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Energy-Aware Smart Spaces: Activity Recognition via PIR Sensors and Real-Time Classification Models

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Abstract – In the age of intelligent structures and energy efficiency, accurate identification of human presence and activity has become essential. Passive Infrared (PIR) sensors, recognized for their energy efficiency and affordability, are essential in smart environmental management systems. This research investigates the use of PIR sensor arrays in contemporary structures to identify occupancy and categorize human activities. With a dataset of 15,000 records gathered in a smart office setting, we assess different machine learning models to categorize activity states: empty, stationary human presence, and active motion. Our tests demonstrate the effectiveness of ensemble models, notably Random Forest and ANN, in attaining high classification precision. This study demonstrates the viability of creating advanced building management systems that improve energy efficiency and security.

Index Terms – Passive Infrared (PIR) Sensor, Occupancy Detection, Human Activity Recognition, Motion Detection, Presence Detection, Smart Building Systems

I. INTRODUCTION

Contemporary structures are progressively incorporating new smart technologies to improve energy use, security, and general comfort for the occupants. One such magnificent system deals with occupancy detection, which lays the foundation of allowing control of lighting, heating, ventilation, and air conditioning (HVAC) systems based on actual human presence. The occupancy detection using PIR sensors has proven to be a cornerstone technology in achieving energy savings and enhanced occupant comfort, as these sensors enable precise and non-intrusive monitoring of space usage [1].

Smart Infrastructure has become increasingly responsive and adaptive with the improvements of Internet of Things (IoT). Standing out from other sensing technologies are Passive Infrared (PIR) sensors, which are more cost efficient, consume little power, and are less complicated. Sensors designed to detect infrared radiation given off by the human body are widely used for motion and presence detection.

Understanding these facts about passive infrared technology, the authors set out to investigate the use of PIR sensors for detecting human presence and classifying human actions with respect to modern office environments. Instead of intrusive techniques, we focus on real-time activity recognition at a higher level by analyzing changes in temperature against a series of 55 readings from a PIR sensor taken at four second intervals. The intention is to improve the automation systems of buildings with the higher precision of identifying the presence of people in the commercial environment where the patterns of usage change dramatically.

II. RELATED WORK

The present literature has demonstrated promising applications of Passive Infrared (PIR) sensors for activity recognition and occupancy-based energy management. For instance, Shokrollahi et al. [2]

conducted a comprehensive review of PIR sensor-based occupancy monitoring systems and highlighted the growing trend of integrating lightweight machine learning models for real-time decision-making. Their work emphasized that PIR sensors are not only cost-effective and privacy-preserving but also suitable for edge-based computing due to their low data complexity. They also discussed hybrid models combining PIR data with contextual cues to improve occupancy estimation in complex environments such as smart buildings. Moreover, Li et al. [3] examined the social aspect of smart offices by studying how privacy is understood by occupants when such sensing technologies are in use. Their results indicated that privacy considerations differ greatly based on spatial and temporal dynamics, particular security issues, and an individual's understanding of the data collection process. These conclusions highlight the need for careful consideration of trust and acceptance where sensors, particularly AI-enabled ones, are used in monitoring systems to ensure that privacy and comfort are preserved at work. Taking these steps further, Lin et al. [4] proposed the PIRILS (Pyroelectric Infrared Indoor Localization System), which is designed for multi-target indoor localization using deep learning-based algorithms specific to the operational features of PIR sensors. By employing a quantized scheme and supplementary data augmentation methods, PIRILS also enhances the diversity of training data which improves the accuracy and stability of the system. This method illustrates the enhanced scope for the combination of artificial intelligence with PIR sensors for developing robust, privacy-conscious indoor localization systems applicable in malls, hospitals, and large office spaces.

While these developments highlight the usefulness of PIR sensors in residential settings, applications in commercial office environments remain largely unstudied. Offices differ from homes in several important aspects:

- The occupancy patterns are more complicated because of meetings, collaborative work, and presence at the desk which can be intermittent.
- People can stay in one position for a long time (e.g. at a desk working on a computer) and during these periods there is no movement that would be detected by PIR sensors.
- There is also a greater demand for privacy-friendly, low-cost, and scalable solutions for tracking occupant presence in open-plan or shared office spaces.

