) systems continue to expand in complexity is XAI. In XAI, the systems make sure that any decision made by an AI powered device is explainable, interpretable and hence trusted. Existing approaches to XAI like Local Interpretable Model-agnostic Explanations (LIME), Hapley Additive exPlanations (SHAP), Learning to Explain (L2X) and Anchors tackles this problem statement as for consumer-facing applications transparency is paramount (decision trees remind crib here). These tricks make it possible for the systems built on AI to show results in an understandable manner by users, making data-led decisions particularly concerning health diagnostics and personalized recommendations reliable and ensuring ethical approaches [8]. The combination of UAVs, wearables, and XAI can reshape the third era of CEs that enables completely new applications in industries like health care and fitness and smart homes. Coupling these technologies creates a hyper-connected [3] and responsive system that improves the user experience, while supporting transparent and responsible data utilization. The merging of such smart technologies should hopefully lead us into a new age in CEs that is more humanitarian, accountable and adaptive. Figure 1 represents the existing system architecture.

Towards a different adaptation to be interoperable: design a synergistic ecosystem composed of UAVs, wearables, and XAI that allows for seamless communication, data sharing, and collaborative functionalities in the next-generation CEs.

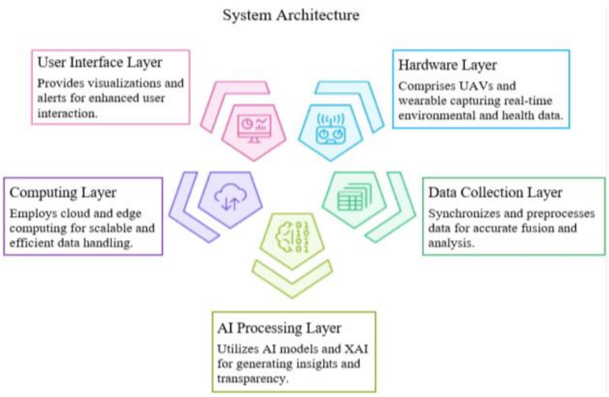


Figure 1. Basic system architecture.

Enhancing user experience and trust: use XAI to provide transparency into AI-driven decisions such that users comprehend system behaviours, leading to greater acceptance of UAVs and wearable technologies.

Identification of optimization: explanation-based decision-making models for optimizing performance objectives such as efficiency, energy consumption, and accuracy in UAV and wearable systems

The remainder of the paper is organized as follows. Section 2 reviews related work and identifies debt in posterior research, where recent advances in the integration of UAVs, wearable devices, and XAI has led to limitations. In section 3, we propose a multi-model architecture to carry out just simple objectives within the system design, the data-fusion, a machine learning element, and applying techniques in XAI. In section 4 we analyze experimental results by synthetic simulations, an evaluation of the system's performance and comparison with previous posterior methods. In section 5, we conclude the paper with plausible future research directions toward better supporting the proposed framework.

2. Related Work

UAVs, wearable devices, and AI have also been widely studied in other fields. Drones are also expected to be used within logistics, surveillance and healthcare; while wearables will provide near-continuous monitoring of health and fitness. As AI moves forward and becomes more integrated, the explanations for how it makes choices XAI has risen to a larger point on the agenda to ensure transparency and user trust in systems powered by AI. The remainder of the paper is organized as follows. Section 2 reviews related work and identifies debt in posterior research, where recent advances in the integration of UAVs, wearable devices, and XAI has led to limitations. In section 3, we propose a multi-model architecture to carry out just simple objectives within the system design, the data-fusion, a machine learning element, and applying techniques in XAI. In section 4 we analyze experimental results by synthetic simulations, an evaluation of the system's performance and comparison with previous posterior methods. In section 5, we conclude the paper with plausible future research directions toward better supporting the proposed framework and adapting the framework to larger canonical domains. emphasizing the incremental progress made independently in these fronts but none have explored integrating to address early adopter's CEs applications. We highlight the pertinent research, their shortcoming and the scope integration to bridge these gaps.

