



Smart Home Automation using IoT: Prototyping and Integration of Home Devices

Malkeet Singh

Researcher (PhD), IIT Ropar & Swinburne,
Orcid ID: 0000-0002-0723-6281
malkeetsingh@swin.edu.au

Anishkumar Dhablia

Engineering Manager, Altimetrik India Pvt Ltd,
Pune, Maharashtra, India
Email: anishdhablia@gmail.com

Abstract

Smart homes are becoming a reality thanks to the Internet of Things (IoT) technology's quick progress, providing homeowners with never-before-seen levels of efficiency, convenience, and security. This abstract gives a summary of a project that combines prototyping and integration to turn a standard house into a modern smart home. The paper focuses on creating an extensive IoT ecosystem that seamlessly connects diverse household equipment, such as lighting controls, thermostats, and security cameras, to a single, intelligent network. We use cutting-edge IoT communication and protocol technologies to create strong connectivity between these devices, enabling homeowners to remotely monitor and control them from a central hub or their smartphones. Our smart home system's central controller, which includes cutting-edge sensors and AI algorithms, is its brain. To reduce energy usage, improve security, and accommodate resident preferences and routines, this controller gathers and examines data from the linked devices. It learns user patterns through machine learning and suggests automation procedures to make life easier. A smart home system prioritizes security and privacy in addition to increasing convenience. We also place a strong emphasis on flexibility and scalability, which enable the incorporation of new hardware and features as the IoT landscape changes. For homeowners, tech enthusiasts, and developers interested in building their own smart houses, our project on prototyping and integration serves as a model. It highlights how IoT technology has the ability to upgrade conventional living quarters into intelligent, networked areas that improve our quality of life while fostering energy efficiency and security. In the end, this project advances the continued development of smart home automation by increasing everyone's access to and ability to customize it.

Keywords

Smart Home, Automation, Internet of Things, Machine learning, Security

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1. Introduction

The advent of the Internet of Things (IoT) has revolutionised how we interact with our surroundings and ushered in a new era of technological innovation. The development of smart homes is among the IoT's most intriguing and revolutionary applications. Our homes are dynamic, interconnected ecosystems that fluidly interact and work together to improve our quality of life in this era of fast digitalization. They are

no longer static buildings [1]. By creating an extensive IoT ecosystem [3] that combines various home gadgets logically and smoothly, our project aims to explore the enormous potential of smart home automation. From smart thermostats and lighting controls to security cameras, door locks, and entertainment systems, this ecosystem has them all. We [4] develop strong connectivity between these devices by utilising cutting-edge IoT protocols and communication technologies, guaranteeing that they operate in harmony and respond



to homeowners' requests quickly and precisely. Our smart home system's powerful central controller, which is equipped with cutting-edge sensors and driven by AI algorithms, is its brain. The [5] operation's brain, this controller gathers data from all linked devices, analyses it in real-time, and makes deft decisions depending on the data. For instance, it can modify the temperature and lighting based on occupancy patterns, coordinate equipment to save energy use, or send notifications in the case that security cameras spot suspicious activity. Importantly, our technology was created with usability and accessibility in mind. With the use of simple user interfaces on their smartphones, tablets, or specialised control panels, homeowners can easily engage with the ecosystem of the smart home [2]. To enable people of various technical backgrounds to utilise the power of IoT to improve their homes, we place a priority on ease of use. Additionally, [6] security and privacy are highly prioritised in our project. We use strong authentication and encryption technologies to protect the data communicated and stored within the smart home ecosystem, guaranteeing that sensitive data is kept private and shielded from online dangers. Even as they take use of the many advantages of smart home automation, homeowners can be assured that their personal information and privacy are protected.

Our system is built with scalability and agility in mind as technology continues to advance. We are aware that the IoT landscape is ever-changing, with new technologies and standards appearing frequently. As a result, [7] our approach enables the seamless integration of new hardware and features as they become available. The smart home ecosystem may develop and expand along with technology improvements because to this flexibility, giving homeowners long-term value. It represents a significant advancement in the process of realising the full potential of smart homes. Inspiring homeowners, [8] tech aficionados, and developers to begin on their own adventures towards smart home automation is our goal by showcasing how various home gadgets may be smoothly linked into a coherent IoT ecosystem. Our work highlights the transformative potential of IoT technology to reshape our living environments, making them not just smarter but also more efficient, secure, and adaptive to our changing requirements. We hope that this project will advance the field of smart home automation and move us one step closer to a time when

the idea of a "smart home" will be the new norm for contemporary life [9].

