PIRVision: Human Presence Detection Using PIR Sensor Arrays with Supervised Learning

(Classification)

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***Abstract*—This project report details the design, implementation, and optimization of a supervised classification model for human presence detection using Passive Infrared (PIR) sensors. The objective was to categorize sensor readings into distinct activity states—Vacancy, Stationary Human Presence, and Other Motion—by leveraging machine learning algorithms. The classification pipeline began with thorough data preprocessing, including merging datasets, timestamp parsing, normalization, and exploratory analysis. Dimensionality reduction via Principal Component Analysis (PCA) was employed to compress the 55 PIR sensor readings. Additionally, Isolation Forest [2] was applied to detect and remove outliers, particularly within ambiguous activity classes. Machine Learning models including Logistic Regression, Support Vector Machine (SVM), and Random Forest [3] were trained and compared, with Random Forest further optimized using hyperparameter tuning. Extensive evaluation using accuracy, confusion matrices, and class-wise precision/recall/f1-scores demonstrated high model performance, particularly with Random Forest achieving over 97% classification accuracy. This project emphasizes the significance of preprocessing, outlier handling, and iterative refinement in sensor-based classification. These findings have direct implications for real-time applications such as smart home automation, energy-efficient HVAC control systems, and security monitoring, where accurate and timely detection of human presence is critical. Such applications are explored in [6, 7] which specifically address human presence detection using PIR sensors [1, 2, 3]. Future work could explore the use of deeper temporal models (e.g., LSTMs) and multimodal sensor fusion techniques for enhanced real-world deployment.**

Keywords—Supervised Learning, PIR Sensors, Random Forest, Outlier Detection, PCA, Classification, Feature Engineering, Smart Homes

I. INTRODUCTION

Human presence detection is central to intelligent systems such as smart homes, office automation, and ambient-assisted living. It enables dynamic resource management for tasks like lighting, security, and HVAC control. Among the various sensing technologies, Passive Infrared (PIR) sensors offer a compelling balance between affordability, energy efficiency, and robustness in indoor deployments [1]. However, raw PIR sensor signals are inherently noisy, and distinguishing between nuanced human behaviours such as vacancy, stationary presence, and dynamic motion remains a computational challenge.

This project explores supervised learning approaches to address this problem using the PIRVision dataset, which consists of over 7652 multivariate time-series records. Each entry includes a timestamp, ambient temperature, and 55 PIR sensor values sampled across a 4-second window. The classification goal is to accurately assign one of three activity states:

- 0: Vacancy
- 1: Stationary Human Presence
- 3: Other Activity/Motion

to each data point.

To solve this, we employed supervised learning techniques including Random Forest, Support Vector Machines (SVM), and Logistic Regression, supported by dimensionality reduction using Principal Component Analysis (PCA) [6] and outlier detection using Isolation Forest [7][8]. Model performance was assessed using multiple metrics including accuracy, confusion matrix, and per-class precision, recall, and F1-scores.

A. Problem Statement and Objective

Despite the widespread use of PIR sensors in motion detection, existing systems often fail to distinguish between nuanced activity states such as stationary presence versus transient motion. This limitation can lead to false activations or inefficient resource utilization in smart environments.

The primary objective of this project is to develop an accurate and scalable machine learning model that can:

- Accurately classify PIR data into one of three activity categories.
- Reduce model complexity and noise through PCA and outlier detection.
- Compare classifier performance before and after cleaning, using clear metrics like accuracy, precision, recall, and confusion matrices.

B. Structure of the Supervised Classification Pipeline

The overall architecture of our model pipeline consists of several core components that operate sequentially to transform raw PIR data into actionable classifications:

- Data Preprocessing:

- Merging multiple datasets, cleaning nulls, parsing timestamps.
  - Standardizing PIR sensor values for consistency.
- Dimensionality Reduction (PCA):
  - Reduces the 55 PIR readings into 10 principal components.
  - Maintains maximum variance while simplifying input features.
- Outlier Detection (Isolation Forest):
  - Focused on detecting noisy or ambiguous samples within class 3 (“Other Activity”).
  - Removes anomalies to improve classifier learning.
- Supervised Learning:
  - Models used: Logistic Regression, SVM, and Random Forest.
  - Best model (Random Forest) was further tuned using GridSearchCV.
- Model Evaluation:
  - Performance evaluated using accuracy, precision, recall, F1-score, and visual tools like confusion matrices and feature importance plots.

This structured pipeline is highly modular and scalable, allowing for integration with real-time systems, and provides a blueprint for future extensions such as incorporating deep learning or real-time sensor fusion.

II. Related Works

A. *PIR-Based Occupancy and Activity Recognition*

Passive Infrared (PIR) sensors have been extensively used in occupancy and presence detection applications, mainly because of their affordability and energy efficiency. Early uses of these sensors were quite basic, primarily focusing on binary motion detection, simply determining whether a space was occupied or vacant, without the capacity to recognize more detailed or subtle activity patterns. For example, some foundational research relied on threshold-based methods that analyzed raw PIR sensor outputs to detect occupancy, but these approaches lacked the flexibility and robustness that machine learning techniques provide (Implementation and Evaluation of Analog-PIR-Sensor-Based Activity..[9].).