More recent research has appreciated these shortcomings. Yun and Lee [5] also pointed out that the analog output of PIR sensors is affected by too many variables which include the body's distance from the sensor, the direction and speed of movement, and the person's bodily features such as shape and gait. Their work showed the possibility of detecting and classifying movements through the more intricate aspects of PIR sensor data analysis, thus proposing solutions to distinguishing occupants from the motionless occupants challenge. A variety of approaches have been tested in an attempt to eliminate this challenge, particularly the use of ultrasonic, CO_2, or camera sensors in combination with PIR sensors, which tend to increase cost, complexity, and privacy issues. In another work [6] that presents a systematic review of fall-detection systems that use low-resolution passive infrared (PIR) sensors (up to 16x 16 pixels) for monitoring older adults. The authors examined 15 studies to evaluate how accurate and reliable these sensors are for detecting human falls. Most studies showed high performance (85-90%+ accuracy), especially when multiple sensors or advanced Al models (CNN, LSTM, 3D-CNN) were used. However, the authors highlight that these systems were mostly tested in controlled environments, and more real-life testing is needed.

Another study [7] focuses on improving the sensitivity of Passive Infrared (PIR) sensors used for motion detection and energy-efficient systems. The authors develop a mathematical model to analyze key sensor parameters and simulate voltage outputs. They evaluate how factors like distance, detection range, and sector angle affect infrared absorption. Overall, the work proposes methods to make PIR sensors more sensitive and effective in real-world applications. To date, there seems to be a gap in the literature addressing the holistic assessment of PIR sensors placed within office environments utilizing machine learning to estimate presence during idle periods. This is how we intend to fulfil this gap by:

- Implementing an actual smart office experiment with varying levels and patterns of occupancy.
- Testing dynamic and static presence detection using time-series PIR data with advanced ML classifiers (e.g., Random Forest, SVM, LSTM) striving for higher order detection.
- Determining workstation setups like private cubicles and shared zones to evaluate workflows with multisensory PIR data in a more seamless approach.
- Designing a permissively inquisitive logic for seamless implementation into space management and energy control systems.

PIR sensor reliability and applicability in office settings will be the primary subject of inquiry alongside occupational-based automation and adaptive data-driven planning through this research.

III. Working Principles and Applications of PIR Sensors

Passive Infrared (PIR) sensors play a pivotal role in modern smart home systems by enabling devices to detect human presence or motion without physical interaction. [8] These sensors detect changes in infrared radiation within their field of view, leveraging the natural heat emitted by warm-bodied entities such as humans or pets.

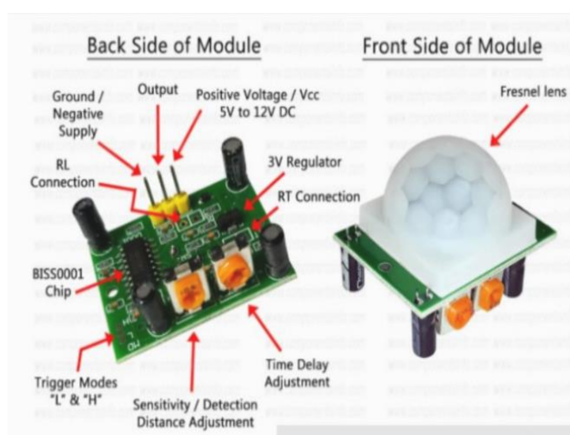

Figure 1 Front and Back side of the Module

A. How PIR Sensors Work

PIR sensors contain pyroelectric materials that generate an electric charge when there is a change in infrared radiation. Most of the time, the sensor is divided into two or more parts that check the IR levels from adjoining zones. This type of measurement enables the determination of motion within the sensor's view instead of a constant temperature.

1) Idle State (No Motion)

The energy emitted from IR radiation is constant when there is no activity. The signal difference is equal to zero; hence the sensor is in standby mode.

2) Motion Detected

Once a person steps into the room, it is observed that one of the elements is receiving more infrared energy leading to a change in voltage. This means that the sensor circuitry considers it as motion and there is a digital output triggered (by default, it is normally HIGH).

3) Signal Processing

The primary voltage output from the sensor is:

- Increased.
- Stripped of external noises.
- Changed into digital signals.

These digital signals are capable of being connected to micro-several controllers, automating appliances, or edge devices for further evaluation.