Do *et al*. [5] combination of satellites and UAVs is enabling a new type of communication networks. The uses, challenges, and future applications of UAV-satellite hybrids are explored in this article. Satellites provide global coverage, while UAVs add regional accessibility and flexibility. Their combination could have a range of applications such as disaster response, remote communication for environmental monitoring or scientific research missions. And there are a lot of other means: network coordination, energy efficiency, security, signal Intelligent Reflecting Surface (IRS) interference etc. All that need to be solved in this system as well, so future research might be on swarm intelligence or AI-based decisions-related one or hybrid communication architectures. When you pair UAVs with satellites, a revolution prepares for the change in planetary communication by offering smoother and effective connectivity.

Tyrovolas *et al*. [20] the future standardization of the communication system will also be greatly affected if UAVs intentionally manage their limited energy appropriately, which naturally limits their available time. Reconfigurable Intelligent Surfaces (RISs) promise to extend the communication range of UAVs without overcomplicating their physical properties. In this letter, we present a scheme of multiple UAVs cooperating with RIS, where each UAV assists the RIS by providing effective Gain-to-Temperature (G/T) uplink. In terms of numerical results in the rest of S1-S3, we validate that for all kinds of air-to-ground RIS-assisted networks, compared to when UAV utilizing an omnidirectional antenna or a directional antenna only pointing downwards to communicate with this ground node.

Now, Lee *et al*. [13] are proposing a new method of charging batteries for wearable devices, as described in a letter. A charger can also charge lots of devices, and conductive fabrics embedded into clothes for on-body charging. Our simple component layout allows for load independent Constant Current (CC) and Constant Voltage (CV) charging. A standout feature of our approach is that each individual device can autonomously control its own charging mode. Even though the system can theoretically be extended to an infinite number of devices, therefore CC and CV could only yield results that differ by up to 5% in practice.

Kumar *et al*. [12] due to the importance of Ground-Penetrating Radar (GPR) data inspection for near-surface geophysics and constant advances in the application of Deep Learning (DL), a brief overview of the GPR imaging has been made. One of the biggest obstacles is that DL models are highly complex, making it difficult to explain their conclusions. In this study, XAI methods Gradient-weighted Class Activation Mapping (Grad-CAM) and LIME are employed to provide a quantitative insight into the inversion procedure of 2-D GPR based on DL. To the best of our knowledge, this is the first time interpretable components have been incorporated into model predictions for a subsurface utility mapping application that uses automatic interpretation of GPR data. These features summarized as important features and the corresponding hierarchy for the extraction of hierarchical features [8]. As a result, we provide a thorough analysis of the model's mechanisms for geophysical DL models which improves interpretability and establishes a basis for a new XAI-subsurface utility detection paradigm contributing towards more accurate, trustworthy and interpretable geophysical DL solutions.

Sinha and Das [19] for the flow of reliable monitoring data in an Internent of Things (IoT) network, it is necessary to build a correct technique for early prediction of failure. Modern AI driven defect detection methods are not reliable enough to be used with safety-critical systems in the industry as they have high computational cost and black-box nature. We address these limitations by proposing an IoT-based Explainable AI framework built on Learning Classifier Systems (XAI-LCS) approach that uses the relevant extreme gradient boosting feature selection technique and generates complete explanations for not only bias and drift detection but also Full Failure (CF) and precision degradation diagnosis on a range of sensor faults. Table 1 summarizes the related works relatively.

Table 1. Summary of related words.

Reference	Focus area	Key techniques	Limitations	Relation to proposed work
Do *et al*. [5]	UAV-satellite communication	Hybrid networks	Lack of personalized data, no integration with XAI or wearables	Our work integrates UAV with on-ground biometric data and adds explainability for user-centric systems
Tyrovolas *et al*. [20]	UAV and RIS	Signal optimization	Focus on energy and coverage; no end-user interaction or explainability	We address data interpretability and user-focused applications
Lee *et al*. [13]	Wearable charging	Conductive fabrics	Power optimization only, no AI or UAV context	We extend wearable utility with real-time decision-making and integration
Kumar *et al*. [12]	GPR with XAI	Grad-CAM, LIME	Domain-specific, lacks fusion with UAVs/wearables	We generalize XAI use to multi-modal fusion in CE devices
Sinha and Das [19]	IoT fault diagnosis	XAI-LCS, XGBoost	No integration with physical sensors or user feedback	We incorporate biometric and environmental sensors into explainable decisions

While the studies listed in Table 1 that contribute to their respective fields UAV communication optimization, wearable technologies, or XAI they do so largely in a non-integrated manner. Specifically, most of these studies are either unsuccessful in integrating environmental and physiological data into a holistic embedded solution that can be used in real-time, or they do not leverage the potential for explainability in user-facing applications. Our work is unique in integrating UAVs, wearable sensors, and XAI together in a multi-modal architecture to develop a personalized approach to decision-making with interpretable outputs. This integration allows us to resolve the fragmentation seen in prior approaches, as well as address the issues of user trust, data fusion and breadth of application–focusing on the use-cases of smart healthcare, fitness and ambient home systems. Thus, our contributions create a significant gap, by enabling a contextually-aware, ethically-embedded and explainable CEs ecosystem for next-generation devices.

