International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

A Machine Learning Framework with Fuzzy Logic for Improved Smart Home Management and Safety

[1]Anubhav Bhalla, [2]Narmadha Thangarasu, [3]Dr. Shilpi Kulshrestha, [4]Dhyan Chandra Yadav, [5]Inzimam ul Hassan

Submitted: 09/01/2024 **Revised**: 15/02/2024 **Accepted**: 23/02/2024

Abstract*:* A Machine Learning (ML) framework is a concept or research article that suggests a framework using ML methods to improve the smart home. The terms "Smart Home Management" (SHM) and "safety" refer to the use of technology and automation to control and monitor various aspects of a home to enhance convenience, efficiency, and security. In this research, the SHM entails managing and improving several components of a house, including energy consumption, security features, and appliance automation. In this study, we propose a fuzzy logic with a bilateral support vector machine (FL-BLSVM) technique to increase the intelligence and effectiveness of smart home systems. In this instance, the ML technique improves the FL-BLSVM classification effectiveness. To evaluate the effectiveness of the recommended strategy, three actual data sources were examined, each of which included 10 devices from a smart home firm. The Adaptive Median Filter (AMF) filter eliminates the noisy data from raw data samples. An analysis known as a Kernel Principal Component Analysis (KPCA) is used to separate the attributes from the segmented data. Accuracy, precision, recall, and F1 score are some of the assessment criteria for classification tasks, according to the research's performance. Smart homes may operate more adaptable, effectively, and securely by using the recommended approach FL-BLSVM.

Keywords: *Machine Learning (ML), Smart Home Management (SHM), Fuzzy logic with Bi-Lateral Support Vector Machine model (FL-BLSVM), Adaptive Median Filter (AMF), Kernel Principal Component Analysis (KPCA)*

1. Introduction

The term SHM and safety refers to the use of cutting-edge technology and automation systems to manage and improve the security and safety of a house. Smart locks, door/window sensors, motion detectors, and security cameras are examples of features included in smart home security systems. In the event of shady behaviour or emergency, real-time warnings and notifications may be delivered [1]. They let homeowners keep an eye on who comes and goes from their house and may provide temporary access credentials to visitors or service providers. Homeowners can monitor their property both inside and outside thanks to smart security cameras. These cameras can record, detect motion, and give live video feeds [2]. Alarm systems for smart homes may also include sirens, strobe lights, and other warning devices. Unauthorized entry, smoke or fire, carbon monoxide leakage, or other crises may set off these alarms. Integration with security cameras enables video verification, giving the event's happenings visible proof. A smart house may be equipped with a variety of smart sensors to monitor environmental elements and improve safety. For instance, water leak sensors, smoke detectors, and carbon monoxide detectors may warn homes of possible dangers and crises [3].

A secure living environment may be maintained with the aid of temperature and humidity sensors. To safeguard their data, users should also read and comprehend the privacy rules of the devices they use. Some SHM systems support the integration of third-party emergency response or monitoring services. These services may automatically warn users in the event of a security breach or an emergency and send out the necessary support [4].

SHM and safety may greatly improve a house's convenience and security by implementing these features and practices, giving homeowners peace of mind whether they are at home or away.

By allowing thoughtful decision-making and adaptable control, integrating a machine-learning framework with fuzzy logic may improve the management and safety of smart homes [5]. Numerous sensors, gadgets, and human interactions in smart homes produce a ton of data. Environmental data (temperature, humidity, and air quality), occupancy status, energy use, and security incidents may all be included in this data. The data is gathered and combined with the ML framework for analysis [6]. The method is

[1]Chitkara University, Rajpura, Punjab, India, anubhav.bhalla.orp@chitkara.edu.in, https://orcid.org/0009-0005-7854-6075
[2]JAIN (Deemed-to-be University), Karnataka, India, Email Id- narmadha.t@jainuniversity.ac.in, Orcid Id- 0000-0001-9628-4236
[3]Department of ISME, ATLAS SkillTech University, Mumbai, Maharashtra, India, Email Id- shilpi.kulshrestha@atlasuniversity.edu.in, Orcid Id- 0000-0003-2249-0736
[4]Maharishi University of Information Technology, Lucknow, India -226036, Email Id- dc9532105114@gmail.com, Orcid Id- 0000-0003-0084-0360
[5]Vivekananda Global University, Jaipur inzimam.hassan@vgu.ac.in, Orcid Id- 0000-0001-7475-7039

required to address missing values, outliers, and noise in the acquired data. In addition, essential characteristics that contribute to the administration and security of smart homes may be extracted using feature engineering approaches. Fuzzy logic offers a method for dealing with incomplete or ambiguous information [7].

Fuzzy logic rules may be developed in the situation using expert knowledge or by learning from previous data. These guidelines outline the connections between input factors (such as temperature and occupancy) and the actions that are produced (such as changing the thermostat or turning off the lights). The accuracy and efficiency of the fuzzy logic rules may be increased by applying ML methods to historical data. Models that maximize rule performance based on specified goals, as shown in Fig. 1, may be trained using supervised learning methods such as decision trees, support vector machines, or neural networks.