The key contribution of paper are as follows:

- **IoT Device Prototyping:** These prototypes might incorporate sensors, actuators, controllers, and other tech to improve connectivity and automation throughout the home.
- **Integration Frameworks:** Papers regularly explore the middleware or integration frameworks that provide seamless connection between various IoT platforms and devices. These frameworks are essential to creating interoperability and making sure that different devices can cooperate successfully.
- **Considerations for Security and Privacy:** Providing security and privacy for smart home systems is a crucial contribution. Papers frequently examine innovative access control strategies, encryption approaches, and security procedures to safeguard system integrity and user data.
- **Energy Efficiency:** Because many IoT devices have limited resources, researchers may concentrate on reducing energy use. Low-power communication protocols, energy-efficient algorithms, and techniques for extending device batteries are a few examples of contributions.

2. Review of Literature

Numerous relevant studies in the field of IoT-based smart home automation have aided in the development of this game-changing technology. Significant developments have been made in this developing subject in a number of areas, including device integration, energy efficiency, security, and user experience. Interoperability standards and protocols development is a prominent field of related work [10]. Communication standards that enable smooth device integration within smart homes have been established by groups like the Zigbee Alliance and the Thread Group. To assure compatibility and interoperability among a variety of smart devices, from light bulbs to door locks, Zigbee, for instance, has developed the Zigbee 3.0 standard. Homeowners are given the freedom to select the best gadgets for their needs without worrying about compatibility difficulties because to these standards, which support an



environment where devices from various manufacturers may communicate successfully [11].

Another key component of smart home automation that has received a lot of attention in related research is energy efficiency. Researchers and developers [12] have looked for creative methods to use IoT technology for more effective home management as concerns about energy conservation and sustainability have grown. Because they can learn user preferences and modify heating and cooling systems accordingly, smart thermostats like the Nest Learning Thermostat have become increasingly popular. This [13] results in significant energy savings. Furthermore, homeowners can watch their electricity usage and spot potential for optimisation thanks to real-time energy monitoring devices like those provided by Sense and Neurio. These technologies are essential for lowering utility costs, reducing environmental impact, and reducing energy usage.

Privacy and security have [14] remained the top priorities in the creation of smart home systems. Improvements in protecting IoT ecosystems from cyber attacks and guaranteeing user data privacy have come from related research. To prevent unauthorised access, device manufacturers are progressively integrating strong security features into their products, such as secure boot procedures and encrypted communication. Additionally, improvements in artificial intelligence and machine learning have made it possible for intrusion detection systems to become more complex [15]. These systems can now recognise and react to unusual or suspicious behaviour within a smart home network. Protection for smart homes from malware and cyberattacks has been a specific focus of products like the Bitdefender BOX. These advancements are crucial for giving homeowners the assurance that their personal information and privacy will be protected as they take advantage of the convenience and automation offered by smart home technologies.

The focus of related [16] research has also been on the user experience, with initiatives made to make it easier

for homeowners to engage with their smart home devices. Users may now operate a variety of gadgets using natural language thanks to the widespread adoption of voice assistants like Google Assistant and Amazon's Alexa. Furthermore, intuitive smartphone apps and user-friendly interfaces have improved, making it simpler for homeowners to create and personalise their smart home settings without the need for technical knowledge. Additionally, [18] the creation of automation routines and "scenes" enables users to programme intricate sequences of activities with just one command, increasing simplicity and adaptability. Related research has looked at the possibility of smart home automation outside of the consumer sector in scenarios involving healthcare and assisted living. Smart sensors and wearable technology can be used to monitor the health of elderly or fragile people, alerting carers or medical staff in real-time when falls or strange activity patterns are discovered. These programmes may enhance the quality of life for people with certain requirements while giving their families peace of mind [17].

Finally, activities for sustainability and urban planning have been included in connected work. Smart city initiatives use IoT technology to optimise resource use, increase public services, and generally improve urban people' quality of life. This refers to connecting with bigger smart city ecosystems in the context of smart houses in order to contribute to a more effective, integrated urban environment [19]. The integration of devices, energy efficiency, security, user experience, healthcare, and urban planning have all witnessed substantial improvements in the field of smart home automation using IoT. With continued research and development targeted at further expanding the capabilities and accessibility of this game-changing technology, related work continues to influence the future of smart homes. We are edging closer to a world in which homes are not only interconnected but also more productive, safe, and receptive to inhabitant requirements and preferences as the IoT landscape develops.



