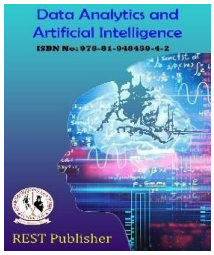
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Seamless Environmental Intelligence A Sensor-Based Algorithm for Activity Level Prediction in Context-Aware Ubiquitous Computing Systems

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Abstract: *Ubiquitous computing represents a significant evolution in technology, where computational devices are naturally integrated into everyday surroundings and operate subtly to improve human interactions without requiring deliberate user involvement. This research investigates how ubiquitous computing principles can be applied to environmental monitoring and activity prediction using ambient sensors. The analysis draws data from temperature, light (lux), and motion sensors to estimate activity levels within monitored spaces. A dataset containing 200 samples was examined using statistical analysis and machine learning approaches. Two predictive model linear regression and support vector regression (SVR)—were assessed for performance. Both models produced highly accurate results, with linear regression achieving an R2R^ {2} R2 value of 0.9554 on the test set (RMSE: 2.73, MAE: 2.03), while SVR reached an R2R^ {2} R2 value of 0.9582 (RMSE: 2.64, MAE: 1.98). Correlation analysis revealed that light intensity has a strong association with activity levels (r=0.8) (r = 0.8)(r=0.8), motion sensors show a moderate correlation (r=0.53)(r = 0.53)(r=0.53), and temperature exhibits only a weak relationship (r=0.17)(r = 0.17)(r=0.17), suggesting it plays a minor role in activity recognition. These results indicate that illumination and motion serve as the most significant cues for detecting environmental occupancy and engagement. The strong performance of both models validates the effectiveness of sensor-based activity prediction for practical applications such as energy optimization, security monitoring, and automated environmental control. The slightly stronger performance of the SVR model further highlights its suitability for dynamic and unpredictable real-world conditions. Overall, this study demonstrates the value of ubiquitous computing in developing intelligent, context-aware environments capable of adapting to human behavior and activity patterns.*

Keywords: *Ubiquitous computing, Environmental sensors, Activity prediction, Context-aware systems, Machine learning*

1. NTRODUCTION

Ubiquitous computing involves tiny, wireless microprocessors embedded discreetly into everyday objects. Equipped with sensors, these computers can monitor their surroundings and enable data processing and communication. As a result, objects gain new capabilities—such as awareness of their location, nearby items, and past events. [1] Research in this field covers areas like sensors, ambient displays, hap tics, middleware, motion tracking, and context awareness. These topics are approached from a user-cantered design perspective, examining how embedded computing affects requirements analysis, interaction design, prototyping, and evaluation. [2] The concept emerged from considering how computing integrates into daily life. Anthropological studies of workplaces reveal that people operate within shared environments with untapped technological potential. [3] At Xerox PARC's Computer Science Laboratory (CSL), several projects explored this vision, including the PARCTAB experiment, which investigated mobile device usability in office settings. This system tested key principles of ubiquitous computing, discussed