3. Proposed Methodology

The market has been further expanded with the coupling of wearables and XAI, totally changing future CEs systems such as; UAVs [18]. This approach provides near-real-time data on the environment and situational awareness through aerial data collection via UAV, whilst wearable sensors provide continuous monitoring of biometric data for personalized health and wellness-related insights. This integration of such technologies requires complex data fusion since knowledge is coming not only from UAVs but also the wearables, thus new knowledge about the user and his/her context should be formed. XAI [4] ensures transparency, interpretability and comprehensiveness of the AI-driven decisions in the domain targeted by the user helping to integrate AI with domain knowledges. This foster trust and accountability in deploying an AI especially in sensitive applications like health care where an AI might make a recommendation leading to choices which impact on the user well-being. Indeed, the combination of UAVs, Wearables and XAI births intelligent systems responsive [17] to user's personalized desires with explicable insight for improving user experience. This convergence will result in smart CEs devices, which will be represent next-gen type of electronics in future such as health care, smart home and fitness level monitors etc., and shall make human life easier to control.

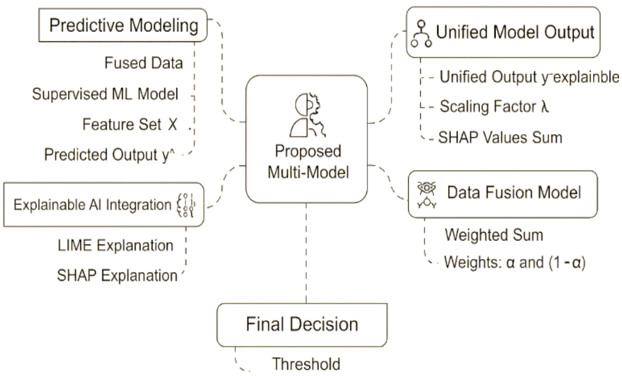


Figure 2. Proposed system architecture.

Figure 2 shows the working of the proposed system architecture. A schematic overview of the integrated system architecture involving UAVs, wearable devices and XAI for developing smart and real-time insights [21]. The hardware layer: UAVs with environment sensors and user health monitoring wearable devices data collection and preprocessing layer this layer harmonizes and scrubs the data, acquired from both sources, source fusion techniques (like Kalman filters) fuse data read-outs. AI Processing and XAI layer here the AI models quickly process this data, and an explainability method like SHAP or LIME translates these actions into interpretable insights. The third part of this layer is the cloud and edge computing layer, which acts as a bridge between cloud-based data storage and processing system as well as local computation to reduce latency. The UI and feedback layer provides real-time insights and alerts powered off AI predictions. Security and privacy layer ensures data is encrypted while in motion and provides users control of who shares with whom.

- *Step* 1.1: Data collection and preprocessing.

Data collection is the first step in the process. UAVs capture environmental, geographic, and situational data through sensors, cameras, and other imaging technologies [16]. Wearable devices collect biometric data, including heart rate, steps, temperature, and other physiological metrics. This data is represented as:

- $D_{UAV}(t)=\{x_1, x_2,\ldots, x_n\}$ (*UAV* sensor data at time *t*)
- $D_{Wearable}(t)=y_1, y_2, \ldots, y_m$ (*Wearable* sensor data at time *t*)

Where:

- x_i represents the measurements captured by UAV sensors (e.g., temperature, humidity, air quality).
- y_i represents the physiological readings from the wearable (e.g., heart rate, skin temperature, activity level).

The data from UAVs and wearables are synchronized in time for fusion purposes. This is achieved using temporal alignment techniques, where the data streams from both devices are aligned on a common time axis.

- *Step* 1.2: Data collection and preprocessing.