In recent years, there has been significant progress in this field, particularly through the use of PIR sensor arrays embedded within wireless sensor networks. These advancements have enabled simultaneous indoor tracking and more fine-grained activity recognition, demonstrating PIR sensors’ potential far beyond simple motion detection (2017) [10]. Additionally, while combining PIR sensors with ultrasonic sensors has improved detection accuracy, much of this work has traditionally concentrated on the physical integration of the sensors rather than on developing more sophisticated methods for signal interpretation and modeling (2023) [11].

Our project builds on these previous efforts, taking inspiration from the comprehensive review presented in the study "Passive Infrared Sensor-Based Occupancy Monitoring in Smart Buildings: A Review of Methodologies and Machine Learning Approaches," [1] which thoroughly examines various techniques and machine learning algorithms applied to PIR sensors in indoor environments. By focusing on supervised learning approaches, we aim to process the multivariate data generated by PIR sensors more effectively, enabling the classification of different human presence states within the sensor’s field of view. This approach promises greater accuracy and nuance in occupancy detection, moving beyond simple binary classification to provide richer insights into human activity in smart building scenarios..

B. *Time Series Classification for Sensor Data*

The classification of sensor data using supervised learning methods has become a prominent strategy in ambient intelligence and smart environment applications. Various algorithms—including Support Vector Machines (SVM), Decision Trees, and Artificial Neural Networks (ANNs)—have demonstrated efficacy in interpreting complex patterns from noisy, multivariate sensor streams. Studies such as Zappi et al. [12] emphasize the critical role of feature engineering and selection in sensor-based classification, particularly when distinguishing between nuanced activities such as walking and standing.

To address challenges associated with the high dimensionality of sensor data, researchers have employed techniques like Principal Component Analysis (PCA) to extract the most informative features, reduce noise, and enhance computational efficiency [13]. Our project adopts this approach by applying PCA to the 55-dimensional PIR data, enabling more efficient learning without sacrificing class separability. Furthermore, we incorporate Isolation Forest, a well-established anomaly detection technique, to remove noisy and ambiguous samples—particularly from class 3 (“Other Activity”)—thereby improving model robustness and generalization [14][15].

Time series classification (TSC) is especially crucial for multivariate sensor systems like PIRVision, where each observation represents a structured sequence of analog signals. Traditional distance-based methods, such as Dynamic Time Warping (DTW) with k-nearest neighbors, can align temporal features but struggle with computational cost and lack sensitivity to cross-sensor dependencies [16]. On the other hand, feature-based techniques extract statistical representations but often require manual domain-specific tuning.

Recent advancements in deep learning—specifically Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs)—have significantly improved time series classification by automating feature learning across time and dimension [17]. While our approach remains lightweight and interpretable by design, it draws inspiration from these deep learning methodologies to structure a pipeline that includes dimensionality reduction, anomaly detection, and comparative evaluation of supervised classifiers.

C. *Anomaly Detection In Sensor Streams*

Environmental sensors such as Passive Infrared (PIR) devices are highly susceptible to noise caused by both sporadic user behaviour and fluctuating ambient conditions. These disturbances can introduce inconsistencies into the recorded data, thereby compromising the quality of training sets and undermining the accuracy of supervised learning models. To address such challenges, anomaly detection has become an essential preprocessing step in sensor-based classification pipelines. Among various techniques, the Isolation Forest algorithm has gained popularity due to its computational efficiency and strong performance in detecting anomalies without requiring labeled outlier data.

Isolation Forest operates by recursively partitioning the dataset and isolating points that behave differently from the majority, making it particularly effective for high-dimensional and noisy datasets [18]. It has previously been employed in applications such as wireless sensor network (WSN) data cleaning [19] and system fault detection in industrial Internet-of-Things (IoT) environments [20]. These studies highlight its utility in improving data quality before applying downstream classification models.

Building on this body of research, our project integrates Isolation Forest specifically to cleanse the class labeled as "Other Activity" (Label 3) in the PIRvision dataset. This class is inherently ambiguous, representing a mixture of diverse motion activities that often lack consistent patterns. By identifying and removing anomalous data points from this class prior to training, we improve the robustness and generalization capability of our classification models, most notably Random Forest and SVM, while minimizing the impact of noise on decision boundaries.

D. *Hyperparameter Tuning and Ensemble Learning*

Hyperparameter tuning is a critical component in maximizing the performance and generalizability of supervised learning models, particularly ensemble-based approaches such as Random Forests. Originally introduced by Breiman for its robustness and low variance via bagging and randomized feature selection, Random Forests have since been widely adopted in sensor-based classification tasks. Recent contributions, such as those by Dorador [37], focus on optimizing Random Forest architectures to balance classification accuracy with interpretability and computational efficiency.