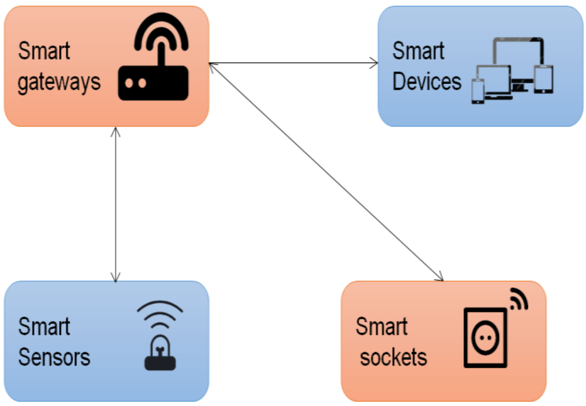

Fig.1. Analysis of smart home management system

The fuzzy logic rules and trained models allow for intelligent decision-making for safe and smart home management. The framework may make judgments about activities like modifying settings, improving illumination, or turning on security measures by analyzing real-time sensor data, occupancy trends, and user preferences. The framework's ability to adapt to changing circumstances and user behavior is made possible by the integration of ML and fuzzy logic. The system may develop its decision-making skills over time by continually learning from new data and modifying the fuzzy logic rules, allowing individualized and context-aware management of smart home gadgets [8].

The ML framework may be used to find patterns and anomalies that might be signs of safety or security problems. It may, for instance, spot strange activity patterns or signal a possible fire or water leak. Due to early detection, the system can launch the proper actions, such as alerting homeowners or calling emergency services [9]. The framework may also reduce energy loss while maintaining comfort levels by learning from previous use patterns and dynamically altering settings. When rooms are empty, it may evaluate occupancy patterns and modify lights and other equipment appropriately to use less energy. The smart house management and safety framework can adapt to changing circumstances, enhance decision-making, and increase the overall effectiveness and security of the smart home environment by merging ML methods with fuzzy logic [10].

Key contributions:

The FL-BLSVM-based ML system, which incorporates fuzzy logic for better SHM and safety, makes numerous important advances. Here are a few of the key contributions made by the strategy:

- FL-BLSVM guarantees data security and privacy in a distributed smart home environment. The system protects user privacy while making use of the network's collective intelligence by training local FL-BLSVM models on individual devices and only exchanging model updates, not raw data.
- The framework may gather contextual information and create context-aware judgments by integrating FL-BLSVM with fuzzy logic. The system can decipher complicated patterns and modify its behavior in response to the unique context of each smart home setting thanks to fuzzy rules and linguistic factors.

The research's remaining elements are arranged as follows: In section 2, the objectives or aims of the study are compared to the preliminary research, and any differences or gaps are recorded. Section 3 provides details on the research strategy and methodology. After going through the data and analysis in Segment 4, evaluating the goals or objectives of the research, and providing interpretations, we completely and meticulously describe the results. Segment 5 of the Study provides an overview of the key parts.

2. Related Works

Research [11] determined the sensing and actuation layer, which includes web cameras for security monitoring, temperature sensors, passive infrared sensors (also known as motion sensors), and smoke sensors. Through a home gateway, the sensors, intelligent electrical appliances, and other IoT devices connect to the Internet. The research examined the design of an inexpensive smart door sensor that would alert a user to door-opening events in a home or workplace through an Android application. The study extracted [12] address the security and availability problems in smart homes and suggest an edge-of-things approach that focuses on moving house control to the edge. Like with existing set-top boxes for home multimedia streaming, the network operator has authority over the administration. The research assessed the system's design, put the required modules in place, and tested it from the standpoint of security and availability. Research [13] suggested based on the discovered movement patterns, the deep learning model are suggested for motion detection and categorization. An algorithm is created using a deep learning model to improve the smart home automation system's intruder detection and reduce the likelihood of false alarms. Based on his walking style, a person observed by the video camera is categorized as an invader or a resident of the property. The overview objective of the goal [14] described the aforementioned issue as a Markov decision process to solve the issue, and then provide an energy management method based on deep deterministic policy gradients. It is important to note that the suggested technique does not need to develop the thermal dynamics model or have previous information on unknown parameters. The Study [15] revealed the absence of quality features like security, privacy, scalability, and interoperability; the challenge of maintaining and adapting to inhabitants' needs for thermal comfort; and the danger to their health. The report also outlined potential directions for future research to guarantee energy-efficient smart homes are free from irrational energy use, health risks, and cyber security threats. The study [16] developed a novel approach using neuro-fuzzy systems, unsupervised clustering, and text mining. The Latent Dirichlet Allocation method is used to extract the components from text analyses. The Expectation-Maximization approach was used to segment the client preferences. Research [17] analyzed the issue simulation and the backpropagation procedure in neural networks, both linear and non-linear networks, are covered in depth. Face recognition in particular, which is the most fundamental need for selecting the most suitable way to construct a smart home, is a direct application of ML that has outstanding results in recognizing human behavior.

3. Experimental Procedure

This section established the strategy utilized to develop the model, discussed the key phases that were involved in building the model, and provided a thorough description of how the steps of the suggested model in Fig. 2 were produced. This conversation has four sections: The first phase is concerned with gathering information. We'll discuss the procedure, feature selection and extraction techniques, and other data pre-processing techniques in the second section. The most crucial details are provided in the third section, which goes through the work done to develop the suggested model and compile the essential experiences. The fourth step compares the associated parameters to assess how well each new and previous model performed.