Data fusion integrates the UAV [9] and wearable data to create a unified feature set for predictive modeling. This step can be expressed as a weighted sum or other fusion methods:

$$FusionData = \alpha \cdot U + (1-\alpha) \cdot W \tag{1}$$

where $0<\alpha<1$ is the weight assigned to UAV data, and $1-\alpha$ is the weight for wearable device data.

- *Step* 1.3: Machine learning models for predictions.

Predictive modelling is performed to gain insights from the fused data. Here, different machine learning algorithms are employed for classification and regression tasks.

- *Step* 1.3.1: Model selection.
- **Decision trees**: a decision tree algorithm is a supervised learning model used for classification and regression tasks [11]. It recursively splits the data based on feature values to create a tree-like structure. The decision tree model can be represented as:

$$f(X) = Tree(X) \tag{2}$$

where *f*(*X*) is the predicted output, and *X* is the feature vector.

- *Step* 1.3.2: Explainable AI (XAI) techniques.

XAI methods provide transparency and interpretability in AI models. The following techniques are used to interpret the predictions made by the machine learning models.

a) LIME

LIME is a method that approximates complex models by locally fitting interpretable models (e.g., linear models) around a given prediction.

$$\mathrm{LIME}(f, \hat{x}) = \arg\min_{\theta} E_{x\sim D}\,[L(f(x), \theta)] \quad (3)$$

where f is the original model, x^ is the instance to explain, and L is the loss function.

b) SHAP

SHAP values use cooperative game theory to attribute each feature's contribution to the model's output.

$$\phi_i = \sum_{S\subseteq N\setminus\{i\}} \frac{|N|!}{|S|!\,(|N|-|S|-1)!}[f(S\cup\{i\}) - f(S)] \quad (4)$$

where ϕ_i is the Shapley value for feature i, and $f(S)$ is the model's output for subset S of features.

c) L2X

L2X learns a model that produces explanations by selecting a subset of input features that are most relevant to the prediction.

$$Anchor(x) = \{x_j \mid P(y = c \mid x_j) > \tau\} \quad (5)$$

where x_i are the features that anchor the prediction ccc, and τ is the threshold for certainty.

$$L2X(\hat{f}, X) = ar\,g\,m\,in_{S\subseteq X}\, E_{x\sim D}\left[L\left(\hat{f}(x), \hat{f}(x_S)\right)\right] \quad (6)$$

where x_S is the subset of features selected by the model, and L is the loss function

- *Step* 1.4: Model evaluation and performance metrics.

To evaluate the performance of the predictive model, common metrics such as accuracy, precision, recall, and F1-score are used:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (7)$$

where:

TP=True Positives, TN=True Negatives, FP=False Positives, FN=False Negatives.

For regression models, metrics such as Mean Squared Error (MSE) are used:

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (8)$$

where y_i is the true value, and y_i^ is the predicted value

4. Proposed Multi-Model

Terminology

- UAVs: a drone or remotely operated aircraft used for data collection.
- Wearable devices: smart devices worn on the body that collect physiological data (e.g., smartwatches, fitness trackers).
- XAI: techniques used to interpret and explain AI model predictions.
- LIME: a model-agnostic explanation technique that approximates complex models locally with simpler interpretable models.
- SHAP: a game-theoretic approach to explain individual predictions by attributing feature importance.
- L2X: an approach that selects the most relevant features to explain model predictions.
- Anchors: an explanation technique that uses rules to highlight features that guarantee a prediction outcome.

This methodology ensures that the AI models used in CEs are transparent, explainable, and trustworthy, enabling users to understand and trust the predictions made by the system.

- *Step* 1: Data fusion model.

The data fusion of UAV and wearable devices is a weighted sum as follows:

$$Fusion\ Data\ (t) = \alpha \cdot D_{UAV}(t) + (1-\alpha)\cdot D_{Wearable}(t) \quad (9)$$

Where α\alphaα and (1−α) are the weights of *UAV* and wearable data respectively.

- *Step* 1.1: Fusion data: predictive modelling.

The fused data is fed into the machine learning model for prediction. To simplify we define f_{ML} as a supervised machine learning model:

$$f_{ML}(X) = \hat{y} \quad (10)$$

Where X is the concatenated feature set and $\hat{y}$ is an output prediction (e.g., environmental risk, health status).