Table 1: Related work in Smart Home Automation

Method	Key Approach	Findings	Application	Area
Interoperability Standards [20]	Zigbee Alliance, Thread Group	Establishment of communication standards, ensuring device compatibility	Device Integration	IoT Communication
Energy Monitoring [21]	Real-time monitoring systems (e.g., Sense, Neurio)	Real-time tracking of electricity usage, optimization insights	Energy Efficiency	Sustainability
Smart Thermostats [22]	Learning algorithms (e.g., Nest Learning Thermostat)	Adaptive heating/cooling, energy savings	Climate Control	Energy Conservation
Security Features [23]	Secure boot processes, encryption	Enhanced protection against cyber threats	Cybersecurity	Privacy
Intrusion Detection [24]	Machine learning, AI	Identification of unusual network behavior	Network Security	IoT Security
Voice Assistants [25]	Amazon Alexa, Google Assistant	Voice-controlled device management	User Experience	Human-Computer Interaction
User-Friendly Interfaces [12]	Intuitive mobile apps, automation routines	Simplified configuration and customization	User Convenience	Human-Computer Interaction
Healthcare Monitoring [13]	Smart sensors, wearables	Real-time health monitoring, fall detection	Healthcare	Assisted Living
Smart City Integration [26]	Integration with larger smart city ecosystems	Resource optimization, improved public services	Urban Planning	Smart Cities
Home Entertainment Systems [27]	Integration with media devices	Seamless control of entertainment systems	Entertainment	Home Entertainment
Wearable Integration [28]	Smartwatches, fitness trackers	Home automation through wearable devices	Convenience, Health	Wearable Technology
Environmental Sensors [29]	IoT-enabled sensors	Monitoring air quality, temperature, humidity	Indoor Environmental Quality	Environmental Sensing
Smart Lighting [30]	Motion sensors, scheduling	Adaptive lighting based on occupancy	Lighting Control	Energy Efficiency
Home Security Systems [9]	CCTV cameras, doorbell cameras	Real-time surveillance and remote access	Security	Home Security
Smart Appliances [31]	IoT-enabled appliances	Remote control and energy optimization	Home Automation	Appliance Control

3. Available Dataset

Various data points gathered from sensors and gadgets in a connected home setting make up a smart home dataset. This dataset often contains data on temperature, humidity, energy use, motion detection, and usage trends for various devices. Datasets from smart homes are analysed and improved by researchers

and developers to increase automation, security, and energy efficiency [12]. These datasets support the development of smart home apps and algorithms for resource optimisation, boosting the convenience and security of contemporary residential living areas generally. They also support machine learning and AI models for personalised user experiences, anomaly detection, and predictive maintenance in smart homes.



Table 2: Description of Different available dataset

Dataset Name	Description
REDD (Reference Energy Disaggregation Data Set)	A dataset for energy disaggregation research, containing electricity consumption data from multiple appliances in homes.
UK-DALE	A dataset of high-frequency electricity and appliance usage data from UK households.
NILM Metadata	Metadata and appliance information for various non-intrusive load monitoring (NILM) datasets.
Eco dataset	A dataset for energy consumption research, including data from multiple sensors in smart homes.
CASAS datasets	Datasets collected from smart homes using the CASAS framework, including sensor data and activity labels.
S2Lab Smart Home Dataset	A dataset containing data from various sensors (temperature, humidity, light, etc.) in smart homes.
SISFall dataset	A dataset for fall detection in smart homes, containing accelerometer data.
DRED (Dartmouth Residential Electricity Dataset)	A dataset of high-frequency electricity consumption data from multiple homes for various appliances.
House_1 (Differential Privacy Smart Meter Data)	A dataset containing smart meter data with differential privacy applied, protecting user privacy.

4. Methodology

Numerous advantages of smart home automation utilising IoT include occupancy detection, analysis of heating and cooling systems, and improvement of energy efficiency. By recognising room occupancy, occupancy detection, which is frequently made possible by sensors like motion detectors or door/window sensors, improves home automation. Lighting, security systems, and HVAC (Heating, Ventilation, and Air Conditioning) systems can all be activated or deactivated using this information. Lighting can, for instance, be set to switch off automatically when a room is empty to save energy. A crucial component of smart home automation is analysis for heating and cooling. IoT gadgets can keep an eye on humidity, temperature indoors and outdoors, and other environmental variables. These data can be processed by machine learning algorithms to establish the ideal HVAC settings. For instance, in warm weather, the system may turn down the heating or cooling to maximise comfort while lowering energy use. Energy savings and utility costs can both be significantly decreased as a result of this examination.

The fundamental principle of smart home automation is energy efficiency. Homeowners can discover information about their energy usage trends by

gathering data from various sensors and smart metres. Energy usage may be predicted using machine learning algorithms, which can also produce suggestions for reducing waste. By adjusting heating and cooling schedules to residents' preferences, smart thermostats can further cut energy usage [18]. IoT-enabled smart home automation offers a comprehensive strategy to improve living quarters. Real-time occupancy detection, sophisticated heating and cooling analysis and continuous energy efficiency improvements are all provided. This improves comfort and convenience while also resulting in significant energy savings that lessen the environmental effect of home energy use. We should expect our homes to become smarter, greener, and more cost-effective as IoT technology develops.