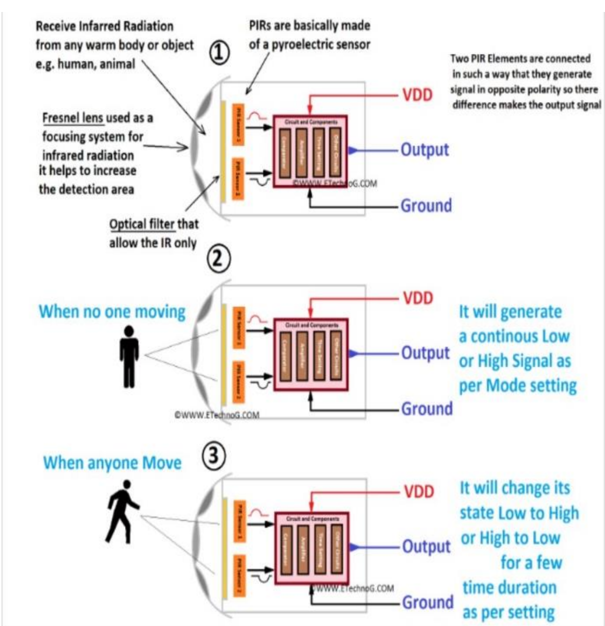

Figure 2 Operating principles of passive infrared (PIR) sensors showing detection mechanisms.

4) Optics and Coverage

For further detection sensitivity and coverage, a Fresnel lens array is implemented over the sensor. It enables the positioning of the sensor in such a manner that its field of view is advanced to extend beyond the typical 100° to 180° horizontally sweeping range by partitioning the infrared signals into Numerous defined zones. Through this, the sensor is capable of detecting motion in a broader range.

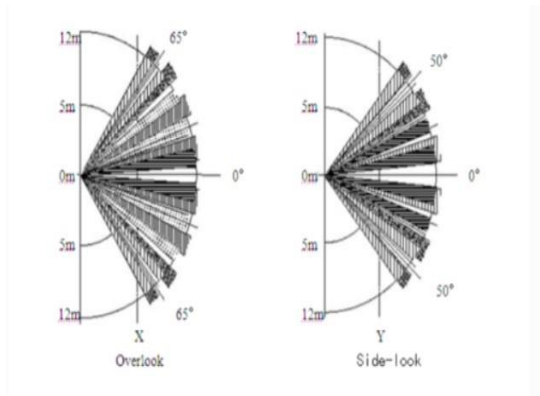

Figure 3 Polar representation of HC-SR501 PIR sensor coverage area in overhead (left) and side-profile (right) orientations, indicating maximum detection range of 12m with angular coverage of 65° horizontally and 50° vertically.

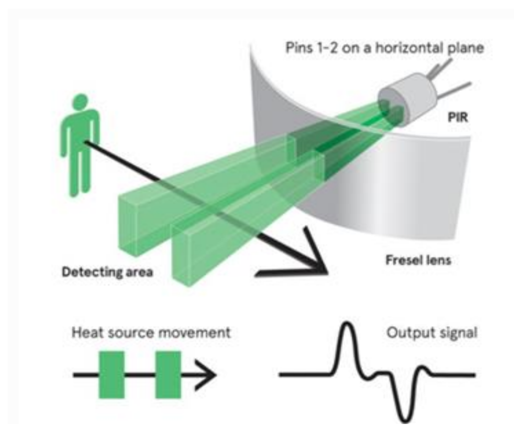

Figure 4 Passive infrared (PIR) sensor detection mechanism illustrating human presence sensing.

B. Application in Smart Homes

In smart homes, integration of the PIR sensors with IoT, AI, and home automation frameworks leads to the development of proactive and intelligent systems. The applications include:

1) Intelligent Lighting

When a person enters a certain area, the lights are activated, and if no motion is detected for a certain period, the lights are deactivated.

Offers convenience, especially when one is occupied, as well as helps save on energy.

2) Security and Intrusion Detection

Hidden activities that can occur in the house are monitored to see if there is any unexpected movement when at home is in “Away” or “Sleep” mode.

Action upon detection may include setting off alarms, notifications to users, or recording video surveillance.

3) HVAC Control

Controls the operation of heating, ventilation or air conditioning (HVAC) systems depending on utilization and occupancy of rooms.

Eliminates possibility of wasteful energy consumed on non-conditioned spaces.

Figure 5 Integrated smart home architecture demonstrating multi-device IoT ecosystem.

4) Elderly Care and Monitoring

Uses movement detection for providing health and safety of aged people.

Motion detection systems can also send warning signals if no movement is sensed for long periods.