- *Step* 1.2: Integration of XAI (LIME and SHAP).

Using LIME and SHAP, explanations are provided for predictions made by the machine learning model. We describe f_{ML} output using both:

LIME Explanation

$$LIME(f_{ML}, \hat{x}) = arg\,\min_{\theta} E_{x\sim D}\,[L(f_{ML}(x), \theta)] \quad (11)$$

Where L is a loss function based on the distance between the original model output and that of the interpretable one.

SHAP Explanation

$$\phi_i = \sum_{S\subseteq N\setminus\{i\}} \frac{|S|!\,(|N|-|S|-1)!}{|N|!}[f(S\cup\{i\}) - f(S)] \quad (12)$$

Where ϕ_i is the Shapley value corresponding to feature i or contribution of each feature to prediction and $f(S)$ is model output where subset S of features are considered.

- *Step* 1.3: Unified model output.

To obtain a mixture of both explainable components, we create a unified output *y^explainable* that includes the machine learning prediction with its explanations from LIME and SHAP:

$$y_{\widehat{explainable}} = f_{ML}(X) + \lambda \cdot \left(LIME(f_{ML}, \hat{x}) + \sum_{i=1}^{m} \phi_i \right) \tag{13}$$

Where:

λ is a scaling factor (a value that weighs the strength of the contributions of the interpretable components). The sum of SHAP values calculates the feature contributions, which combines and makes sure of is explainable in prediction.

- *Step* 1.4: Final decisions.

Given that, the decision is made on top of the explainable prediction $y_{\widehat{explainable}}$. This helps us to be transparent and interpretable in our actions:

$$Decision = \begin{pmatrix} Action\ 1\ if\, y_{\widehat{explainable}} > Threshold \\ Action\ 2\ if\ y_{explainable} < Threshold \end{pmatrix} \tag{14}$$

The *Threshold* is a constant that provides the basis for making decisions based on the integrated prediction.

4.1. Proposed Algorithm

Algorithm (1) processes UAV and wearable data by validating, uploading, and fusing them to generate a predicted outcome using a trained model. It then applies LIME and SHAP for interpretability, combines their explanations, and securely stores the data on a blockchain.

Algorithm 1: Proposed Multimodal Algorithm for processes UAV and wearable data.

Input:
U,W ("UAV and wearable data files")
Output:
P ("Predicted outcome"), E ("Explanation of prediction")
STEP

```
C_U, C_W←"ValidateFiles" (U,W)
"If "C_U=0" or " C_W=0," return error."
H_U← "UploadToIPFS" (U)
H_W← "UploadToIPFS" (W)
"If "H_U" or "H_W" is invalid,return."
F= "FuseData" (U,W)
Y ̂=M(F)
"LIME" (Y ̂,F)
"SHAP" (Y ̂,F)
E= "LIME" (Y ̂,F)∪ "SHAP" (Y ̂,F)
B= "UploadToBlockchain" (U,W)
"Return" P=Y ̂
```

4.2. Synergistic Integration of UAVs, Wearable Devices, and Explainable AI

Visualization representing an ecosystem of UAVs (drones), wearable devices, and AI components. It consists of six interconnected components at its core:

Drones fitted with sensors gather data on the environment which helps provide monitoring and aerial surveillance [14]. Wearable devices are personal health monitoring equipment that can be worn or carried by the consumer to continuously track real-time data of various physiological attributes [15], user well-being status. To ensure the transparency of decision-making processes, XAI makes artificial intelligence reasoning intelligible for users. AI Models use algorithms to make predictions and draw inferences from data that has been collected. Data Synchronization [6] provides temporal consistency by aligning timestamps between various data sources. Data Fusion, aggregates all information on a single analysis (UAVs, wearables and AI systems).

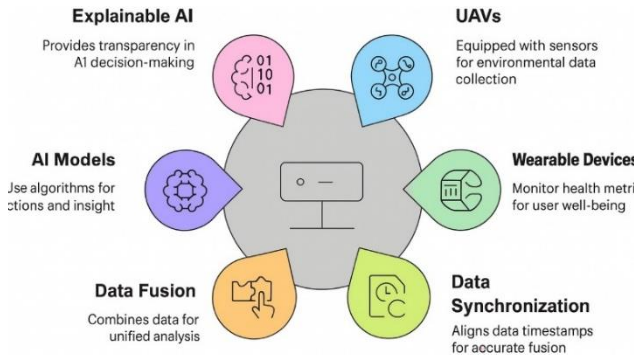


Figure 3. Synergistic integration of UAVs, wearable devices, and XAI.