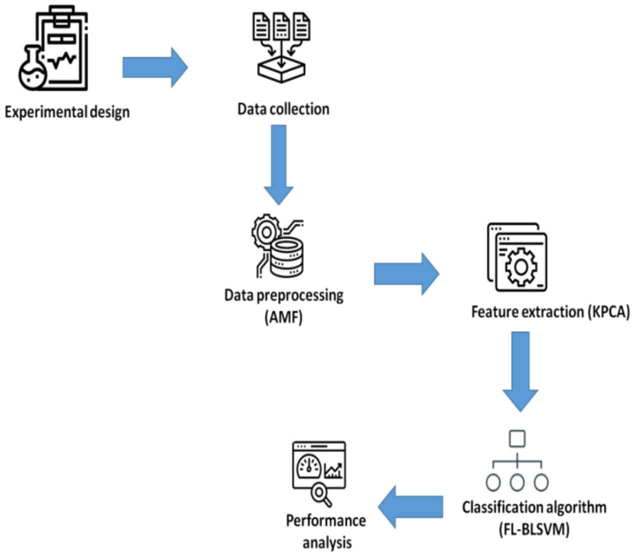

Fig.2. Experimental Design

3.1. Data Collection

The experiments in this section use three real data sources, each of which comprises 10 devices from a smart home company, to evaluate the effectiveness of the proposed FL-BLSVM algorithm. Every data set has a direct connection to a smart home. Enumerate each data collection's hardware in step four. It is necessary to note that all items with blank fields have been removed [18]. The utilization of the record creation date, activity generation time, and device operating states in 1335, 1660, and 1696 have also been noticed by firm engineers as important elements of user behavior clustering for a certain device which is shown in Table 1.

Table 1. Data set is linked to the smart home

Data set	# devices	# records
Exhibition Hall (ID: 1696)	6	22719
Program test room (ID: 16660)	4	17456
Research and development center (ID:1335)	4	17715
Total	14	57890

3.2. Data Pre-Processing using Adaptive Median Filter (AMF)

The AMF approach has improved the standard median filter. The use of spatial processing reduces impulse noise. The AMF recognizes each pixel in the skin image together with its surrounding pixels to determine if noise is present or not. It operates better than other filters since it safeguards fine visual details and reduces non-impulse noise. Additionally, there is a good chance that it can adjust to abrupt loudness. The disorder of an image is the same for the median channel and the mean channel. The median channel for two descriptions may vary, as in Equation (1).

$$med(n_k) = \{n_i + 1^a = 2i + 1(ODD)) \ \frac{[n_i+n_{i+1}]}{2} a = 2i(even) \quad (1)$$

Here n_i is the i^th the biggest observed data and n_1; n_2; n_3... n_i are the observed data. Consider a situation where there are seven samples overall in the data collection 2, 3.5, 1, 3, 1.5, and 4 and the median filter yields an output of 2.5. If the pulse is n + 1 or longer, the signal will be kept; otherwise, it will be eliminated from the series. Because it may minimize pulse noise while keeping local characteristics, the median filter differs from other filters. This method then sends the signal it produces to the feature extraction stage.

3.3. Feature Extraction by using Kernel Principal Component Analysis (KPCA)

An approximate covariance matrix of the data in Equation (2) is diagonalized using a basis transformation known as Principal Component Analysis (PCA).

$$D = \frac{1}{k}\sum_{i=1}^{k} \quad v_l v_i^S \quad (2)$$

The orthogonal projections onto the Eigenvectors or the new coordinates in the tile Eigenvector basis are principal components. In this work, this setting is further developed into a nonlinear setting of the following kind. If the data were initially nonlinearly mapped onto a feature space using Equation (3),

$$\Phi: Q^M \to E, v \to V \quad (3)$$

We'll show that, for certain values, even if it has arbitrarily large dimensionality, we can still do KPCA in E. For now, let's assume that Equation (4) translates data into feature space. KPCA for the covariance matrix,

$$\underline{D} = \frac{1}{k}\sum_{i=1}^{k} \quad \Phi(v_l)\Phi(v_l)^S \quad (4)$$

Applications for denoising and wavelet transforms often employ KPCA, a nonlinear variant. The traditional PCA approach tries to reduce the number of dimensions when the manifold is linearly buried in the observation space. The manifold is linearized using the kernel technique, one of the two components, to satisfy the requirements of the PCA, the second component of KPCA. To automatically convert data into a pairwise formula between the mapped data in the feature set, KPCA employs feature mapping. The kernel calculates this pairwise formula. The nonlinear dimensionality reduction of KPCA would be ineffective for a suboptimal projection that does not satisfy these conditions.

3.4. Fuzzy logic with BI- Lateral Support Vector Machine model (FL-BLSVM)

Fuzzy logic and BI- Lateral Support Vector Machines (FL-BLSVM) are two distinct ML methods. Fuzzy logic is a mathematical framework that deals with inference and decision-making in the presence of ambiguity, in contrast to SVM, which is a supervised learning approach used for classification and regression issues. However, integrating FL-BLSVM may result in a hybrid model. One such hybrid model that integrates the SVM framework with fuzzy logic is the FL-BLSVM. In an attempt to improve the performance of the SVM, the FL-BLSVM model takes into consideration the ambiguity and imprecision of the input data.