5) Gas Cylinder Burst Prevention

PIR sensors are useful in domestic kitchens and commercial cooking facilities as they can be integrated into an environment where flammable gas is used or stored. These sensors together with gas leakage detectors form part of a proactive safety system.

Gas Leakage Due to Motion Detection: The system can trigger immediate ventilation, set off alarms, and cut off gas supply to avert ignition if a gas leak is detected and PIR sensors spotting motion at the same time.

Chaperoning out of hours: Observation of motion around gas cylinders at abnormal working hours can result in emergency alerts being sent to the facility or house managers.

6) Child Safety Monitoring

Sensor equipped homes bring an extra layer of supervision to child's safety which automatically reduces potential hazards in dangerous zones.

Danger zone surveillance: Monitors alert or sound alerts when movement of a child is detected near kitchens, staircases or electrical sockets.

Safety features: Energizes automatic locks on cabinets or turn on lights at the top of the staircase when figure motion is detected.

7) Integration with Machine Learning

PIR information may be used with machine learning models to:

Automatically configure optimal routines based on user behavior.

Use sensor fusion (PIR in combination with sound, weight, or video) to differentiate between human movement and pets.

Enable heating or lighting based on predicting occupancy trends.

C. Advantages for Smart Homes

- Low cost and low power requirements make it suitable for constant monitoring in home settings.
- No video or audio data collected makes it suitable for bedrooms, bathrooms, and other private spaces, demonstrating privacy friendliness.
- Integration with smart hubs like Home Assistant, Google Home, or Alexa is straightforward and requires no extensive configuration.

D. Challenges

- Line of sight only detection limits motion detection to only areas in front of walls and furniture.
- Static detection failure: no means of knowing whether a person is sitting still in the room and not moving.
- Pets or sudden ambient temperature changes may trigger unwarranted activation without proper configuration.

IV. DATASET DESCRIPTION

A. Data Collection

The dataset was collected using a network of 55 analog Passive Infrared (PIR) sensors strategically deployed throughout an office workspace. Sensor readings were recorded every 4 seconds over a period of several weeks, resulting in approximately 15,000 instances. Each entry corresponds to a timestamped snapshot of environmental and occupancy conditions.

B. Features

The dataset comprises the following features:

Date and Time: Timestamp indicating when the observation was recorded.

Label: Class representing occupancy status:

0 – Vacancy

1 – Stationary human presence

3 – Other activity or motion

Temperature: Ambient temperature recorded in degrees Fahrenheit.

PIR_1 to PIR_55: Raw analog signals from each of the 55 PIR sensors.

C. Preprocessing

The dataset underwent the following preprocessing steps:

Missing values were imputed using linear interpolation.

Min-Max normalization was applied to PIR sensor readings to scale values between 0 and 1.

Duplicate entries were identified and removed.

To balance class distributions and enrich the dataset, synthetic noise was introduced through the controlled augmentation, expanding 7,600 entries to 15,000 samples while preserving data uniqueness.

D. Feature Engineering

Due to the high dimensionality of PIR data, initial experiments were conducted with various feature selection techniques. However, retaining the full set of

55 PIR features yielded superior performance across most models. The temperature feature showed minor influence but was retained for completeness in environmental context.

V. METHODOLOGY

Several supervised classification models were trained to classify occupancy based on PIR and temperature data.

A. Models Used

- Logistic Regression
- Decision Tree
- Random Forest
- K-Nearest Neighbours and so on

B. Training and Testing

- Dataset split: 80% training, 20% testing
- Evaluation Metrics: Accuracy, Prediction Speed, Confusion Matrix

C. Model Implementation

After evaluating several machine learning models based on the PIR sensor dataset in modern building contexts, it was found that the most appropriate models are relative to the specific use case. For edge devices with real-time, resource limitations, such as those found in smart buildings, the Fine Tree and Linear SVM models are the best.

Both of these models perform exceptionally well in testing (approximately 99.6% accuracy) and have extremely fast prediction, low training times, and low overhead cost, allowing them to quickly and accurately provide results.

For other powerful hardware, cloud infrastructure, and environments where model complexity and training time is not an issue, Medium Neural Networks and Bagged Trees perform the best. These models also have high estimation accuracy (99.86%) which demonstrates good generalization and reliability, a necessity when used in actual dynamic building environments. Other models such as K-Nearest Neighbors and RUSBoosted Trees, do not perform as well due to slow prediction times and intensive computational needs, albeit their theoretical advantages.