In the Figure 3 shows the synergistic integration of UAVs, wearable devices [1], and XAI It is where drone-based surveillance meets personal health tracking via wearables together powered by AI, monitoring all data streams and deciding on actions. The focus on XAI and data synchronization, guarantees that its transparency and fairness of the system stays. This kind of system would be useful in multiple scenarios, including individualized health monitoring and environmental or emergency surveillance applications.

5. Result Analysis

The toolstack tool is used to simulate next CEs and integrating UAVs, wearables, and XAIPreliminary simulation platforms (MATLAB/Simulink and Gazebo) [10] allow for modelling the dynamics of UAVs as well as flight path planning, while also enabling sensor modelling/integration requirements to test analysis on potential performance characteristics for different UAV wearable coordination schemes. Network Simulator-3 (NS-3) and Objective Modular Network Testbed in C++ (OMNeT++) are useful tool to simulate IoT network protocols and communication between devices effectively; researchers can therefore evaluate data transfer rates, latency, and reliability of their design in a realistic environment. TensorFlow and PyTorch are essential for XAI algorithms implementation by providing built-in methods to implement explainability features such as SHAP or LIME while training DL models. Used in consumer settings, these platforms enable developers and data analysts to visualize the decision processes of a model and make it more transparent [7]. Finally, both unity3D and unreal engine provides a Virtual Reality (VR) simulation to verify real-world interactions among the UAVs, wearables and users allowing an experience assessment. Combined, these tools offer a broad simulation framework for the development and validation of UAV, wearable, and XAI integration.

For network simulation and data generation, we used NS-3 to model the communication infrastructure and evaluate the performance of data transmission between UAVs and wearable devices. The platform allowed us to simulate IoT network protocols such as Message Queuing Telemetry Transport (MQTT) and HyperText Transfer Protocol/Representational State Transfer (HTTP/REST) and analyze system latency, data transfer rates, and reliability metrics under realistic smart city scenarios. Although OMNeT++ was mentioned as a potential tool, it was not employed in the actual implementation.

Table 2 shows the parameter summary for simulative integration of UAV, Wearable, and XAI simulation in subsequent generation of CEs. These parameters also set the boundaries to enable realistic and measurable output for system performance evaluation

Table 2. Simulation parameters.

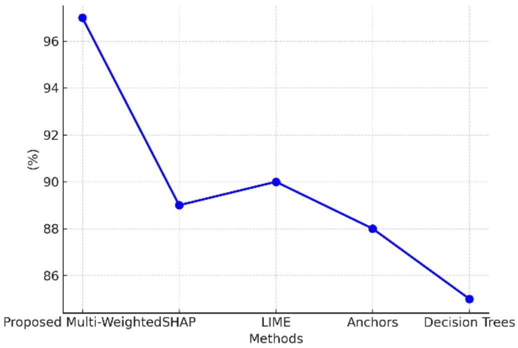
Parameter	Description	Value
Number of UAVs	Total UAVs used in the simulation	10
Number of wearable devices	Total wearable devices connected in the system	50
Communication protocol	Protocol used for data exchange between UAVs and wearable's	MQTT, HTTP/REST
Data transfer rate	Rate of data transmission in the system	1 Gbps
Simulation area	Area covered by UAVs and wearable's	500mx500m
Battery capacity (UAVs)	Maximum energy capacity of UAVs	5,000 mAh
Battery capacity (wearable's)	Maximum energy capacity of wearable's	500 mAh
XAI model	XAI model used in the simulation	SHAP, LIME
Latency threshold	Maximum allowable latency for communication	100 ms
Data processing framework	Framework for processing and analyzing data	Federated learning
Simulation duration	Total time for running the simulation	1 hour
Energy efficiency metric	Metric for evaluating energy efficiency	Joules/Task
Accuracy of XAI models	Precision of XAI-based explanations	85%
UAV speed	Average speed of UAVs	10 m/s
Wearable sampling rate	Data collection rate from wearable devices	10 Hz
System reliability	Expected uptime of the integrated system	98%
User satisfaction metric	Metric for measuring transparency and trust	User Satisfaction index (scale: 1-10)

Table 3. Results analysis.