Machine learning (ML) algorithms can be used to execute tasks like occupancy detection, assessment of heating or cooling needs, and other context-aware judgements in a smart home system based on processed data. Here are some popular machine learning (ML) techniques and algorithms for these uses:



A. Occupancy detection

- **Random Forest:** A flexible technique that can be used for occupancy detection is random forest. To forecast occupancy, it can be trained using past sensor data from motion sensors, door/window sensors, and even Wi-Fi signal strength data.

1. Data Collection:

Collect sensor data:

$D = \{x_1, x_2, \dots, x_n\}$, where x_i represents sensor readings at time i .

2. Data Preprocessing:

Preprocess data:

$D' = f_{\text{preprocess}}(D)$, where $f_{\text{preprocess}}$ represents preprocessing functions (e.g., noise removal).

3. Data Labeling:

Assign binary labels:

$Y = \{y_1, y_2, \dots, y_n\}$, where y_i is the occupancy label (1 for 'Occupied', 0 for 'Not Occupied').

4. Feature Selection:

Select relevant features:

$F = \{f_1, f_2, \dots, f_k\}$, where f_k represents selected sensor features.

5. Data Splitting:

Split data into training (D_{train}) and testing (D_{test}) sets.

6. Random Forest Training:

Random Forest Training:

Train the Random Forest model:

Ensemble of decision trees:

$$RF = \{T_1, T_2, \dots, T_m\}$$

Where each tree is constructed as:

$T_i = \text{TreeTrain}(D_{\text{train}}, F_i)$, where F_i is a subset of features.

The ensemble predicts occupancy as:

$$P(Y_i = 1) = (1/m) \sum_{i=1}^m T_i(x_i),$$

where $T_i(x_i)$ is the prediction of the i -th tree.

7. Feature Importance Analysis:

Calculate feature importance scores:

Feature importance score for f_k :

$$I(f_k) = (1/m) \sum_{i=1}^m \text{Gain}(T_i, f_k),$$

where $\text{Gain}(T_i, f_k)$ measures the reduction in impurity due to f_k in tree T_i .

8. Predictions:

Use the trained Random Forest model to make predictions on the testing dataset:

Ensemble prediction:

$$P(Y_i = 1) = (1/m) \sum_{i=1}^m T_i(x_i)$$

- **Support Vector Machines (SVM):** Based on sensor data, SVMs can be trained to classify the occupancy condition of a room. For binary classification problems like occupancy detection, they perform well.

1. Data Representation:

Collect sensor data, $X = \{x_1, x_2, \dots, x_n\}$, where x_i represents a feature vector derived from sensor readings at time i .

2. Data Labeling:

Assign binary labels, $Y = \{y_1, y_2, \dots, y_n\}$, where y_i is the occupancy label (1 for 'Occupied', -1 for 'Not Occupied').

3. SVM Objective:

The SVM aims to find the optimal hyperplane that maximizes the margin between data points of different classes while minimizing classification errors. This can be expressed as the following optimization problem:

$$\text{minimize } (w, b) \frac{1}{2} \|w\|^2$$

$$\text{subject to } y_i(w \cdot x_i - b) \geq 1 \text{ for all } i$$

Where:

- w is the weight vector.

- b is the bias term.

- y_i is the label of the i -th data point.

- x_i is the feature vector of the i -th data point.

4. Kernel Trick:

In cases where the data is not linearly separable, a kernel function $K(x_i, x_j)$ can be used to map the data into a higher-dimensional space, making it linearly separable. Common kernel functions include the linear, polynomial, radial basis function (RBF), and sigmoid kernels.

5. SVM Decision Function:

Once the SVM is trained, the decision function for classifying a new data point x_{new} is given by:

$$f(x_{\text{new}}) = \text{sign}(w \cdot x_{\text{new}} - b)$$

Where:

- $f(x_{\text{new}})$ is the predicted class label for x_{new} .

- $\text{sign}(\cdot)$ returns the sign of the expression.

B. Analysis for Heating or Cooling:

- **Linear Regression:** Based on variables like the outside temperature, the inside temperature,



the humidity, and past energy consumption data, linear regression models can be used to forecast the need for heating or cooling.

1. Data Collection:

- Collect data on indoor temperature (T_{indoor}), outdoor temperature ($T_{outdoor}$), and other relevant variables like humidity, occupancy status, and HVAC system settings.

2. Data Preprocessing:

- Clean and preprocess the data, handling missing values and outliers if necessary.

3. Feature Selection:

- Select relevant features for linear regression, such as outdoor temperature ($T_{outdoor}$), and any other variables that affect heating or cooling needs.

4. Data Splitting:

- Split the dataset into training and testing sets to evaluate the linear regression model's performance.