These, coupled with the fact that Fine Tree performs exceptionally well makes the model perfect for smart buildings, as it requires low time and high accuracy. The testing accuracy achieved during the evaluation was exceptionally high, reaching up to 99.94%. For visualization purposes, only the top 100 observations were plotted, where a strong alignment between actual and predicted class labels can be clearly observed.

These graphs illustrate the model's consistency and reliability in classifying occupancy states, reinforcing the effectiveness of PIR sensor data for intelligent activity recognition in smart office environments.

Confusion Matrix				True Class			True Positive Rate	False Negative Rate	Training Accuracy (%)	Testing Accuracy (%)	Prediction Speed (k-obs/sec	Training Time (sec)
				0	1	3						
Tree	Fine Tree	Predicted Class	3			100%	100.00%					
			1	1.10%	99.60%		99.60%	0.40%	99.50%	99.68%	40000	130.86
			0	98.90%	0.40%		98.90%	1.10%				
	Tree	Predicted Class	3			100%	100.00%					
			1	1.30%	99.60%		99.60%	0.40%	99.50%	45.80%	160000	126.16
			0	98.70%	0.40%		98.70%	1.30%				
	Coarse Tree	Predicted Class	3			100%	100%					
			1	2.10%	98.40%		98.40%	1.60%	98.70%	98.78%	150000	125.63
			0	98.00%	1.60%		98.00%	2.00%				
Ensemble	Efficient logistic Regression	Predicted Class	3			100%	100.00%					
			1	3.90%	97.60%		97.60%	2.40%	97.80%	97.92%	51000	121.58
			0	96.20%	2.40%		96.20%	3.80%				
	Efficient Linear SVM	Predicted Class	3			100%	100%	95.00%				
			1	12.50%	97.90%		97.90%	2.10%	95.00%	97.92%	31000	219.01
			0	87.50%	2.10%		87.50%	12.50%				
Naive Bayes	Kernel Naive Bayes	Predicted Class	3	0.001	0.036	100%	99.80%	0.20%				
			1	3.60%	99.80%		99.80%	0.20%	98.60%	98.47%	140	423.26
			0	96.30%	0.20%	0.001	96.30%	3.70%				
	Linear SVM	Predicted Class	3			100%	100%					
			1	2.00%	99.50%		99.50%	0.50%	99.10%	99.16%	60000	130.68
			0	98.00%	2.00%		98%	2.00%				
	Quadratic SVM	Predicted Class	3	0		100%	100%					
			1	1.50%	99.70%		99.70%	0.30%	99.40%	99.48%	33000	129.3
			0	98.50%	0.30%		98.50%	1.50%				

Figure 6 Confusion matrices and performance metrics comparing machine learning models

SVM	Cubic SVM	Predicted Class	3			100%	100%					
			1	1.40%	99.80%		99.80%	0.20%	99.50%	99.58%	35000	269.93
			0	98.70%	0.20%		98.70%	1.30%				
	Fine Gaussian SVM	Predicted Class	3	0.001	0.001	100%	100%					
			1	0.10%	99.10%		99.10%	0.90%	99.60%	99.65%	54000	295.39
			0	99.80%	0.80%		99.80%	0.20%				
	Medium Gaussian SVM	Predicted Class	3	0.001		100%	100%					
			1	1.60%	99.80%		99.40%	0.20%	99.40%	99.54%	36000	302.15
			0	98.40%	0.20%		98.40%	1.60%				
	Coarse Guassian SVM	Predicted Class	3			100%	100%					
			1	2.50%	99.50%		99.50%	0.50%	99.00%	99.09%	17000	312.96
			0	97.50%	0.50%		97.50%	2.40%				
KNN	Fine KNN	Predicted Class	3	0.001		100%	100.00%					
			1	1.30%	99.90%		99.90%	0.10%	99.50%	99.58%	1600	345.25
			0	98.60%	0.10%		98.60%	1.40%				
	Medium KNN	Predicted Class	3	0.001	0.002	100%	100%					
			1	1.90%	99.10%		99.10%	0.90%	99.00%	99.13%	1500	377.71
			0	98.00%	1.90%		98%	2.00%				
	Coarse KNN	Predicted Class	3	0.001	0.009	98%	97.90%	2.10%				
			1	2.20%	97.70%		97.70%	2.30%	97.80%	97.78%	1500	412.64
			0	97.70%	1.40%	0.021	97.70%	2.30%				
	Cosine KNN	Predicted Class	3	0.001	0.002	100%	100.00%					
			1	1.70%	99.10%		99.10%	0.90%	99.10%	99.16%	1300	450.68
			0	98.20%	0.80%		98.20%	1.80%				
	Cubic KNN	Predicted Class	3	0.001	0.019	100%	100%					
			1	1.90%	99.10%		99.10%	0.90%	99.00%	99.06%	41	1598.1
			0	98.00%	0.70%		98.00%	2.00%				
	Weighted KNN	Predicted Class	3	0.001		100%	100%					
			1	1.90%	100.00%		100%		99.30%	99.20%	1100	495.45
			0	98.00%			98%	2&				