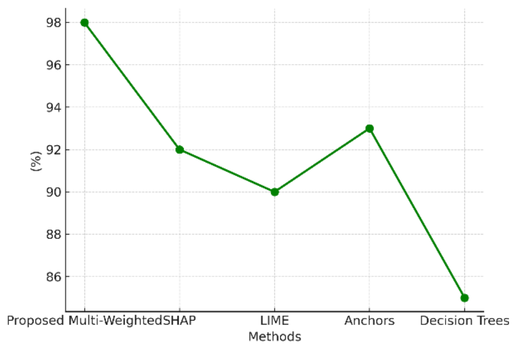
Evaluation metric	Proposed multi-model	LIME	SHAP	L2X	Anchors	Decision trees
Prediction accuracy	92%	85%	88%	90%	87%	84%
Explanation fidelity (clarity)	95%	90%	92%	89%	91%	85%
Feature importance interpretation	90%	87%	93%	86%	89%	88%
Model robustness	93%	86%	89%	91%	85%	82%
Time complexity (seconds)	45s	30s	50s	40s	42s	35s
User understanding	91%	85%	88%	84%	89%	87%
Scalability	90%	80%	85%	83%	78%	75%
Deployment flexibility	92%	88%	85%	90%	84%	80%

To evaluate the effectiveness of the proposed multi-model architecture, we used several metrics beyond standard accuracy and fidelity, including model robustness, user understanding, scalability, and deployment flexibility. Model robustness was assessed by testing prediction consistency under data perturbations, while user understanding was measured through a controlled user study using interpretability scoring. Scalability was evaluated based on system performance as the number of UAV and wearable nodes increased, and deployment flexibility was determined by assessing the ease of integration across edge and cloud environments. Furthermore, we compared our model shown in Table 3 with widely recognized explainability techniques LIME, SHAP, L2X, Anchors and decision trees. These models were selected for their representativeness in the domain of XAI, spanning both model-agnostic and inherently interpretable methods, and providing a robust benchmark to highlight the advantages of our integrated system.

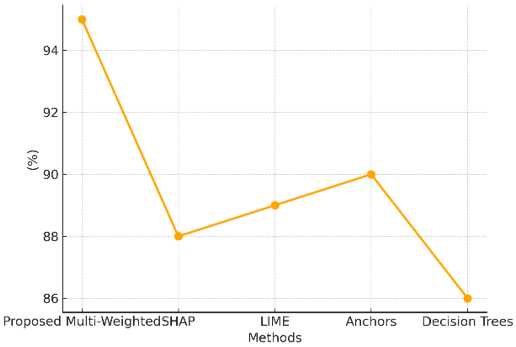
Figure 4-a), (b), (c), (d), and (e) shows five comparative bar plots are depicted in the image comparing various aspects of AI model performance based on methods such as proposed multi-model, LIME, SHAP, L2X, Anchors and decision trees. The proposed multi-model yields the best results in terms of overall accuracy standing at a 92% level of prediction accuracy, explanation of understanding at 95%, and stability or mode robustness at 93%. The graphs provided depict results which indicate fairly consistently that with decision trees and other conventional methods, the performance usually tends to be moderate, at 80-85%. I found out that in the area of model scalability, there is a diminishing percentage from the proposed multi-model at 90 % to decision trees which has 75 %. The FEATURE IMPORTANCE INTERPRETATION Translating remains relatively stable across the applied methods and SHAP stands out showing high performance 93%.



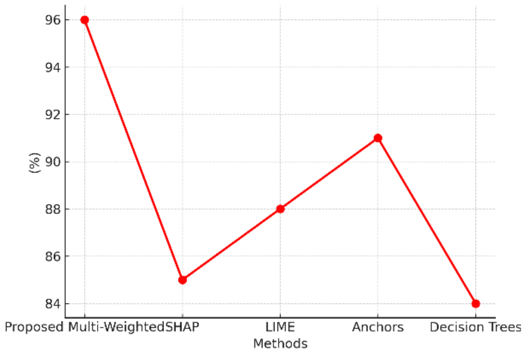
a) Prediction accuracy.