In FL-BLSVM, the input data is fuzzified using fuzzy logic, turning clear inputs into fuzzy sets or linguistic variables. The degree to which the input belongs to a given set is indicated by the membership values that this fuzzification procedure gives to each fuzzy set. The SVM model then incorporates the fuzzy inputs as features. Utilizing membership functions and linguistic factors, transform crisp inputs into fuzzy sets. Using the fuzzy sets produced by the fuzzification process, define the appropriate features. Utilize the fuzzy features as inputs and the appropriate target labels to train the model using the SVM method. Make additional examples into fuzzy sets and use the SVM decision function to categorize them using the training model. The FL-BLSVM model may handle uncertain and imprecise data more effectively by introducing fuzzy logic into SVM, possibly enhancing the model's performance in certain circumstances. When working with ambiguous data or when the definition of fuzzy sets and membership functions is provided, it may be very helpful. It's important to keep in mind that an FL-BLSVM model's precise implementation and specifics might change based on the issue area and the fuzzy logic approaches used. Alternative hybrid models that integrate fuzzy logic with different machine-learning methods to accomplish comparable strategies include the following:

3.4.1. Fuzzy Logic Algorithm

A mathematical framework known as fuzzy logic is used to cope with ambiguity and imprecision in thinking and decision-making. The idea of fuzzy sets, which allow for partial membership rather than rigid binary membership, is the foundational idea of fuzzy logic. The range of values that the fuzzy logic system will operate across should be determined. This entails defining the input and output variables as well as their corresponding domains or ranges. For each input and output variable, provide linguistic variables. The qualitative phrases used to characterize the variables are represented by linguistic variables. Each linguistic variable should be given a membership function that specifies the level of membership for each value falling within the variable's range. Membership functions might be triangular, trapezoidal, or Gaussian in form. By calculating the degree of membership for each input value across the linguistic variables, convert crisp input values into fuzzy values. For the supplied input values, the membership functions must be evaluated. Create a set of fuzzy rules that connect algorithm 1's fuzzy outputs and fuzzy inputs.

Algorithm 1: Fuzzy Logic

Input: *Did, Rid, Device Value.*

Output: *on, off, set value*

Step 1*: Starting the beginning timer as TS:*

Step 2*: Obtain the values from the gadgets:*

Step 3*: [Initialize]*

Step 4*: Val1 ←Did;*

Step 5*: Val2←Rid;*

Step 6*: Val3←Device value;*

Step 7*: Obtain data from a database (DB1):*

Step 8*: IF*

Step 9*: Found Val2, Val2←false;*

Step 10: *Then*

Step 11: *write ('Device not found);*

Step 12: *Await user input before storing it in the database*

Step 13: *return (Rid, Did, Dname, Type, Range, Input Require) from the room and device table*

Step 14:*ELSE IF*

Step 15: *Found Val2, Val2 ←false;*

Step 18: *THEN return (Dname, Type, Range, Input require) from the room and device table*

Step 20: *Send this information to the module that detects context*

Step 21: *fetch the database DBI:*

Step 22: *From the dependency table, revert (depend)*

Step 23: *Use the fuzzy logic method:*

Step 24: *A. Define the terminology and linguistic variables (initialize)*

Step 25: *B. membership function construction (initialize)*

Step 26: *C. Use the membership function to fuzzify the supplied data from the crisp form.*

Step 27: *D.PROC I to VIII (inference)*

Step 28: *E. GOTO PROCE (inference)*

Step 29: *F. Convert output data to non-fuzzy values after combining a result (Defuzzification)*

Step 30: *Create the device's command based on the scenario's output:*

Step 31: *Return (Val4) from database DBI*

Step 32: *SEND val2←val4;*

Step 33: *The timer expires, and the value is stored in TF;*

Step 34: *Total time (TR)=TF-TS;*

Step 35: *Exit;*

The consequent defines the fuzzy output or action, while the antecedent consists of one or more fuzzy propositions that evaluate to some degree of truth. Based on the fuzzy inputs, determine the level of truth for each rule in the rule base. This entails mixing the input variable membership values with each rule's fuzzy propositions. The operator's minimum, maximum, and product are often used for rule assessment. For each output variable, combine the results of the rule evaluation stage to create a single fuzzy set. This is accomplished by combining the fuzzy sets using aggregation operators like maximum or algebraic sum. Reverse the aggregated fuzzy output sets into crisp values so that they may be processed or used in other ways. There are several defuzzification techniques that, depending on the size and form of the fuzzy collection, provide a crisp output value. Examples include centroid, mean of maximum, and weighted average. The fundamental stages of a fuzzy logic algorithm are described in these steps. Depending on the particular issue at hand and the amount of specificity necessary in creating linguistic variables, membership functions, and fuzzy rules, the algorithm's complexity and degree of customization may change.