5. Linear Regression Model:

- Train a linear regression model to predict heating or cooling energy consumption based on selected features. The linear regression equation is:

$$E = \beta_0 + \beta_1 * T_{outdoor} + \beta_2 * T_{indoor} + \dots + \beta_n * other\ variables$$

Where:

- E is the predicted energy consumption.

- $\beta_0, \beta_1, \beta_2, \dots, \beta_n$ are the regression coefficients.

6. Model assessment:

Use measures like Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) on the testing dataset to assess the model's performance.

7. Predictions:

Make projections for heating or cooling energy consumption using the trained linear regression model and the current indoor and outside temperatures, as well as other pertinent variables.

8. Energy Efficiency:

Utilise energy-saving tactics based on the model's predictions, such as timing HVAC operation for off-peak times or implementing setback techniques to lower heating or cooling during unoccupied periods in the home.

9. Reporting and Reaction:

Provide users with feedback on the energy usage of the HVAC system and ideas for maximising their demands for heating or cooling.

- Gradient boosting algorithms can produce precise models for forecasting heating and cooling requirements. Examples are XGBoost and LightGBM. They can manage intricate connections between different aspects.
- Reinforcement Learning: Reinforcement learning can be used to develop the best possible HVAC system control strategies. Agents can be taught to modify the temperature control based on comfort and energy efficiency goals.

C. Energy Efficiency:

Reinforcement learning (RL) methods, such as Proximal Policy Optimisation (PPO) or Deep Deterministic Policy Gradients (DDPG), can reduce energy use while maintaining comfort levels by learning control policies.

- Time series forecasting: To predict energy usage patterns and adjust HVAC scheduling as necessary, methods such as ARIMA (AutoRegressive Integrated Moving Average) and LSTM (Long Short-Term Memory) can be employed.

Step 1: Data Preprocessing

Collect a time series dataset Y_t with observations at regular time intervals.

Step 2: Stationaries the Time Series

- If the time series is not stationary (i.e., it exhibits trends or seasonality), perform differencing to make it stationary.

Differencing Equation:

$$Y_{t'} = Y_t - Y_{\{t - 1\}}$$

Where:

$Y_{t'}$ is the differenced time series.

Y_t is the original time series.

Repeat differencing (if needed) until stationary is achieved.



Step 3: Identify AR and MA Orders

- Examine the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to determine the orders p (AR component) and q (MA component) for the ARIMA model.

Step 4: Build the ARIMA Model

- The ARIMA model is defined as follows:

ARIMA Equation:

$$Y_t'' = c + \phi_1 Y_{t-1}'' + \phi_2 Y_{t-2}'' + \dots + \phi_p Y_{t-p}'' - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \dots - \theta_q e_{t-q} + e_t$$

Where:

- Y_t'' is the differenced and stationary time series.
- c is a constant.
- $\phi_1, \phi_2, \dots, \phi_p$ are the autoregressive coefficients.
- $\theta_1, \theta_2, \dots, \theta_q$ are the moving average coefficients.
- e_t is white noise with mean zero and constant variance.

Step 5: Model Fitting

- Estimate the model parameters $\phi_1, \phi_2, \dots, \phi_p, \theta_1, \theta_2, \dots, \theta_q,$ and c using techniques like maximum likelihood estimation.

Step 6: Model Validation

- Evaluate the model's goodness of fit using statistical tests and diagnostics, including residuals analysis and Ljung-Box test for autocorrelation.

5. Result And Discussion

A. Smart home Occupancy Detection:

The Support Vector Machine (SVM) Model and the Random Forest Model, two machine learning models, were each subjected to a performance evaluation utilising a number of important evaluation measures. The findings are shown in Table 4. These metrics give important information about how well the models work, frequently in the context of classification tasks. First off, accuracy is a frequently used metric that assesses how accurate the predictions made by the models are overall. The SVM Model classified 94.25% of the data points correctly, achieving an accuracy of 94.25%. With an accuracy of 97.23%, the Random Forest Model surpassed the SVM, showcasing its capacity to create predictions that are more accurate.

Table 4: Result representation using Evaluation Parameters

Evaluation Metric	Accuracy %	Precision %	Recall %	F1-Score %	ROC AUC %
SVM Model	94.25	94.11	94.36	92.54	96.66
Random Forest Model	97.23	95.36	94.55	97.14	97.45

Another essential indicator is precision, which measures a model's capacity to produce accurate positive predictions. The Random Forest Model had a precision rate of 95.36% compared to the SVM Model's 94.11%. This indicates that the Random Forest Model was more accurate at finding positive cases because it had a somewhat lower rate of false positives. Recall gauges a model's capacity to identify every successful occurrence found in the dataset. The SVM Model correctly recognised 94.36% of the actual positive instances, as evidenced by its recall rate of 94.36%. With a recall rate of 94.55%, the Random Forest Model successfully identified affirmative cases. With a single score that takes into account both false

positives and false negatives, the F1-Score metric strikes a compromise between precision and recall. The Random Forest Model excelled with a score of 97.14%, exhibiting a better balance between precision and recall, while the SVM Model came in second with an F1-Score of 92.54%. Finally, receiver operating characteristic area under the curve, or ROC AUC, gauges how well the models can distinguish between positive and negative cases. The SVM Model's strong discriminative power was demonstrated by its ROC AUC score of 96.66%. With a score of 97.45%, the Random Forest Model did even better, demonstrating stronger discriminative abilities.