In the context of PIR sensor data, where feature spaces are high-dimensional and class distributions are often imbalanced, the role of hyperparameter tuning becomes especially prominent. Techniques such as GridSearchCV offer systematic exploration of model parameters—such as the number of trees (n_estimators), maximum tree depth (max_depth), and minimum leaf size (min_samples_leaf)—to identify configurations that yield optimal performance on unseen data [36].

Our work draws upon these principles by applying GridSearchCV to tune the Random Forest classifier used in the PIRvision activity recognition task. The tuning process improved classifier stability and test set performance, validating its effectiveness in line with prior literature on sensor learning frameworks [35].

III. METHODOLOGY

This section delineates the systematic approach followed to design, preprocess, model, and evaluates the PIR sensor data for human presence detection.

A. *Data Preprocessing*

The dataset employed in this study captures multivariate activity from a real-world office environment using 55 Passive Infrared (PIR) sensors alongside ambient temperature data. Each data point is labeled with one of three human activity classes: Vacancy (Label 0), Stationary Presence (Label 1), and Other Activities (Label 3). The primary classification task involved assigning the appropriate label to each record based on the sensor inputs.

a) Temporal Alignment and Type Casting

To maintain chronological consistency, the separate 'Date' and 'Time' attributes were concatenated into a single DateTime field using Python's pandas library. This facilitated proper indexing and time-series-based explorations. The Label column was converted to integer format to ensure compatibility with machine learning libraries. Furthermore, the Temperature_F feature, initially of type string in some cases, was coerced into a numeric type.

b) Class Imbalance Handling

Exploratory data analysis revealed a heavy class imbalance with the Vacancy label disproportionately represented, as shown in Fig. 1. This imbalance can bias classifiers toward the majority class. The class imbalance ratios were as follows:

- Vacancy : Stationary = 7.50 : 1
- Vacancy : Other = 10.94 : 1

To mitigate this issue, during the model training phase, we applied class weighting (class_weight='balanced') in classifiers such as Random Forest and Support Vector Machines (SVM) to promote equitable learning from minority classes [5].

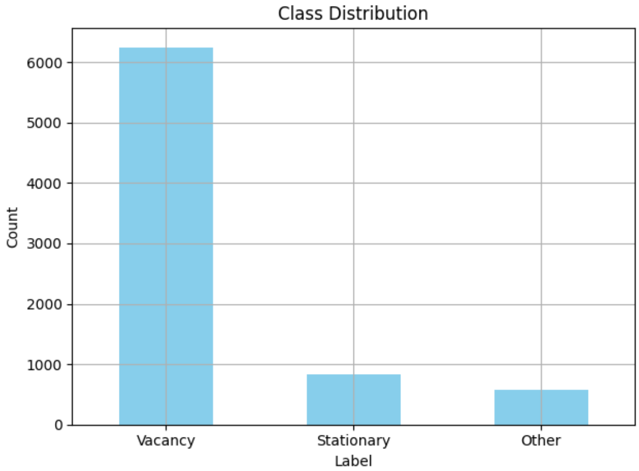

Fig. 1. Class Distribution Before Preprocessing

c) Feature Standardization

Given the wide dynamic range and varying magnitudes across the 55 PIR sensor channels, each feature (PIR_1 to PIR_55) was standardized to zero mean and unit variance using the StandardScaler from scikit-learn [9]. Importantly, to prevent information leakage, the scaler was fit only on the training subset and then applied to the test subset.

d) Exploratory Data Visualization

To gain preliminary insights into the dataset, several visual analytics were conducted on the preprocessed training data. These visualizations were pivotal in shaping preprocessing strategies and modeling decisions.
Two such visualizations are as follows:

- Correlation Heatmap: A heatmap (Fig. 3) visualized correlations among PIR sensors and temperature. Notably, several adjacent sensors showed strong positive correlations, suggesting possible spatial overlap or proximity effects in sensor placement.
- Temporal Distribution of Activity: A line graph (Fig. 2) plotted activity label frequencies across 24 hours. Activity levels peaked during typical working hours (9 AM to 6 PM), validating the real-world office setting and providing rationale for potential time-based features.