3.4.2. Bi- Lateral Support Vector Machine (BLSVM)

It handles high-dimensional feature spaces and is especially good at handling complicated datasets. Finding an ideal hyperplane to divide data points into distinct classes while minimizing the margin of the distance between the hyperplane and the closest data points of each class is the basic goal of BLSVM. Maximizing the margin and decreasing the classification error are two objectives of BLSVM. Start by gathering training data that has been tagged, with each data point having a class label attached to it. The data should be classified as either class 0 or class 1 as BLSVM is a binary classifier. Different approaches may be used to solve issues involving many classes. Select from the data those characteristics that are instructive for the categorization job and relevant. Categorical characteristics may also be encoded; however numerical features work better for BLSVM. To guarantee that no one characteristic dominates the learning process, normalize or standardize the feature values. Scaling techniques like min-max scaling and z-score normalization are often used. The BLSVM model is trained using the labeled data in the BLSVM Model Training stage. The goal is to identify the ideal hyperplane that divides the two groups by the greatest margin. BLSVM solves this issue using a mathematical optimization method. To transfer the data into a higher-dimensional space where it could become linearly separable, BLSVM can apply kernel functions. The linear kernel, polynomial kernel, Gaussian (RBF) kernel, and sigmoid kernel are examples of common kernel functions. The kind of data and issue complexity determine which kernel should be used. To determine the ideal hyperplane, BLSVM optimization includes solving a quadratic programming issue. The goal of the optimization procedure is to maximize the margin while minimizing a cost function that penalizes incorrectly categorized data points. The data points that are on the margin or very close to it are used to calculate the Lagrange multipliers to establish the support vectors. Techniques like grid search and randomized search may be used for this. In several fields, including text classification, picture recognition, bioinformatics, and finance, BLSVM s are successful. Due to their capacity for handling complicated data distributions, resistance to overfitting, and sound theoretical underpinning, they are frequently used.

3.4.2.1. Mathematical model of BLSVM

As a result of the description above, the ideal separation surface may be defined as the following restricted optimization problem which are represented in Fig.3 and aiming to minimize the function shown in Equation (5-8)'s coefficients.

$$\phi(u) = \frac{1}{2}\|u\|^2 = \frac{1}{2}(u.u) \tag{5}$$

Equation (5-7) allows us to define the Lagrange function as follows:

$$K(u,a,\alpha) = \frac{1}{2}(u.u) - \sum_{j=1}^{m} \alpha_j\{[(u.v_j)+a]-1\} \tag{6}$$

$$\sum_{j=1}^{m} z_j\alpha_j = 0 \tag{7}$$

$$\alpha_j \geq 0, j = 1,2,\dots,m \tag{8}$$

Where $\alpha_j > 0$ is the coefficient of Language. The problem is finding the Lagrange function's minimum of .. u and α. u and α seek partial differential and make them equal to zero, The original issue may be reduced to the dual issue below, which is straightforward: the restrictions that Equation represents (9-12):

$$R(\alpha) = \sum_{j=1}^{m} \alpha_j - \frac{1}{2}\sum_{j,i=1}^{m} \alpha_j\alpha_i z_j z_i(v_j.v_i) \tag{9}$$

$$u^* = \sum_{j=1}^{m} \alpha_j^* z_j v_j \tag{10}$$

$$\alpha_j(z_j(u.v_j + a) - 1) = 0, j = 1,2,\dots,m \tag{11}$$

$$e(v) = sgn\{(u^*.v) + a^*\} = sgm\{\sum_{j=1}^{m} \alpha_j^* z_j(v_j.v) + a^*\} \tag{12}$$

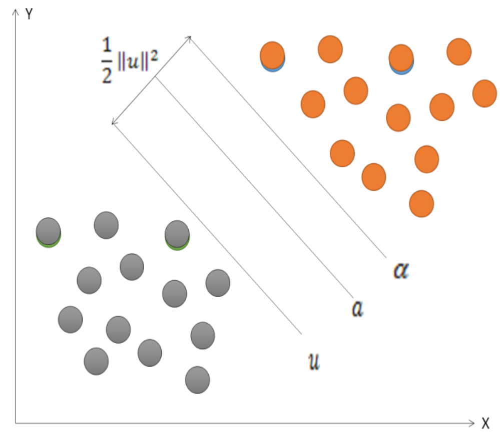

Fig.3. Structure of BLSVM

4. Results and Discussion

4.1. Results

The specific results and effectiveness of FL-BLSVM or any other ML framework with fuzzy logic will depend on various factors, including the quality and availability of training data, the design of the fuzzy logic system, and the implementation within a smart home environment.

4.1.1. Accuracy

A statistical parameter called accuracy is used to assess how well a categorization model or system is performing. It calculates the percentage of the model's total predictions that were accurate forecasts. In the FL-BLSVM setting, accuracy is determined by dividing the total number of examples represented in Equation (13), divided by the number of cases that were properly categorized (true positives and true negatives). It is often stated as a percentage. A greater accuracy score indicates that a higher percentage of the model's predictions were accurate, while a lower accuracy value denotes that there were more inaccurate predictions.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{13}$$

Table 2. Numerical Outcomes of Accuracy

Methods	*Accuracy (%)*
NB [19]	35
LR [20]	48
RF [21]	66
FL-BLSVM [Proposed]	88

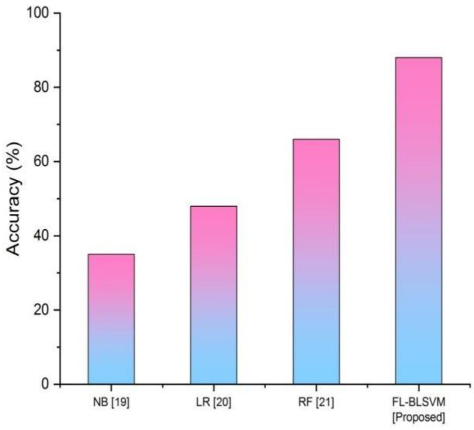

Fig.4. Comparison of Accuracy

The Accuracy for the suggested and current strategies is compared in Fig. 4. With a high accuracy performance of FL-BLSVM of 88%, the proposed technique outperforms the already-in-use NB (35%), LR (48%), and RF (66%). Table 2 displays the suggested method FL-BLSVM, which outperformed other in-use methods in terms of data classification accuracy.