Figure 7 Confusion matrices and performance metrics comparing machine learning models

Ensemble	Boosted Trees	Predicted Class	3			100%	100%					
			1	0.90%	99.90%		99.90%	0.10%	99.70%	99.68%	34000	560.38
			0	99.20%	0.10%		99.20%	0.80%				
	Bagged Tress	Predicted Class	3			100%	100.00%					
			1	0.80%	99.90%		99.90%	0.10%	99.70%	99.86%	39000	650.72
			0	99.20%	0.10%		99.20%	0.80%				
	Subspace Discriminant	Predicted Class	3		0.001	100%	99.80%	0.20%				
			1	27.10%	99.60%		99.60%	0.40%	90.40%	90.60%	11000	667.42
			0	72.90%	0.30%	0.002	72.90%	27.10%				
	Subspace KNN	Predicted Class	3	0		100%	100%					
			1	1.00%	99.90%		99.90%	0.10%	99.60%	99.75%	86	1254
			0	99.00%	0.10%		99.00%	0.10%				
	RUSBoosted Trees	Predicted Class	3			100%	100%					
			1	1.30%	99.80%		99.80%	0.20%	99.50%	99.61%	41000	1312.4
			0	98.70%	0.20%		98.70%	1.30%				
Neural Network	Narrow Neual Network	Predicted Class	3	0		100%	100%	0.00%				
			1	0.70%	99.90%	0	99.90%	0.10%	99.70%	99.72%	50000	1591.3
			0	99.20%	0.10%		99.20%	0.70%				
	Medium Neural Network	Predicted Class	3	0.001		100%	100%					
			1	0.90%	99.90%		99.90%	0.10%	99.70%	99.86%	150000	1594.8
			0	99.10%	0.10%		99.10%	0.90%				
	Wide Neural Network	Predicted Class	3	0		100%	100%					
			1	0.70%	9990.00%		99.90%	0.10%	99.70%	99.86%	43000	1594.2
			0	99.20%	0.10%		99.20%	0.70%				
	Bilayered Neural Network	Predicted Class	3	0.001		100%	100%					
			1	0.70%	99.90%		99.90%	0.10%	99.70%	99.65%	73000	1592.8
			0	99.30%	0.10%		0.30%	0.70%				
	Trilayered Neural Network	Predicted Class	3	0		100%	100%					
			1	0.60%	99.90%		99.90%	0.10%	99.70%	99.68%	79000	1591.8
			0	99.40%	0.10%		99.40%	0.60%				

Figure 8 Confusion matrices and performance metrics comparing machine learning models