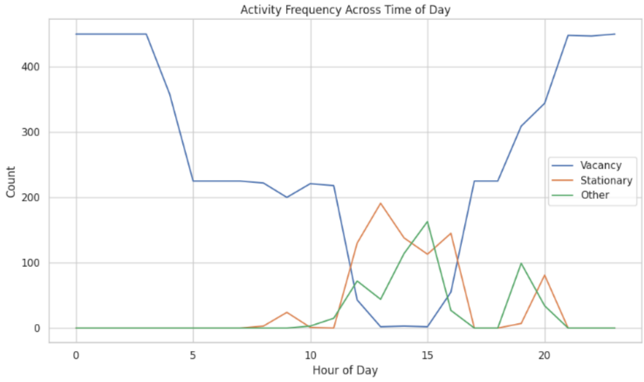

Fig. 2. Activity Frequency Across Time of Day

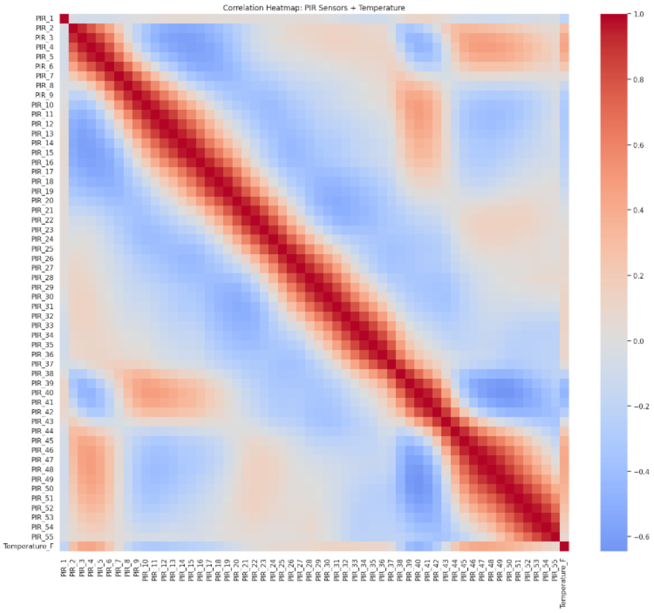

Fig. 3. Correlation Heatmap: PIR Sensors + Temperature

B. *Dimensionality Reduction using Principal Component Analysis (PCA)*

Given the high dimensionality of the dataset, with 55 PIR sensor channels, dimensionality reduction was employed to address potential redundancy and multicollinearity among features. Principal Component Analysis (PCA) was chosen as a robust technique to project the original sensor readings into a lower-dimensional orthogonal space while preserving most of the variance.

a) Motivation for PCA

High-dimensional data can degrade model performance due to the "curse of dimensionality" and risk of overfitting. Preliminary correlation analysis (see Fig. 3.) showed strong linear relationships between adjacent PIR sensors, supporting the hypothesis of redundant information across channels. Therefore, reducing the dataset into fewer, uncorrelated principal components was not only beneficial but necessary for enhancing computational efficiency and generalization.

b) PCA Application and Component Selection

PCA was performed on the standardized PIR sensor values (not including the temperature or label columns). Initially, the analysis remained:

- 10 Principal Components for model training and evaluation
- 2 Principal Components for data visualization and outlier detection

This dimensionality choice retained over 95% of the variance in the original data, as determined by the cumulative explained variance plot (not shown here but computed during experimentation).

C. *Outlier Detection using Isolation Forest*

Outlier detection was a crucial step in refining the training data, especially for the ambiguous "Other Activities" class (Label 3), which was prone to noise and irregular patterns. These outliers could impair classifier learning by introducing inconsistencies not representative of the general activity space.

a) Focus on Ambiguous Activity Class (Label 3)

Exploratory analysis highlighted the high variability in PIR sensor activations for Other Activities. Unlike Vacancy or Stationary Presence, which exhibited relatively consistent sensor activation profiles, Label 3 encompassed diverse and sporadic motion patterns, warranting targeted outlier identification.

b) PCA-Enabled Projection

Before outlier detection, Principal Component Analysis (PCA) was applied to reduce the 55-dimensional PIR sensor feature space to two principal components. This 2D embedding preserved the most critical variance and enabled more effective anomaly localization.

c) Isolation Forest-Based Anomaly Detection

The Isolation Forest algorithm [7, 15], a tree-based anomaly detection technique, was employed on the PCA-reduced space. This unsupervised method is effective in high-dimensional settings and identifies anomalies based on their isolation in random partitioning.

- The model was configured with a contamination rate of 10%, implying that 10% of Label 3 samples were treated as outliers.
- Detected outliers (marked with -1) were removed from the dataset.
- The resulting "cleaned" Label 3 subset more accurately reflected the dominant behavioral patterns in ambiguous activity samples.

d) Visual Confirmation of Outlier Segmentation

Fig. 4. Illustrates the PCA 2D projection of Label 3 samples with inliers and outliers distinctly colored. The clustering of inliers and separation of outliers validated the Isolation Forest's efficacy in isolating noise-prone data points.