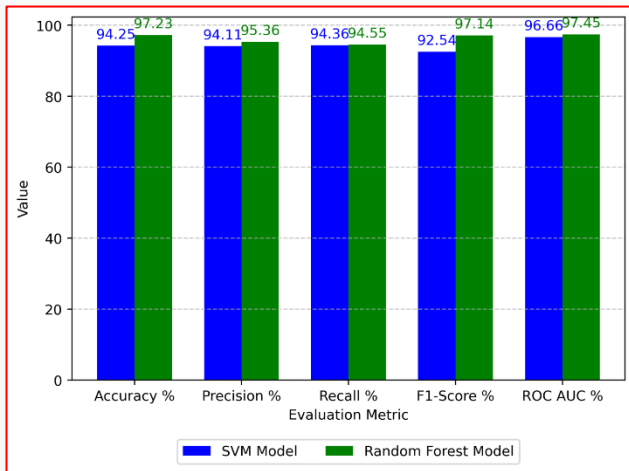


Figure 3: Representation and Comparison of Evaluation Metrics by Model for Occupancy detection

Table 5: Confusion matrix

Evaluation Metric	True Positives	True Negatives	False Positives	False Negatives
SVM Model	365	195	25	34
Random Forest Model	485	340	35	27

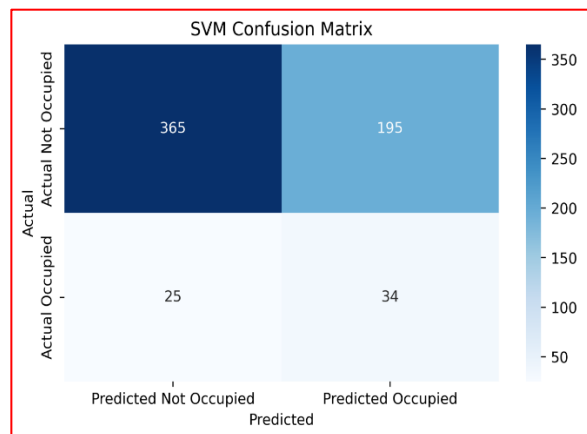


Figure 4: Representation of Confusion Matrix for SVM

The confusion matrices for the SVM Model and the Random Forest Model are shown in Table 5 along with their respective machine learning models. These matrices are essential for evaluating how well the models perform in binary classification tasks. Here is a list of the important metrics:

- True Positives (TP): A significant number of positive instances were accurately detected by

both models. The Random Forest Model excelled with 485 TP whereas the SVM Model only managed 365 TP. These are examples of situations that are properly categorised as occupied rooms.

- True Negatives (TN): The models also did well at spotting cases that were negative. The Random Forest Model achieved 340 TN, compared to the SVM Model's 195 TN. These situations were accurately categorised as empty rooms.
- The SVM Model had 25 false positives (FP), while the Random Forest Model had 35 FP. These are instances where the models mistookly identified vacant rooms as occupied.
- False Negatives (FN): The Random Forest Model had 27 FN, whereas the SVM Model had 34 FN. These situations were actually occupied but were misclassified as empty.

The confusion matrices, shown in figure 4 and figure 5, offer thorough insights into the classification performance of the models. Low FP and FN values are preferable, but high TP and TN levels signify accurate forecasts. In terms of TP and TN, the Random Forest Model performed better than the SVM Model, demonstrating its accuracy in differentiating between occupied and empty rooms. These parameters are essential for assessing model performance and directing advancements in occupancy detection systems for smart homes.