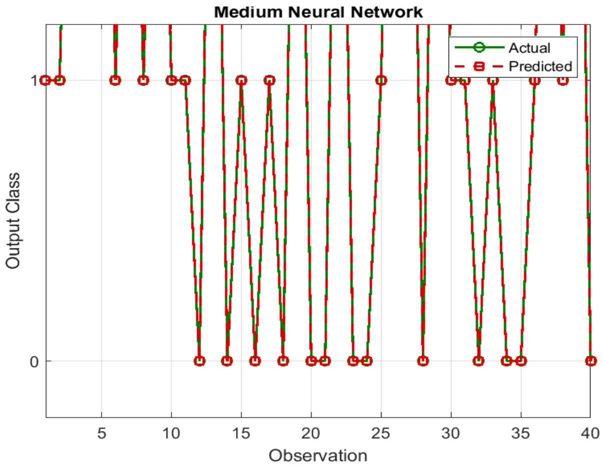

Figure 9 Medium NN

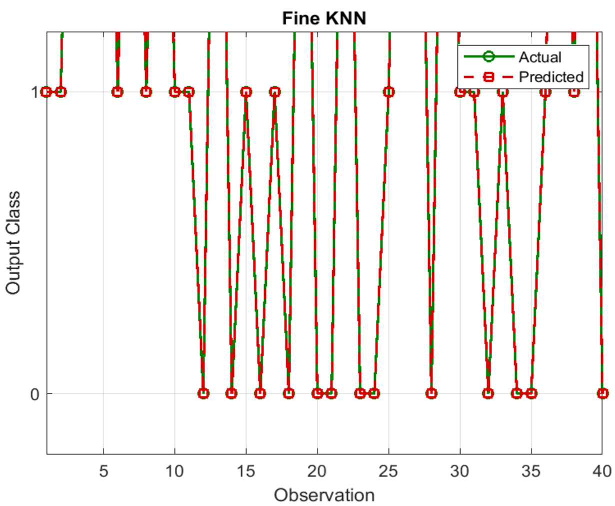

Figure 10 Fine KNN

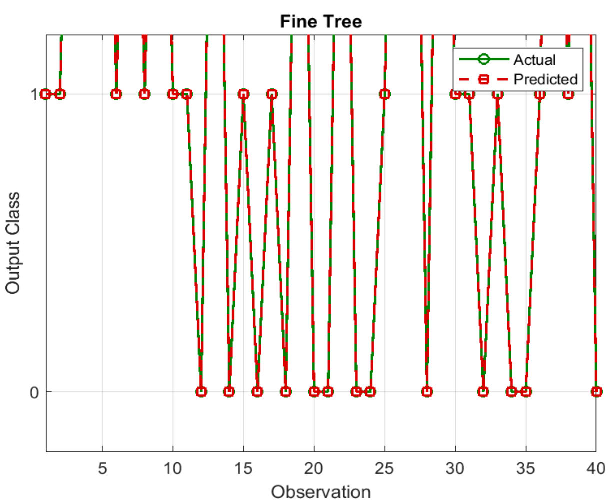

Figure 11 Fine Tree

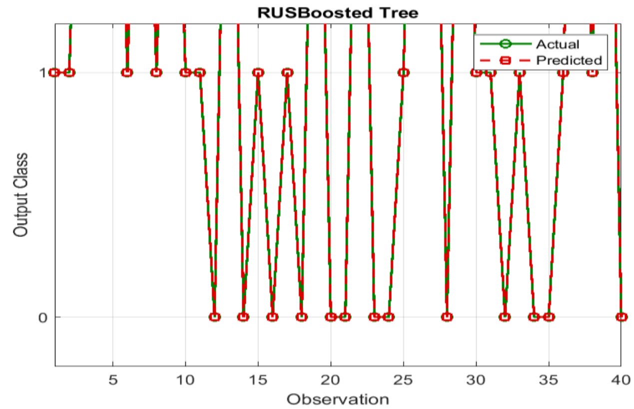

Figure 12 RUBoosted Tree

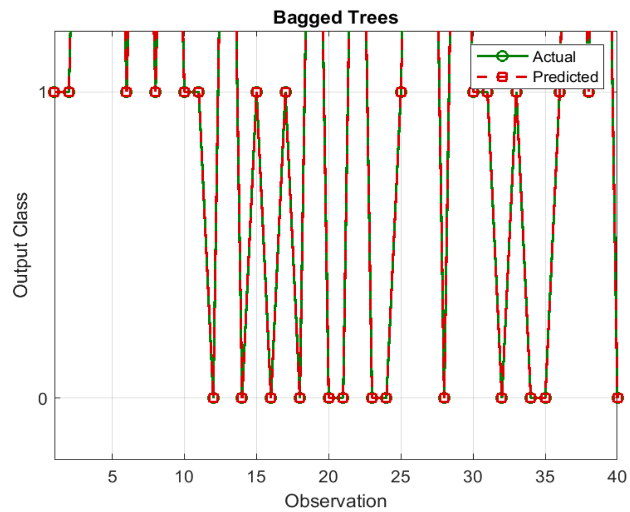

Figure 13 Bagged Tree

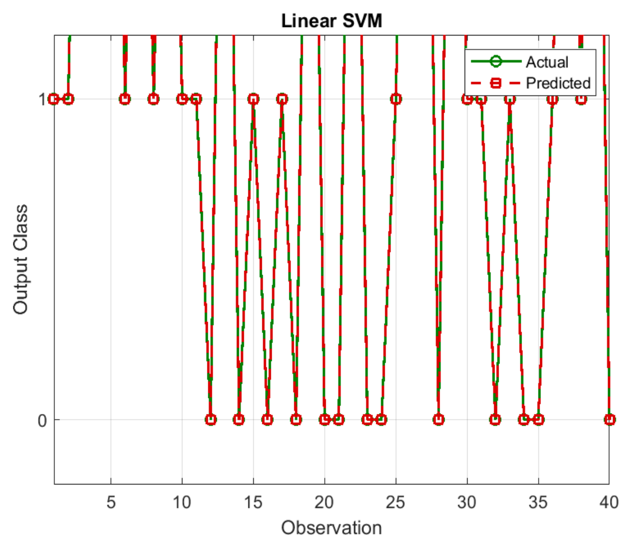

Figure 14 Linear SVM

VI. Security Perspectives in Smart Buildings Using PIR Sensors

Examining security perspectives when employing Passive Infrared (PIR) sensors within smart building infrastructures.

The growing interconnection of smart buildings through IoT devices and sensors such as Passive Infrared (PIR) sensors has brought data security and privacy to the forefront of critical concerns. Passive Infrared sensors function primarily to detect motion which activates systems for lighting automation as well as climate management and security alerts. PIR sensors fail to collect explicit personal data such as video or audio recordings but their motion pattern data remains capable of disclosing private details about users' daily routines and behaviors. Privacy concerns become more significant in multi-occupant environments when motion logs connect timestamps with sensor data.

Cybersecurity experts identify that unauthorized PIR sensor data access allows attackers to chart occupancy patterns which puts the safety of the building at risk. To protect against data tampering and spoofing attacks it is essential to adopt secure communication protocols (like TLS, MQTT with authentication) as well as local data processing and anomaly detection models. Edge AI systems like Fine Tree and Linear SVM enable local data processing which lowers external network reliance and naturally enhances security.

Modern smart homes and cities require AI-based automation to be integrated with security measures according to Verma et al. [9]. The researchers present layered security systems that combine image processing techniques with cryptographic methods and end-to-end encryption for both secure data transmission and storage of sensitive sensor information against unauthorized access.

VII. Proposed Variant: AI-Augmented PIR Sensor for Intelligent Motion Detection

To address the shortcomings of passive infrared (PIR) sensors in today's smart environments, this research suggests a new type of PIR sensor called an “AI-Augmented PIR Sensor.” Despite the widespread