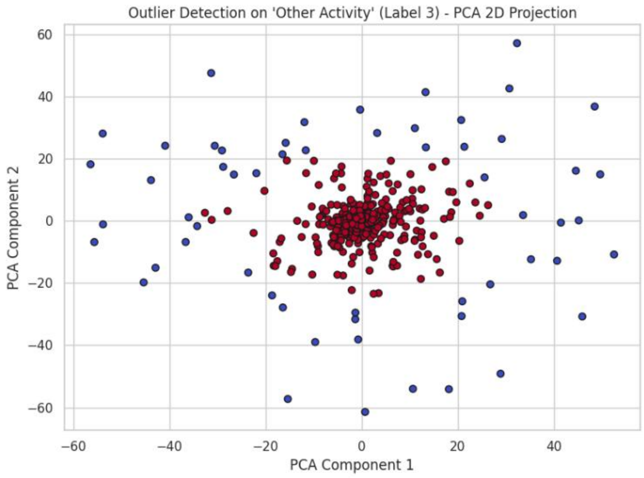

Fig. 4. Outlier Detection on ‘Other Activity’ (Label 3) – PCA 2D Projection

D. *Supervised Learning Models*

To model human activity states from PIR and temperature data, three supervised learning algorithms were trained and compared: Random Forest, Support Vector Machine (SVM), and Logistic Regression. All models used the PCA-transformed version of the 55-dimensional PIR dataset (reduced to 10 components) to optimize efficiency and avoid multicollinearity:

a) Random Forest Classifier:

An ensemble-based classifier that constructs multiple decision trees and aggregates their outputs to improve predictive accuracy and control overfitting [5].

Each tree is trained on a bootstrap sample of the data and outputs a class prediction. The final prediction is made via majority voting:

$y\hat{} = mode\{T_1(x), T_2(x), \dots, T_N(x)\}$ …Eq. 1.

Where:

- $T_i(X)$ is the prediction from the i-th decision tree
- N is the number of trees in the forest

Each tree splits nodes based on the feature that maximizes information gain, using criteria such as Gini Impurity:

$Gini(S) = 1 - \sum_{i=1}^{C} p_i^2$ …Eq. 2.

Where:

- p_i is the probability of class S
- C is the number of classes

Here, we have trained using a hyperparameter optimization grid search (GridSearchCV) to identify the optimal configuration. The grid included:

- Number of trees (n_estimators) = [100, 200]
- Tree depth (max_depth) = [None, 10, 20]
- Leaf size (min_samples_leaf) = [1, 2, 4]

The best-performing model used:

- n_estimators = 100
- max_depth = None
- min_samples_leaf = 1

The classifier was trained with class_weight='balanced' to offset the heavy class imbalance. Upon evaluation on the PCA-transformed test set, Random Forest achieved the highest accuracy and balanced F1-scores, making it the top-performing model.

b) Support Vector Machine (SVM)

SVM constructs hyperplanes (Eq. 3) in high-dimensional spaces to maximize the margin (Eq. 5) between classes. The radial basis function (RBF) kernel ($K(x_i, x_j)$ was used, and class_weight='balanced' was applied to mitigate class imbalance [21]. SVM showed clear decision boundary formation in PCA-transformed space.

$f(x) = w^\top x + b$ …Eq. 3.

$binary\ case: y_i(w^\top x_i + b) \geq 1\ \forall_i$ …Eq. 4.

$optimization\ objective: \min_{w,b} \frac{1}{2}||w||^2$ …Eq. 5.

$max_\alpha \sum_i \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i \alpha_j y_i y_j K(X_i, X_j)\ subject\ to:\ 0 \leq \alpha_i \leq C,\ \sum_i \alpha_i y_i = 0$ …Eq. 6.

Where:

- α_i are language multipliers
- C is the regularization parameter

c) Logistic Regression

A linear model used as a baseline, Logistic Regression estimates class probabilities using the softmax function.

Logistic Regression models the probability that a given input X belongs to class $y = 1$ using the logistic (sigmoid) function:

$P(y = 1 \mid x) = \sigma(W^T X + b) = \frac{1}{1+e^{-(W^T X + b)}}$ …Eq. 7.

Where:

- $\sigma(z)$ is the sigmoid function
- W is the weight vector
- b is the bias
- X is the input feature vector

For multiclass classification, softmax is used:

$P(y = k|X) = \frac{e^{w_k^T X}}{\sum_{j=1}^{k} e^{w_j^T X}}$ …Eq. 8.

Though simplistic compared to ensemble methods, it served as a reliable benchmark and was computationally efficient.

All models were first trained on the original dataset (prior to outlier removal) and then retrained using the cleaned dataset obtained after removing ~10% of noise-prone samples in the Other Activities class via Isolation Forest. The PCA-reduced dataset (10 components) served as input features for all models.

Fig. 5 displays the classification accuracies of all three models after training on cleaned data.

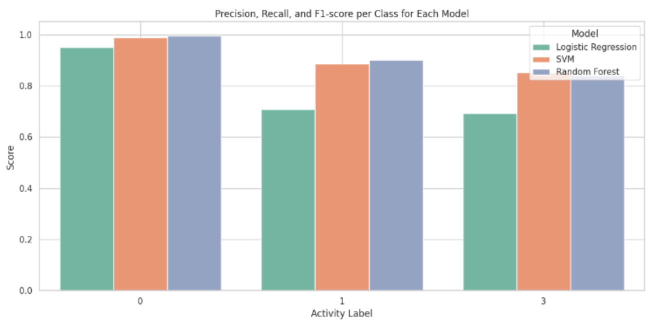

Fig. 5. Model Accuracy Comparison (Random Forest, SVM, Logistic Regression)

IV. RESULT AND DISCUSSION

This section evaluates the outcomes of our PIR-based activity classification pipeline through visualizations, statistical performance metrics, and dimensionality analyses. The findings highlight the importance of preprocessing, dimensionality reduction, anomaly filtering, and model selection in shaping classification outcomes.