4.1.2. Precision

Precision refers to the system's capacity to reliably categorize situations as safe or hazardous in the context of FL-BLSVM for enhanced SHM and safety. Out of all the occurrences that the system categorized as dangerous, it calculates the percentage of instances that were accurately labeled as unsafe. A high accuracy number means that the system has a low false positive rate, which means that it properly classifies dangerous instances as such without misclassifying safe instances, as shown in Equation (14), as safe. This is essential to keeping the smart home system trustworthy and secure. Precision may be described as follows in the context of binary classification utilizing fuzzy logic and bilateral SVM for SHM and safety:

$$precision = \frac{TP}{TP+FP} \qquad (14)$$

Table 3. Numerical Outcomes of Precision

Methods	***Precision (%)***
NB [19]	26
LR [20]	34
RF [21]	45
FL-BLSVM [Proposed]	48

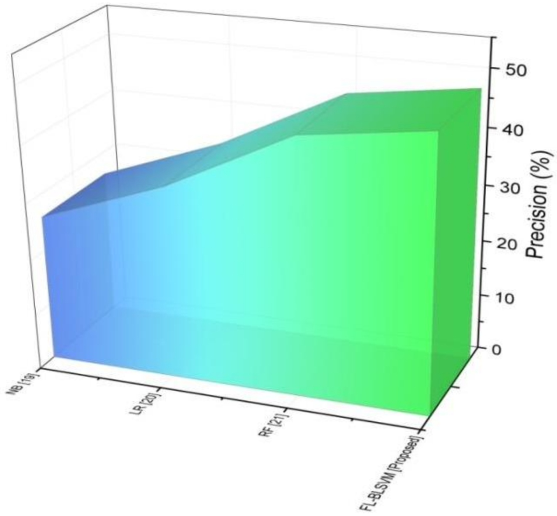

Fig.5. Comparison of Precision

The Precision for the suggested and current approaches is compared in Fig. 5. With a high Precision performance of FL-BLSVM of 48%, the proposed technique outperforms the already-in-use NB (26%), LR (34%), and RF (45%). Table 3 displays the suggested method FL-BLSVM, which outperformed other in-use methods in terms of data classification Precision.

4.1.3. Recall

A high recall value suggests that the system has a low false negative rate, which means it can efficiently detect and identify harmful situations, reducing the possibility of missing possible safety risks in the context of smart homes. The recall is a crucial parameter to take into account when concentrating on safety management in a smart home since it shows how correctly the system can detect and identify harmful circumstances, which are represented in Equation (15). The capacity of the system to accurately detect dangerous instances out of all the genuinely unsafe instances is referred to as recall in the context of FL-BLSVM for enhanced smart home management and safety. A true positive is defined as an instance that was accurately detected as being dangerous out of all occurrences.

$$Recall = \frac{FN}{FN+TP} \qquad (15)$$

Table 4. Numerical Outcomes of Recall

Methods	***Recall (%)***
NB [19]	28
LR [20]	39
RF [21]	52
FL-BLSVM [Proposed]	59

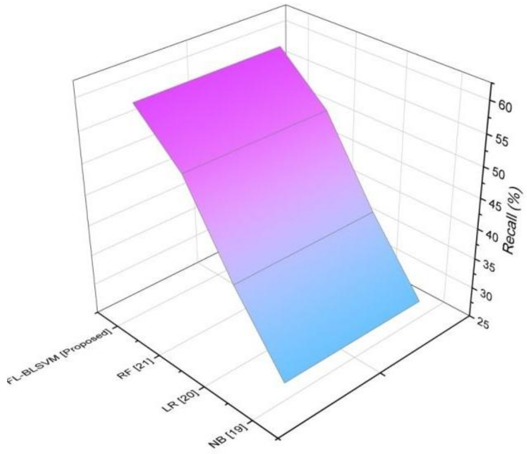

Fig.6. Comparison of Recall

Fig.6 compares the Recall for the recommended and existing techniques. The suggested method exceeds the already in-use NB (28%), LR (39%), and RF (42%), with a high Recall performance of FL-BLSVM is 59%. The recommended technique FL-BLSVM is shown in Table 4, and it performed better in terms of data classification Recall than other approaches already in use.

4.1.4. Mean Square error rate (MSE)

Mean Square Error (MSE) is not often used as a performance statistic for FL-BLSVM or other classification models. For regression assignments where the objective is to predict continuous values rather than categorize examples into discrete groups, MSE is often utilized. The performance of the model is measured by the MSE value, which reflects how well the predictions match the actual data as shown in Equation (16). To decide whether MSE is the best measure for gauging the effectiveness of FL-BLSVM, it is crucial to take into account the particular needs and characteristics of the smart home application.

$$MSE = \frac{1}{m}\sum_{j=1}^{m} \left(\hat{\phi}_j - \phi_j\right)^2 \quad (16)$$