use of PIR sensors due to their affordability and simplistic design, they are commonly associated with drawbacks like context-blindness leading to false alarms, source motion indiscernibility (human vs. animal), and no contextual awareness. As mentioned earlier, the variant proposes solutions to these issues by adding a light AI model through TinyML on edge microcontrollers that can classify motion patterns in real time. In addition, this sensor system employs multi-sensor fusion where PIR data is augmented with supplementary data from ultrasonic, temperature, and CO_2 sensors for enhanced detection accuracy in dynamic indoor environments.

Beyond the fundamental capabilities of motion detection, the system also facilitates occupancy estimation and directional sensing by deploying a matrix of PIR sensors—offering real-time tracking of space utilization crucial in smart buildings for automated HVAC, lighting, and security control. The variant features LoRa or Wi-Fi IoT connectivity to communicate with smart building hubs for centralized data collection and management, guaranteeing effortless data synchronization. Data processing in this model is unique as all data is processed locally without needing.

VIII. Conclusion and Future Work

This research focused on using Passive Infrared (PIR) sensors for occupancy detection and activity recognition in smart offices. Using an ensemble of machine learning techniques on a dataset consisting of over 15,000 readings from the sensors, we proved that both static and dynamic presence recognition with high accuracy can be achieved using ensemble methods like Random Forests and artificial neural networks. We further discussed the importance of PIR sensors for increasing energy efficiency and security from the viewpoint of smart infrastructure.

In order to alleviate some challenges posed by traditional PIR systems, we developed an AI-Enhanced version that places small machine learning algorithms onto edge devices for on-device processing, allowing for activity recognition without compromising privacy. This approach improves accuracy, context awareness, and scalability of the detection systems.

Future Work will focus on the following:

Broadening the dataset to include other settings such as educational facilities, libraries, and co-working spaces. Adding vision and sound data from other sensors in privacy-preserving ways. Improving occupancy counting and directionality using 3D sensor grids. Long-term scaling trials for real-world building management system performance integration.

This foundation enables the deployment of intelligent, autonomous, and energy-aware spaces that balance performance, privacy, and cost-effectiveness.

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