A. Temporal Trends in Human Activity

The analysis of activity frequency over time (Fig. 2) uncovered significant temporal regularities. Class 0 (Vacancy) was dominant during nighttime hours (20:00–05:00), while stationary human presence (Class 1) peaked during standard office hours (10:00–16:00). Other motion activities (Class 3) occurred sporadically, with noticeable spikes in the late afternoon. These patterns align with expected behavioral rhythms in an office setting and suggest that temporal features (e.g., hour of day) could serve as valuable predictive signals in the learning model.

B. Dimensionality Reduction via Principal Component Analysis (PCA)

Principal Component Analysis was employed to reduce the original 55 PIR sensor input. As shown in Fig. 6, the first principal component alone captures approximately 25% of the total variance, while the first 10 components retain 95% of the variance. This dimensionality reduction significantly streamlined the classification task by removing redundant sensor information and decorrelating input features.

The PCA-transformed space (Fig. 7) illustrated a tight cluster for Vacancy (Class 0), whereas Stationary (Class 1) and Other Activity (Class 3) classes overlapped partially, explaining some of the classification ambiguity. Compact representation improved computational efficiency and generalization.

C. Outlier Detection and Its Impact on Class 3

Isolation Forest, an unsupervised anomaly detection algorithm, was applied specifically to Class 3 (“Other Activity”) after PCA projection. The algorithm identified approximately 10% of the samples as anomalies (Fig. 8). These outliers exhibited spatial deviations from dominant activity clusters, likely representing inconsistent behaviors or sensor noise.

Removing these outliers reduced intra-class variability and sharpened class boundaries, especially for Class 3. This step was instrumental in improving classification accuracy and reducing false positives in downstream tasks.

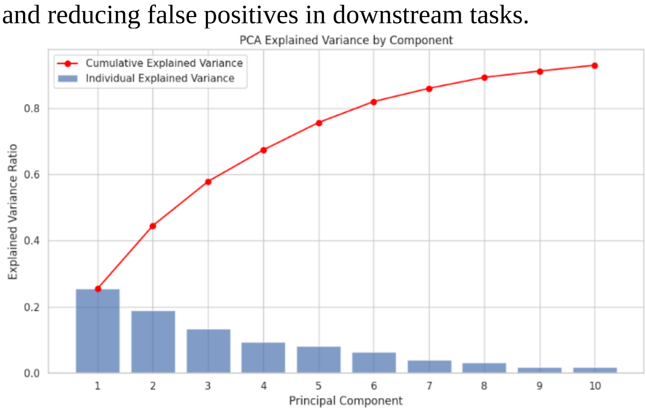

Fig. 6. Principle Component Variance by Component

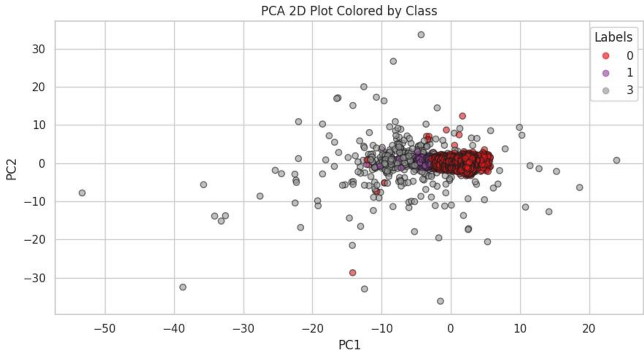

Fig. 7. 2D PCA Scatter Plot Colored by Activity Class

D. Feature Importance Prior to PCA

Before dimensionality reduction, sensor-level feature importances were evaluated using a Random Forest model. Sensors such as PIR_47, PIR_48, and PIR_40 are consistently ranked as the most discriminative (Fig. 9). A long tail of minimally important sensors justified the application of PCA, which preserved variance while discarding uninformative inputs. This also highlights the potential for hardware optimization by focusing on critical sensor placements in real-world deployments.

After PCA, PC1 dominates the importance ranking, accounting for over 40% of the predictive power (Fig. 10). PC3 and PC8 are also significant contributors. This suggests that the first principal component captures most of the variance relevant to distinguishing between activity classes.