Table 5. Numerical outcomes of MSE

Methods	*MSE (%)*
NB [19]	12
LR [20]	18
RF [21]	22
FL-BLSVM [Proposed]	10

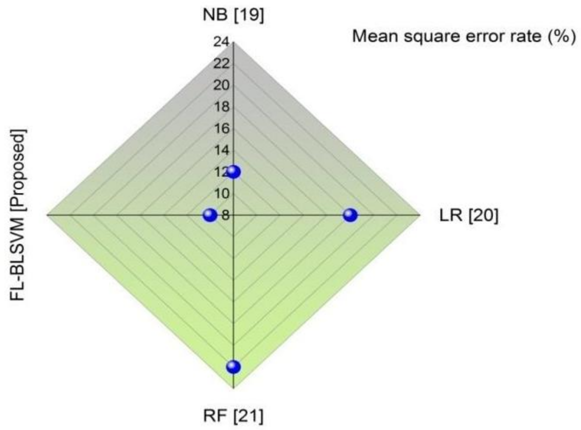

Fig.7. Comparison of MSE

The MSE for the suggested and current approaches are shown in Fig. 7. With a low MSE performance of FL-BLSVM of 10%, the proposed technique outperforms the currently used NB (12%), LR (18%), and RF (22%). Table 5 displays the suggested method FL-BLSVM, which outperformed other in-use methods in terms of data classification MSE.

4.1.5. F1-score

A performance indicator called the F1 score combines precision and recall into a single number to provide a fair assessment of the efficacy of a classification algorithm. The F1 score may be used to evaluate the system's accuracy in identifying situations as safe or hazardous in the FL-BLSVM context for enhanced smart home management and safety. According to Equation (17), a higher F1 score implies a better overall performance of the FL-BLSVM system in controlling the smart home environment and assuring safety. It illustrates the system's capacity to reduce false positives (precision) and capture a greater percentage of really dangerous situations (recall).

$$F1 - score = \frac{(precision)\times(recall)\times 2}{precision+recall} \quad (17)$$

Table 6. Numerical outcomes of F1-score

Methods	*F1-score (%)*
NB [19]	32
LR [20]	44
RF [21]	58
FL-BLSVM [Proposed]	72

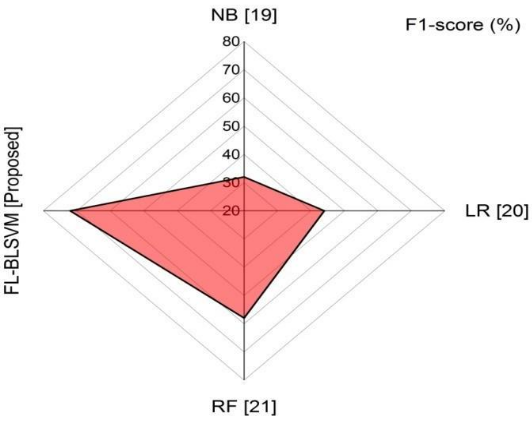

Fig.8. Comparison of F1-score

The F1-score for the suggested and current strategies is contrasted in Fig. 8. The proposed approach outperforms the already used NB (32%), LR (44%), and RF (58%), while FL-BLSVM performs at a high F1-score of 72%. Table 6 displays the suggested method FL-BLSVM, which outperformed other existing methods in terms of data categorization F1-score.

4.2. Discussion

A ML framework for smart home management and safety that incorporates FL-BLSVM and fuzzy logic provides various advantages and provocative debate topics. The study tested [19] in support of Naive Bayes (NB), one of the most widely used ML classification techniques. The physical design of the artificial intelligence-based smart house was created using Arduino hardware, and it was then attempted to be adjusted to the real-world setting with software assistance. Research provided [20] utilizing Logistic Regression (LR), a complete report on activity levels and the general health of activity detection inside smart homes is produced, and a smart home environment that automatically adapts to resident needs is created. The Study showed [21] in terms of effectiveness and efficiency, Random Forest (RF) may compete with other cutting-edge techniques and be utilized to detect strong human actions. Combining the already existing FL-BLSVM with our proposed FL-BLSVM in a machine-learning framework for smart home management and safety tackles uncertainties, improves decision-making, protects privacy, and allows adaptive control [22]. The combination of these methods creates opportunities for real-time adaptation, tailored experiences, and energy optimization in smart homes. The complexity and trade-offs that the integration introduces must be carefully managed to achieve the ideal balance of interpretability, accuracy, and user pleasure.

5. Conclusion

The management and safety of smart homes may greatly benefit from FL-BLSVM integration. The system can manage uncertainty, establish precise classifications, and improve decision-making in the context of smart homes by combining the advantages of both techniques. The modeling of ambiguous and imprecise variables made possible by fuzzy logic allows the system to manage a wide range of complicated inputs, including temperature, humidity, occupancy, and environmental conditions. It is simpler to analyze and comprehend the behavior of the system thanks to the rule-based system and linguistic variables that give a human-readable description of smart home situations and choices. Instances are classified as safe or dangerous based on a variety of characteristics including sensor data, human behavior, and ambient conditions using FL-BLSVM, a potent classification algorithm. The technology is capable of quickly identifying possible dangers to the safety of the passengers and taking appropriate action to reduce risks. The FL-BLSVM connection allows the system to prioritize safety in real time and make intelligent judgments. The system can adapt to shifting conditions and improve its accuracy over time by continually learning from prior data. Examine the SVM model with a different set of test data after training. Accuracy, precision, recall, F1 score, and MSE are frequent assessment criteria for classification tasks. By enabling the smooth functioning and security of the smart home ecosystem, this integration helps homeowners live in homes that are more effective, pleasant, and safe.