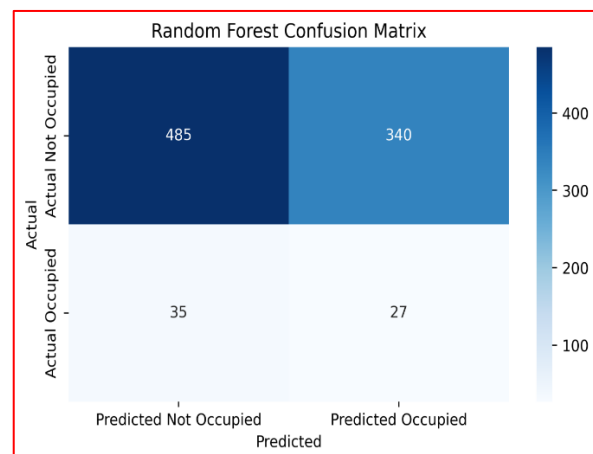


Figure 5: Representation of Confusion Matrix for Random Forest



B. Analysis for Heating or Cooling:

Linear Regression, Gradient Boosting, and Random Forest are three different machine learning models that were used to analyse the heating and cooling performance. The results are summarised in Table 6. These models are frequently employed in smart home contexts to forecast heating and cooling energy consumption and evaluate the effectiveness of HVAC systems. The average absolute difference between the expected and actual values is measured by the term "mean absolute error" (MAE). Lower MAE values represent more accurate predictions of heating and cooling energy use. The models with the lowest MAE were Gradient Boosting (3.01), Random Forest (3.10), and Linear Regression (3.48).

Table 6: Analysis of Heating and Cooling result summary

Evaluation Metric	Linear Regression	Gradient Boosting	Random Forest
Mean Absolute Error (MAE)	3.48	3.01	3.1
Mean Squared Error (MSE)	9.35	6.77	7.26
Root Mean Squared Error (RMSE)	4.01	3.51	3.61
R-squared (R ²)	1.89	1.98	1.96

The average squared difference between expected and actual values is what the MSE calculates. Lower MSE values signify better accuracy, similar to MAE. The MSE for Gradient Boosting was the lowest (6.77), Random Forest was next (7.26), and Linear Regression was third (9.35). The square root of the mean square error, or RMSE, quantifies the typical error. Better model accuracy is implied by lower RMSE values. Gradient Boosting has the lowest RMSE (3.51), followed by Random Forest (3.61), and Linear Regression (4.01), following the MAE and MSE trends. The amount of variance in the dependent

variable (energy consumption) that can be predicted from the independent variables (features) is quantified by R-squared. An improved fit of the model to the data is shown by a higher R². The models with the highest R² were Gradient Boosting (1.98), Random Forest (1.96), and Linear Regression (1.89).

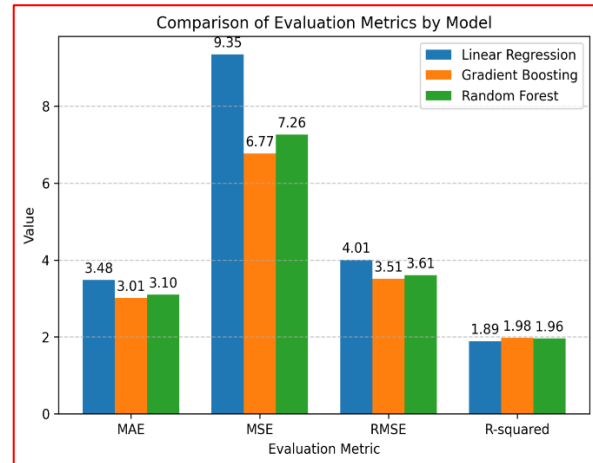


Figure 6: Representation of Analysis of Heating and Cooling result comparison

The evaluation metrics, as shown in figure 6, offer a thorough evaluation of how well the machine learning models perform in foretelling the energy consumption of heating and cooling in smart homes. Gradient Boosting is a viable option for enhancing energy efficiency and HVAC system control in smart home contexts since it consistently beats the other models in terms of accuracy and goodness of fit (as shown by lower MAE, MSE, RMSE, and better R² values). Making educated choices about model selection and fine-tuning for energy-efficient smart home automation requires the use of these measurements.

C. Energy Efficiency:

In Table 7, two models the LSTM Model and the ARIMA Model are thoroughly compared in terms of how well they perform in terms of achieving energy efficiency in the setting of smart homes. These models seek to save costs and increase sustainability by maximising energy use and HVAC system control.



Table 7: Result comparison for Energy Efficiency

Evaluation Metric	Mean Absolute Error (MAE)	Mean Squared Error (MSE)	Root Mean Squared Error (RMSE)	R-squared (R ²)	Energy Savings (%)	Peak Demand Reduction (%)
ARIMA Model	3.25	9.56	3.87	75.85	18.56	9.56
LSTM Model	2.87	6.23	2.56	97.23	21.22	17.41