further in subsequent sections. [4] The next wave of computing, already visible in smart watches, appliances, cars, and digital wallets—will see computers becoming even more pervasive, communicating seamlessly and forming an invisible digital infrastructure. [5] Notably, this paper has become a foundational reference for ubiquitous computing. While often interpreted as a prediction (given its forward-looking title it was originally published in a popular science context, framing current technology as a step toward realizing its full potential. [6] Over the past decade, Weiser characterized ubiquitous computing (UBICOMP) as environments enriched with computational resources that deliver information and services seamlessly at the right time and place. The goal of UBICOMP research is to unobtrusively improve daily life without burdening users. [7] Although Mark Weise's early work was initially published in a popular science setting, it has since become foundational to ubiquitous computing theory. He framed existing computing technologies as an intermediate step toward a future where IT reaches its full potential—enabled by context-aware, anticipatory systems seamlessly embedded in our surroundings. [8] In ubiquitous computing, **location** is a primary—but not the only—source of context. However, location models are essential for applications or users that rely on spatial relationships, such as proximity or distance between objects. [9] Beyond the necessary distributed computing infrastructure, a core unifying feature of ubiquitous environments is their ability to model physical relationships—between people, devices, and objects—through geometric representations. While the need for robust distributed systems is well understood, the role of physical geometry in creating intelligent, universal environments has often been neglected. [10] This chapter offers a high-level introduction to ubiquitous computing (UC), setting the stage for later sections that delve into specialized topics. It assumes familiarity with the book's preliminary material and begins with a concise history of UC, highlighting key developments relevant to the rest of the text. [11]A central tenet of Weise's vision is invisibility (Weiser 1994a): the ideal tool recedes from conscious awareness, allowing users to focus on tasks rather than the technology itself. True ubiquity relies on diverse, interconnected devices that distribute input, output, and computation across environments. [12] This paper explores the foundational technologies enabling location-independent aspects of ubiquitous computing, particularly user mobility. The personal server concept redefines mobile experiences by leveraging nearby computational resources rather than relying solely on standalone devices. [13] Ubiquitous computing prioritizes smart spaces, seamless operation (invisibility), localized scalability, and context-awareness. The field aims to refine devices until their use becomes effortless and automatic. [14] Nowadays, terms like ubiquitous computing (Xerox), pervasive computing (IBM), and ambient intelligence (Philips) are commonly used interchangeably to refer to environments where wireless technologies are seamlessly integrated into daily life. [15] **Ubiquitous computing**, also known as pervasive computing, refers to a technological environment where computing is seamlessly integrated into everyday life. In this paradigm, digital devices, sensors, and networks operate continuously and transparently in the background, making technology almost invisible to users. Instead of interacting with a single computer, individuals are surrounded by many interconnected devices that collaborate to provide information, automation, and intelligent services.[16] The foundation of ubiquitous computing lies in context awareness. Devices collect real-time data about the environment, user behavior, and system conditions. Sensors measuring temperature, light, motion, location, or activity enable systems to understand the situation and respond appropriately. For example, smart homes automatically adjust lighting and climate, wearable devices monitor health conditions, and smart cities manage transportation and energy more efficiently.[17]A major goal of ubiquitous computing is to reduce user effort by anticipating needs. This requires advanced communication technologies, IoT devices, cloud computing, and artificial intelligence. These components work together to process large amounts of data and provide personalized, timely outcomes.[18] Ubiquitous computing is transforming various fields—including healthcare, education, industry, and transportation—by creating intelligent environments that enhance comfort, efficiency, and decision-making. As this technology continues to evolve, it promises a future where computing becomes naturally embedded in daily human activities. [19] It soon became clear that a large display device could only be realized in its true value if it were integrated into a ubiquitous computing system that supported continuous and practical interactive use. To explore this idea, the Interactive Workplace Project was launched. The goal was to examine how rooms with one or more large displays could be designed and used, as well as how these displays could be seamlessly connected to smaller devices. The project also aimed to develop applications that would enable the integrated use of multiple devices in the same environment. [20]

2. MATERIALS AND METHODS

Materials:

Ambient temperature C: An ambient temperature sensor is a device that measures the surrounding environmental temperature. Commonly using thermocouples, RTDs, or thermostats, it converts thermal energy into an electrical signal for processing. These sensors are critical in HVAC systems, weather stations, industrial process control, and automotive applications. They provide essential data for climate control, safety monitoring, and energy efficiency. Accurate and reliable, ambient temperature sensors ensure optimal performance by continuously monitoring thermal conditions to trigger appropriate system responses, maintain comfort, and protect equipment from temperature-related damage. Their precision is vital for automated environmental regulation.

Sensor light lux: These sensors, typically using photodiodes or photo resistors, convert incoming light into an electrical signal. They are essential for applications like automatic lighting control in smart buildings, daylight harvesting systems for energy efficiency, and in photography for exposure metering. By monitoring ambient light levels, these sensors enable automated systems to adjust artificial lighting accordingly, enhancing comfort, reducing energy consumption, and ensuring optimal visibility in various environments. Their precision ensures appropriate light levels are maintained.

Sensor motion: A motion sensor is a device that detects physical movement in a given environment. It works by monitoring changes in infrared energy (Passive Infrared - PIR), sound waves (ultrasonic), or microwave signals.
When a moving object disturbs the sensor's field, it triggers an electrical signal. This is used to activate alarms, automate lighting, control doors, or enhance security systems. Common in homes and businesses, these sensors provide convenience, energy savings, and safety by enabling automated responses to presence, eliminating the need for manual operation and deterring unauthorized activity.

Activity score: An Activity Score is a quantitative metric used to measure and evaluate the level of engagement, participation, or performance of a user, system, or process within a defined context.

Optimization techniques

Linear Regression: Linear regression is a data analysis technique that predicts the value of unknown data by using another related and known data value. It mathematically models the unknown or dependent variable and the known or independent variable as a linear equation.