References

[1] Andrade, R. O., Ortiz-Garcés, I., & Cazares, M. (2020, July). Cybersecurity attacks on Smart Home during the Covid-19 pandemic. In 2020 Fourth World Conference on Smart Trends in Systems, Security, and Sustainability (WorldS4) (pp. 398-404). IEEE.

[2] Ray, A. K., & Bagwari, A. (2020, April). IoT based Smart home: Security Aspects and security architecture. In 2020 IEEE 9th international conference on communication systems and network technologies (CSNT) (pp. 218-222). IEEE.

[3] Pujari, U., Patil, D. P., Bahadure, D. N., & Asnodkar, M. (2020, May). Internet of things based integrated smart home automation system. In 2nd International Conference on Communication & Information Processing (ICCIP).

[4] Almomani, A., Al-Nawasrah, A., Alomoush, W., Al-Abweh, M., Alrosan, A., & Gupta, B. B. (2021). Information management and IoT technology for the safety and security of smart home and farm systems. Journal of Global Information Management (JGIM), 29(6), 1-23.

[5] Yar, H., Imran, A. S., Khan, Z. A., Sajjad, M., & Kastrati, Z. (2021). Towards smart home automation using IoT-enabled edge-computing paradigm. Sensors, 21(14), 4932.

[6] Das, R. R., Krishnamurthy, B., & Das, S. (2022, December). Securing IoT devices using Ensemble ML in Smart Home Management System. In 2022 IEEE Symposium Series on Computational Intelligence (SSCI) (pp. 915-922). IEEE.

[7] Kabir, S., Gope, P., & Mohanty, S. P. (2022). A Security-enabled Safety Assurance Framework for IoT-based Smart Homes. IEEE Transactions on Industry Applications, 59(1), 6-14.

[8] Arab, M. B., Rekik, M., & Krichen, L. (2022). Suitable various-goal energy management system for smart home based on photovoltaic generator and electric vehicles. Journal of Building Engineering, 52, 104430.

[9] Jhuang, Y. Y., Yan, Y. H., & Horng, G. J. (2023). GDPR Personal Privacy Security Mechanism for Smart Home System. Electronics, 12(4), 831.

[10] Khanpara, P., Lavingia, K., Trivedi, R., Tanwar, S., Verma, A., & Sharma, R. (2023). A context-aware internet of things-driven security scheme for smart homes. Security and Privacy, 6(1), e269

[11] Hoque, M. A., & Davidson, C. (2019). Design and implementation of an IoT-based smart home security system. Int. J. Networked Distributed Comput., 7(2), 85-92.

[12] Batalla, J. M., & Gonciarz, F. (2019). Deployment of smart home management system at the edge: mechanisms and protocols. Neural Computing and Applications, 31, 1301-1315.

[13] Taiwo, O., Ezugwu, A. E., Oyelade, O. N., & Almutairi, M. S. (2022). Enhanced intelligent smart home control and security system based on deep learning model. Wireless communications and mobile computing, 2022, 1-22.

[14] Yu, L., Xie, W., Xie, D., Zou, Y., Zhang, D., Sun, Z., ... & Jiang, T. (2019). Deep reinforcement learning for smart home energy management. IEEE Internet of Things Journal, 7(4), 2751-2762.

[15] Aliero, M. S., Qureshi, K. N., Pasha, M. F., & Jeon, G. (2021). Smart Home Energy Management Systems in Internet of Things networks for green cities demands and services. Environmental Technology & Innovation, 22, 101443.

[16] Nilashi, M., Abumalloh, R. A., Samad, S., Alrizq, M., Alyami, S., Abosaq, H., ... & Akib, N. A. M. (2022). Factors impacting customer purchase intention of smart home security systems: Social data analysis using ML techniques. Technology in Society, 71, 102118.

[17] ALZAABI, H. O. (2021). Intelligent Energy Consumption for Smart Homes using Fused ML Technique (Doctoral dissertation, The British University in Dubai (BUiD)).

[18] Liang, T., Zeng, B., Liu, J., Ye, L., & Zou, C. (2018). An unsupervised user behavior prediction algorithm based on machine learning and neural network for smart home. IEEE Access, 6, 49237-49247.

[19] Zeydin, P. A. L. A., & Özkan, O. (2020). Artificial Intelligence Helps Protect Smart Homes against Thieves. Dicle Üniversitesi Mühendislik Fakültesi Mühendislik Dergisi, 11(3), 945-952.

[20] Gorjani, O. M., Bilik, P., & Koziorek, J. (2022, May). Activity recognition within smart homes using logistic regression. In 2022 ELEKTRO (ELEKTRO) (pp. 1-4). IEEE.

[21] ud din Tahir, S. B., Jalal, A., & Batool, M. (2020, February). Wearable sensors for activity analysis using SMO-based random forest over smart home and sports datasets. In 2020 3rd International Conference on Advancements in Computational Sciences (ICACS) (pp. 1-6). IEEE.

[22] Dela Cruz, G. B. & Dr. Althaf Hussain Basha, S. K. (2022). Network Optimization Using Learning and Distributed Intelligence through Cognition Based Networks. Technoarete Transactions on Industrial Robotics and Automation Systems (TTIRAS), 2(1), 1-7.