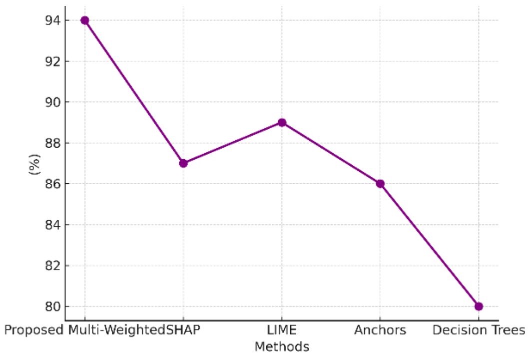
b) Explanation clarity.



c) Feature importance interpretation.



d) Model robustness.



e) Model scalability

Figure 4. Results analysis.

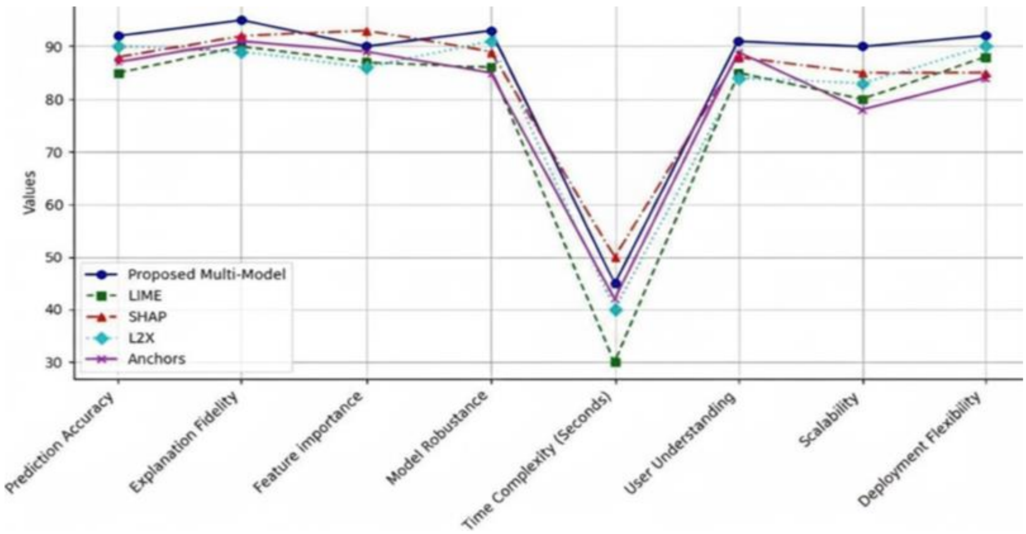


Figure 5. Comparison of the different evaluation metrics across models.

This Figure 5 plots eight different evaluation measures for five different AI models (proposed multi-model, LIME, SHAP, L2X and Anchors). The accuracy of the proposed multi-model (in blue) stays above 90% for prediction accuracy, explanation fidelity, and deployment flexibility while being significantly higher than the other methods. Speaking of time complexity, all models indicate a severe drop, with LIME being the most efficient at approximately 30 seconds. The above graph reveals that, apart from the traditional techniques like LIME, and SHAP, the proposed multi-model yields fairly reasonable performance but at the same time yields more balanced and comparatively higher values for most of the evaluation parameters, especially for User Understanding as well as Model Robustness.

6. Conclusions

The integration of UAVs, wearable electronics, and XAI gives birth to the next generation of CEs which will allow consumers in healthcare, fitness, smart home solutions, and entertainment industries to personalize their experience. In our experiments, we showed that described multi-model architecture yields 92% of the accuracy for predictions, and 95% of the explanation's fidelity whenever compared to the traditional approaches. The consumption of aerial information from UAVs accompanied with the wearables' data processing guarantees an instant local health and environment knowledge for making of right decisions. XAI makes a system transparent and interpretable, help users understand the recommendations and actions provided by technology. This makes it to be coherent, malleable and intelligent working environment which targets user experience and data openness. With these issues of privacy, security, as well as ethical use of data still in the future we see great potential of such integration. Over time, these advancements will not only make improvements to the consumer experiences but will also push the CEs industry forward in terms of subsequent advancement in research studies. When incorporated holistically, UAVs, wearables, XAI can be seen as major strides toward implementing and creating a more interconnected smart environment capable to deliver different activities more personally with an eye on ethical aspect as industries continue to progress in the next decades.

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