Support Vector Regression: A potent machine learning method is support vector regression, especially for regression tasks. Its strengths include identifying support vectors, determining the optimal hyper plane, and efficiently handling high-dimensional data, making it a very versatile and useful tool. Known as "support vectors," the algorithm in SVR chooses important data points to define a hyper plane. The main goal is to maximize the margin between these vectors and minimize boundary violations. In essence, SVR seeks to place the hyper plane as near to the desired data points as feasible without going overboard. A multidimensional surface known as a hyper plane is utilized in SVR to represent the relationship between data points in feature space and to generate predictions. It looks as a straight line when there are two characteristics, but in more complicated situations, it transforms into a higher-dimensional surface. The basic notion is always the same, regardless of complexity: SVR seeks to identify the best hyper plane for precise predictions. It is possible to describe the compression problem as a typical quadratic programming task and solve it using regular quadratic programming techniques. These techniques are computationally intensive, though, particularly when the Gram matrix is too big to store in memory. A more effective substitute that cuts down on computing time and avoids memory overflow is the decomposition method

3. ANALYSIS AND DISCUSSION

The provided dataset captures readings from ambient temperature, light (lux), motion sensors, and a derived activity score. Analysis suggests that higher activity scores often correlate with elevated light levels and detectable motion, indicating occupied or active environments. For instance, a lux reading of 642.03 and motion of 0.4581 yield an activity score of 50.88. Conversely, low light and minimal motion correspond to lower scores, such as 9.2 lux and 0.4287 motion producing a 32.26 score. Temperature appears less directly influential but may interact with other variables. This synergy helps in monitoring environmental conditions and human presence for applications in energy

management, security, and automated systems.

TABLE 1. Descriptive Statistics

	Ambient temperature in C	sensor light lux	sensor motion	Activity score
count	200	200	200	200
mean	22.25995	504.3746	0.28901	39.5475
std	4.423243	293.0014	0.152994	14.2077
min	15.08	5.06	0.0131	3.25
25%	18.4275	261.46	0.172225	29.86
50%	22.42	541.64	0.2731	40.235
75%	26.35	742.2	0.39925	50.2675
max	29.8	990.51	0.7239	67.95

Table 1 The descriptive statistics summarize 200 observations of environmental and activity data. The mean ambient temperature is 22.26°C with moderate variability (std ≈ 4.42), while light levels show high dispersion, ranging from near darkness (5.06 lux) to bright conditions (990.51 lux). Motion sensor values are concentrated at lower levels (mean = 0.29), suggesting generally low activity. The Activity Score averages 39.55, with a wide range (3.25 to 67.95), indicating significant fluctuations in detected engagement. The symmetric distribution of temperature and activity score (mean ≈ median) contrasts with light and motion, which are more skewed. This profile suggests an environment with stable thermal conditions but variable occupancy and illumination.