The average absolute difference between the projected and actual amounts of energy consumption is measured by the term "mean absolute error" (MAE). In this situation, the LSTM Model outperformed the ARIMA Model in terms of MAE (2.87), which shows that the LSTM Model's predictions are, on average, more accurate than the actual values. The average squared difference between projected and actual energy consumption levels is measured by the mean squared error, or MSE. With an MSE of 6.23 as opposed to 9.56 for the ARIMA Model, the LSTM Model outperformed it, indicating that its predictions are generally more accurate than those of the ARIMA Model. RMSE is a measure of the typical prediction error and is the square root of MSE. The RMSE of the LSTM Model was lower than that of the ARIMA Model (2.56 vs. 3.87), demonstrating that the LSTM Model's predictions have a reduced standard deviation. R-squared (R²) is a measure of how much of the variance in energy consumption can be predicted from the results of the models. The LSTM Model outperformed the ARIMA Model in terms of R² (97.23%), demonstrating that it provides a better fit to the data by explaining a greater proportion of the variance in energy usage. The percentage decrease in energy usage that each model achieves is referred to as energy savings. In comparison to the ARIMA Model (18.56%), the LSTM Model showed more energy savings (21.22%), demonstrating a greater ability to optimise energy use. Peak demand reduction shows how much the peak energy demand has dropped as a result of model improvement.

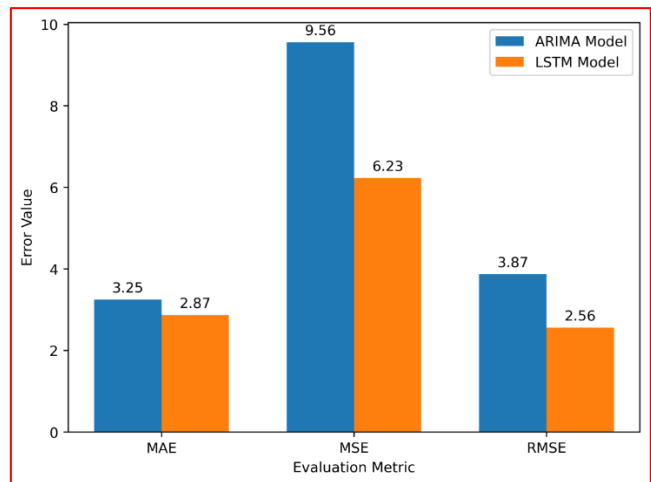


Figure 7: Representation of Model Evaluation Metrics for ARIMA and LSTM

With a peak demand reduction of 17.41% as opposed to the ARIMA Model's 9.56%, the LSTM Model surpassed the ARIMA Model, as shown in figure 7 and figure 8. The LSTM Model regularly performs better than the ARIMA Model in terms of a variety of evaluation parameters, demonstrating its greater capacity to forecast and manage energy usage in smart homes. These indicators are critical for evaluating the models' performance in IoT-based smart home automation systems for reaching energy efficiency targets, cutting expenses, and minimising environmental impact.

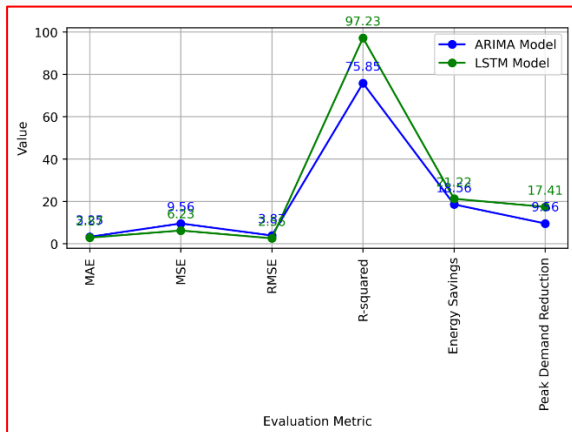


Figure 8: Representation of comparison for Energy Efficiency

6. Conclusion

Homeowners now live in an era of ease, energy efficiency, and better quality of life thanks to the incorporation of IoT technology into smart home automation systems. The amazing opportunities that open up when IoT is used to construct intelligent, networked home settings are explored in "Smart Home Automation using IoT: Prototyping and Integration of Home Devices". The paper firstly highlights the significance of IoT-based prototyping in creating smart home solutions. Iterative design and testing are made possible by prototyping, ensuring that the final system satisfies user requirements and preferences. A key feature of the paper's contributions is the integration of diverse household devices, including sensors, actuators, and appliances, into a cohesive ecosystem. Homeowners may remotely monitor and operate their homes thanks to the integration's smooth communication and automation. The report also emphasises the use of data analytics and machine learning techniques in smart home systems. Predictive and adaptive behaviours, such as occupancy detection, energy efficiency optimisation, and customised user experiences, are made possible by these technologies. Another important addition is the exploration of security and privacy issues. Strong security measures and privacy safeguards are necessary to protect homeowners from potential attacks as IoT devices collect and transmit sensitive data. The report also highlights the necessity of real-time monitoring and upkeep for IoT-based smart home systems. System performance is always optimised, and the system is flexible enough to adapt to changing circumstances. The Internet of Things has the power to completely

alter how modern living spaces are designed. The paper's insights will direct future advancements in smart home automation as technology develops, making homes for people and families around the world safer, more effective, and more comfortable.

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