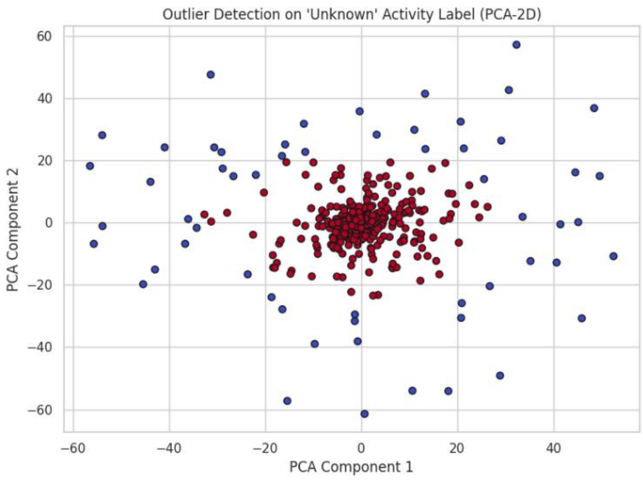

Fig. 8. Isolation Plot Outlier Plot for Class 3

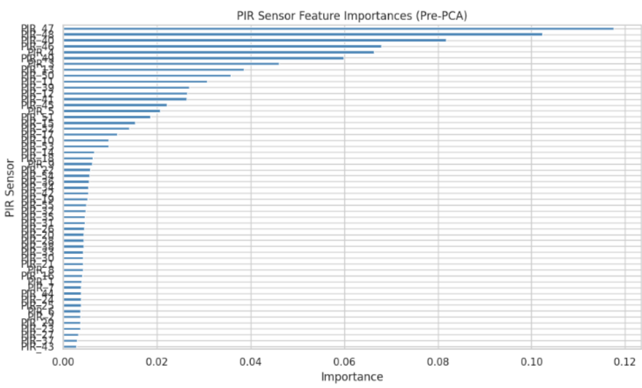

Fig. 9. Pre PCA-Feature Importance

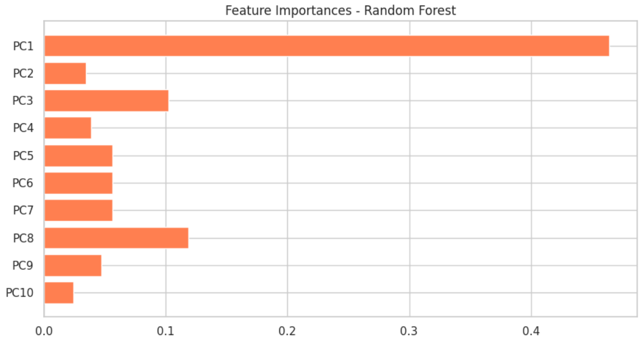

Fig. 10. Feature Importance After PCA

E. *Classifier Performance and Comparision*

As discussed earlier, three models were benchmarked:

- Random Forest (RF) achieved the highest performance with an accuracy of 97.4%, demonstrating resilience to noise and imbalanced data (Fig. 5).
- Support Vector Machine (SVM) followed with approximately 96% accuracy but was more sensitive to class overlap.
- Logistic Regression underperformed, particularly for minority classes (1 and 3), achieving below 92% accuracy.

Confusion matrices revealed that most misclassifications involved confusion between Stationary and Other Activity, attributable to overlapping sensor signatures. The use of class-balanced weights helped mitigate this, but finer-grained pattern recognition remained challenging. (In the figures 11.a, 11.b, 11.c, label 3 is named as label 2)

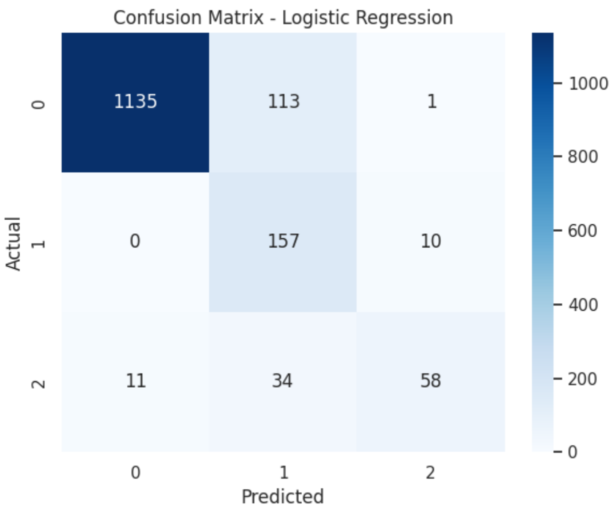

Fig. 11a. Confusion Matrix – Logistic Regression

V. FUTURE CONTRIBUTIONS AND ENHANCEMENTS

Although this study primarily focuses on classical supervised learning with feature engineering, recent literature suggests several promising directions that could further enhance performance in PIR-based activity recognition systems.