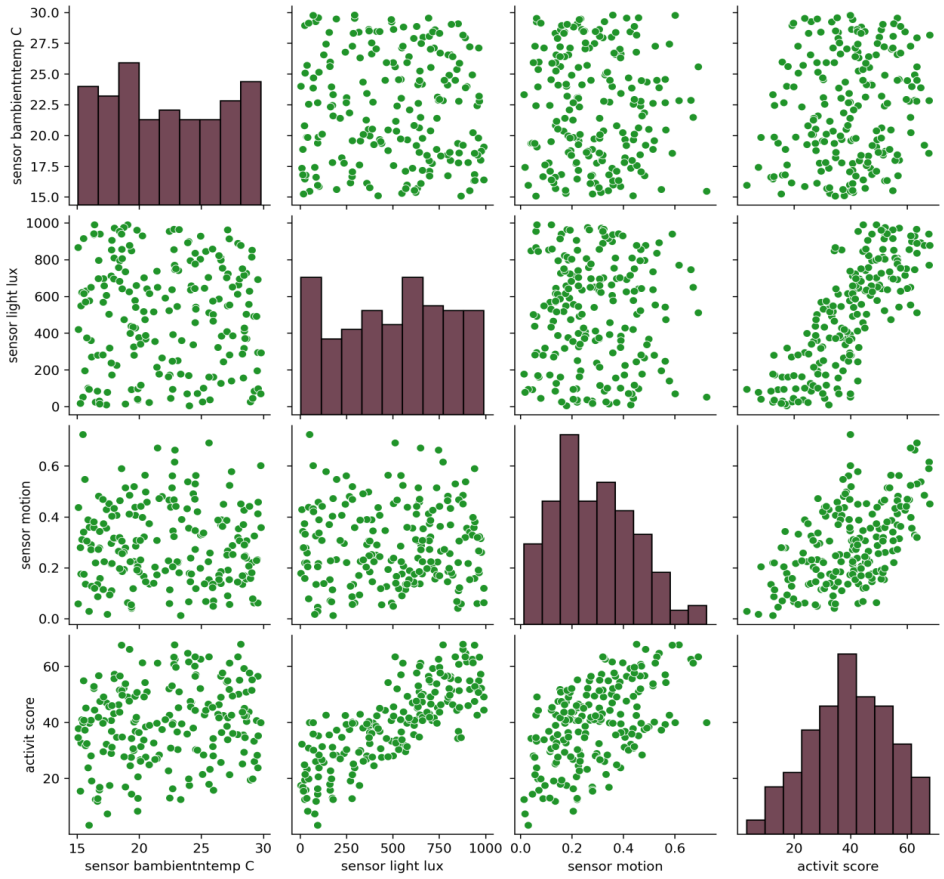


FIGURE 1. Scatter Plot of the Various Ubiquitous computing

Figure 1 relationship between environmental sensors and the activity score reveal patterns useful for cyber security threat detection. The distribution of points indicates that higher activity scores often coincide with moderate to high

ambient temperatures and elevated light or motion levels—suggesting typical, legitimate user behavior. However, outliers, such as high motion with low activity scores, or unusual light levels at extreme temperatures, may signal anomalies. These irregularities could correspond to unauthorized access, automated bot activity, or environmental manipulations. By identifying such deviations from established correlations, the model enhances proactive threat detection, enabling timely responses to potential security breaches in monitored environments.