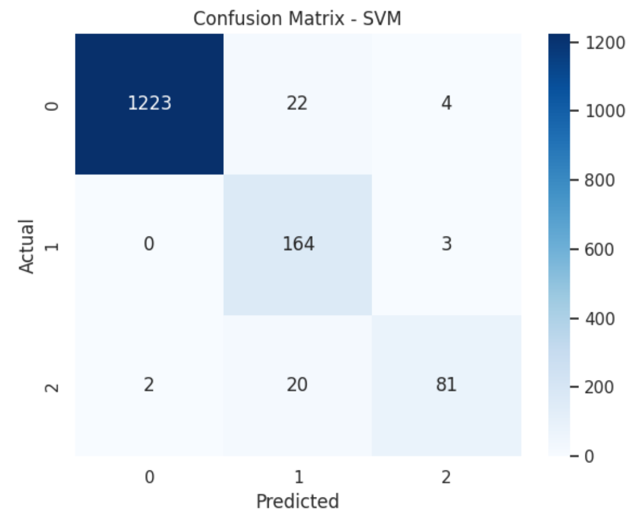

Fig. 11b. Confusion Matrix – SVM

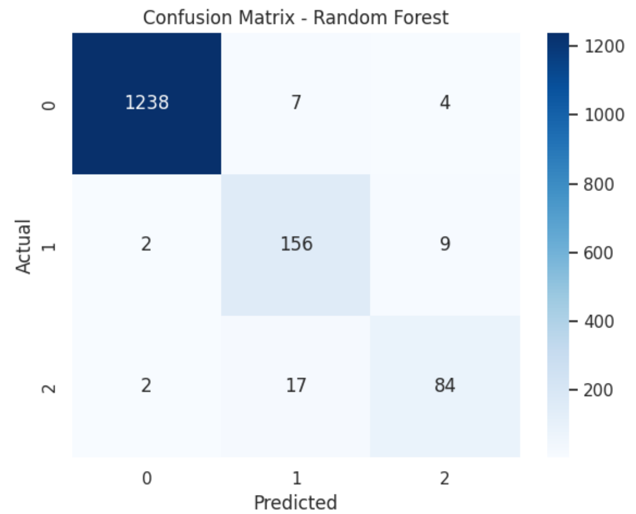

Fig. 11b. Confusion Matrix – Random Forest

A. *Deep Learning Architecture*

Emerging architectures such as lightweight Convolutional Neural Networks (CNNs) [22] and Temporal Convolutional Networks (TCNs) [23][24] can model both spatial correlations and temporal patterns across sensor activations. These models, when adapted to multivariate time-series from PIR arrays, have shown state-of-the-art results in recognizing complex motion dynamics. Such approaches could outperform PCA-based pipelines by learning richer non-linear representations.

B. *Self-Supervised Pretraning*

Self-supervised methods like SimCLR, MoCo, and contrastive learning present an opportunity to exploit large volumes of unlabeled PIR data. These techniques could learn latent representations through pretext tasks, reducing dependence on costly manual annotations. After pretraining, a lightweight classifier could be fine-tuned for activity detection, potentially improving generalization across domains.

The SimCLR framework developed by Chen et al. [25] offers a promising approach for contrastive learning with sensor data. Saeed et al. [26] demonstrated multi-task self-supervised learning specifically for human activity detection, while [27] applied contrastive learning techniques to sensor-based activity recognition with reduced annotation requirements.

C. Attention-Based Models and Transformers

Transformer-based models, even in their lightweight forms, offer the advantage of attention mechanisms that can dynamically prioritize informative time windows or sensor regions. These models can replace or complement PCA by learning to attend to the most discriminative input features without the need for linear transformations.

The visual attention mechanisms described by Xu et al. [28] could be adapted to prioritize informative sensor regions. The transformer architecture introduced by Vaswani et al. [29] has been successfully applied to continuous prediction tasks by Zhang et al. [30], suggesting potential applications in PIR-based activity recognition systems.

D. Domain Adaptation Techniques

For deployment across diverse environments, models trained in one setting must effectively generalize to others. Techniques such as Domain Adversarial Neural Networks (DANNs) or Transfer Component Analysis (TCA) could be employed to adapt to new office layouts or sensor arrangements with minimal retraining. Ganin et al. [31] demonstrated how domain-adversarial training can create domain-invariant features by learning representations that are indistinguishable between source and target domains. Joint adaptation networks by Long et al. [32] provide another promising approach for transferring knowledge across domains through layer-wise adaptation. These techniques offer potential solutions for adapting PIR-based activity recognition systems to new environments without extensive retraining or recalibration.

E. Class Imbalance Handling with SMOTE

To further address the class imbalance issue inherent in activity recognition data, future implementations could integrate Synthetic Minority Over-sampling Technique (SMOTE) during model training. This approach would generate synthetic samples for underrepresented classes (Stationary, Other Activity), helping classifiers learn decision boundaries more effectively and reducing bias toward the dominant (Vacancy) class. The SMOTE technique, refined by Chawla et al. [33] remains relevant for addressing class imbalance in sensor data by creating synthetic examples along the line segments joining nearest neighbors of minority classes. Zhao et al. [34] implemented similar class balancing techniques in the context of smart buildings monitoring, demonstrating improved recognition rates for minority activity classes without compromising overall detection performance.

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