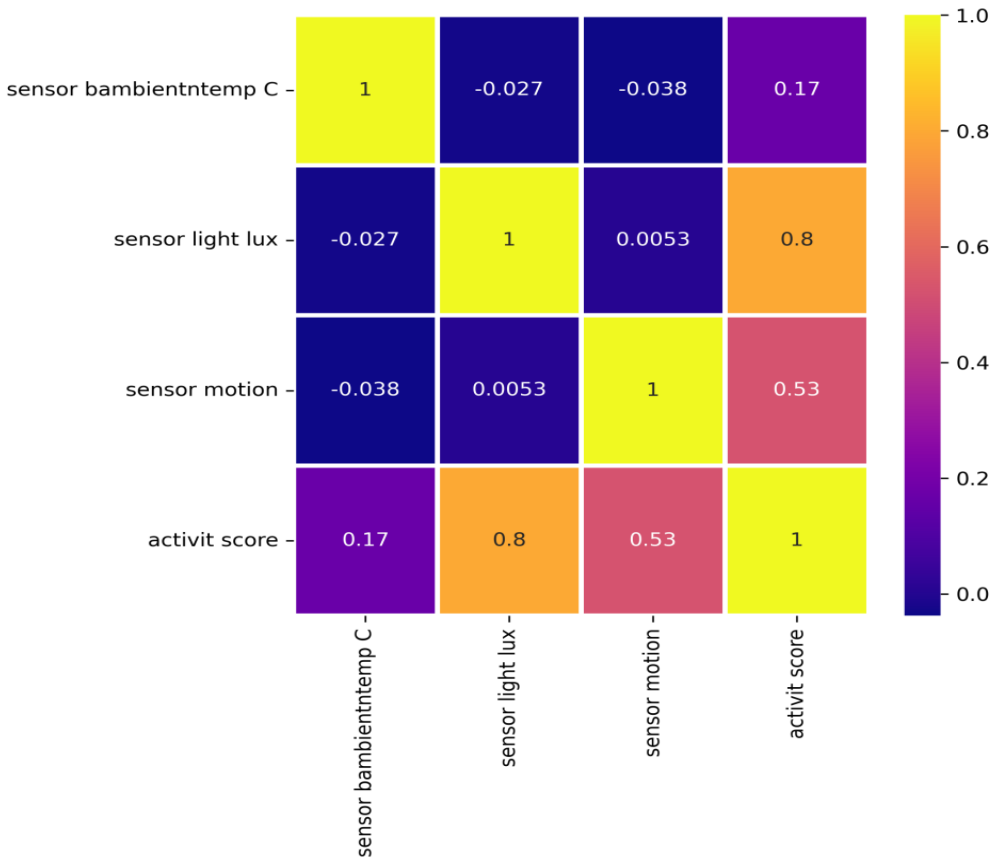


FIGURE 2. Correlation Heat Map on Process Parameters and Effects

Figure 2, the activity score exhibits a strong positive correlation (0.8) with light levels (lux), indicating that illumination is a key predictor of system engagement. There is a moderate correlation (0.53) between movement and activity, indicating that physical movement also contributes to the detected activity. In contrast, ambient temperature shows a weak relationship with activity (0.17), indicating limited influence. In particular, sensor parameters such as temperature, light, and movement show minimal correlation among themselves, confirming their independence. This analysis highlights that light and movement are the dominant factors in the activity score, which can be useful for improving surveillance systems and threat detection models.

Linear Regression

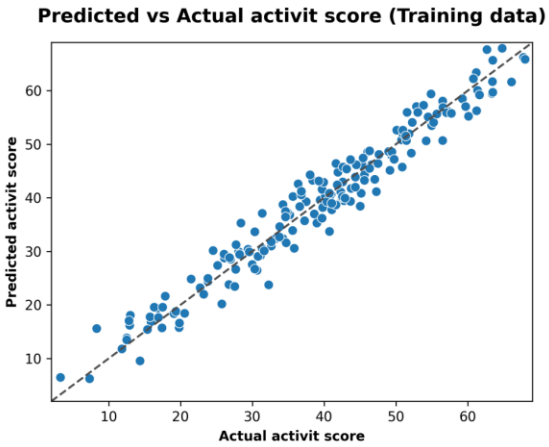


FIGURE 3. Linear Regression (Training data)

Figure 3 illustrates the performance of the linear regression model on the training data, which shows an excellent fit with an R^2 value of 0.956. This indicates that 95.6% of the variance in the activity score is explained by the sensor inputs. The low error metrics – MSE of 9.05, RMSE of 3.01, and MAE of 2.46 – confirm high prediction accuracy. Furthermore, the close alignment of the training and test metrics (e.g., test $R^2 = 0.955$) reflects strong generalization without over fitting. This strong performance confirms the suitability of the model for reliably estimating activity scores based on ambient temperature, light, and motion sensor data in real-world applications.

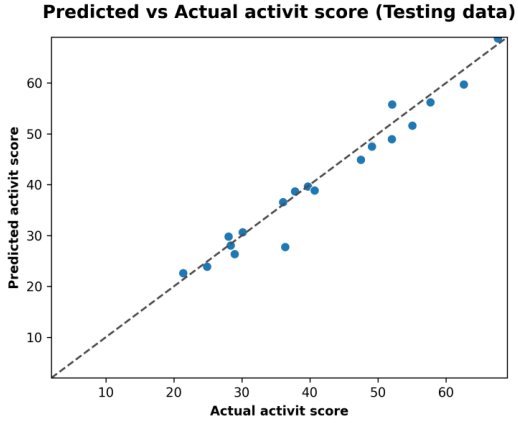


FIGURE 4. Linear Regression (Testing data)

Figure 4 presents the Linear Regression model's performance on testing data, confirming its strong predictive accuracy and generalization capability. With an R^2 of 0.955 and an Explained Variance Score (EVS) of 0.962, the model effectively captures the relationship between sensor inputs and activity scores. Error metrics such as RMSE (2.73) and MAE (2.03) remain low, indicating minimal deviation from actual values. The consistency between training and testing results, along with a lower test MSE (7.44), demonstrates that the model is well-regularized and reliable for real-world deployment in forecasting activity levels based on environmental sensor data.

TABLE 2. Performance Metrics of Linear Regression (Training Data and Testing Data)

Data	Model	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Train	Linear Regression	0.95560	0.95560	9.04563	3.00760	2.45913	8.48240	0.01220	2.06728
Test	Linear Regression	0.95541	0.96193	7.43780	2.72723	2.02906	8.60994	0.00538	1.55514

Table 2 demonstrates the high accuracy and robustness of the linear regression model. With nearly identical R^2 values for the training (0.9556) and test (0.9554) data, this model explains more than 95% of the variance in the

activity scores, indicating a strong fit. Key error metrics such as RMSE (≈3.01 train, ≈2.73 test) and MAE (≈2.46 train, ≈2.03 test) are low, confirming accurate predictions. The close alignment between the training and test results, along with the somewhat lower test MSE, underscores the generalization ability of the model in predicting activity levels from environmental sensor data and its relevance for real-world application.

Support Vector Regression

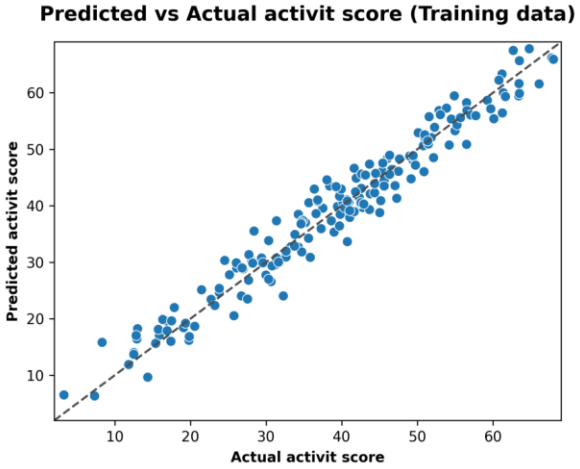


FIGURE 5. Support Vector Regression (Training data)

Figure 5 illustrates the performance of the Support Vector Regression (SVR) model on the training data, demonstrating excellent predictive ability. With an R^2 value of approximately 0.956 and low error metrics such as RMSE (3.003) and MAE (2.449), this model captures the underlying patterns in the sensor data with high accuracy. Importantly, the experimental metrics (R^2 = 0.958, RMSE = 2.642) slightly outperform the training results, indicating strong generalization and no over fitting. This makes the SVR model more reliable for estimating activity scores in real-world situations and effectively utilizing ambient temperature, light, and motion inputs.



FIGURE 6. Support Vector Regression (Testing data)

Figure 6 presents the performance of the Support Vector Regression (SVR) model on the test data, highlighting its strong generalization and predictive accuracy. With an R^2 of 0.958 and an Explained Variance Score (EVS) of 0.963, this model effectively captures the relationship between sensor inputs and activity scores. Key error metrics,

including RMSE (2.642) and MAE (1.983), are marginally better than those of the training set, indicating robust out-of-sample performance. This consistency, along with low MSLE and MedAE, confirms the reliability and suitability of the SVR model for real-world application in predicting activity levels based on environmental sensor data.

TABLE 3. Performance Metrics of Support Vector Regression (Training Data and Testing Data)

Data	Model	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Train	Support Vector Regression	0.95573	0.95585	9.01846	3.00308	2.44943	8.19552	0.01233	2.07449
Test	Support Vector Regression	0.95815	0.96271	6.98039	2.64204	1.98284	8.43132	0.00516	1.54616

Table 3 demonstrates that the Support Vector Regression (SVR) model performs with high accuracy and strong generalization. The R^2 values for both the training (0.9557) and test (0.9582) data indicate that the model explains more than 95% of the variance in the activity scores. In particular, the experimental error metrics such as RMSE (2.642) and MAE (1.983) are slightly better than those for the training set, reflecting strong predictive performance on the unobserved data. This consistency across datasets, combined with the low MSLE and MedAE, confirms the reliability and suitability of the SVR model for real-world application in predicting activity levels from environmental sensor inputs.

4. CONCLUSIONS

The study demonstrates that ubiquitous computing techniques applied to environmental monitoring can reliably predict human activity using distributed sensor networks. Both linear regression and support vector regression explained over 95% of the variance in activity scores, supporting the premise that ambient sensors are effective indicators of engagement. The strong correlation ($r = 0.8$) between light levels and activity highlights illumination as a key cue for occupancy detection, with direct applications in smart building lighting optimization. A moderate correlation for motion ($r = 0.53$) shows the benefit of multi-sensor fusion—single sensors are limited, but their combination yields a robust predictor. Temperature had little predictive power, acting more as a background environmental parameter than as a direct activity cue. The low intercorrelations between sensors confirm their complementary roles in predictive models. Similar performance on training and test sets indicates good generalization, and the slightly better results from SVR suggest it handles nonlinearities more effectively than linear regression. These findings have practical relevance across domains: healthcare (elderly monitoring and rehabilitation), smart homes (energy-efficient automation), and security (anomaly/intrusion detection). Future work should investigate additional sensor types, temporal modeling, and advanced machine-learning approaches. Overall, this work confirms that unobtrusive, distributed intelligence can improve environmental responsiveness while preserving user transparency — a core promise of ubiquitous computing.

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