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SMART HOME AUTOMATION SYSTEM FOR ENERGY CONSUMPTION USING TENSORFLOW-BASED DEEP ENSEMBLE LEARNING

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Abstract

Over the past decades, the evolution of new wireless technology has led to increased attention toward Smart Home Automation Systems (SHAS). In the smart home, numerous smart devices are interconnected with the proliferation of the Internet of Things (IoT) technology to provide users with a more comfortable lifestyle. Prior research on the smart home system has enacted machine learning and deep learning techniques to forecast the consecutive activities in the smart home. This research paper aims to enhance the future decision-making of energy consumption with the assistance of environmental factors and home appliances by exploiting the Tensorflow-based deep ensemble learning technique. The enhancement of future decision-making in smart home automation systems primarily involves the classification of energy consumption levels from the knowledge of external environmental factors and energy consumption levels of home appliances through the phases of data preprocessing, feature selection, fuzzy logic-based data labeling, and finally, classification of energy consumption using TensorFlow based deep ensemble learning technique. The data obtained from the effective feature selection technique is subjected to labeling via the fuzzy logic system to classify the energy consumption of smart home appliances. Finally, this work classifies the level of energy consumption based on the labeled knowledge of smart home data using a tensorflow-based deep ensemble learning model. The experimental model implements the proposed deep ensemble learning model in the tensorflow framework, which improves the decision-making performance of energy utilization in the smart home system. Experimental results illustrate that the proposed deep ensemble learning model yields superior classification performance than the other baseline classifiers, such as Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) on the smart home dataset.

Keywords:

Feature Selection Techniques, Fuzzy Logic, Tensorflow Framework, Ensemble Deep Learning Model

1. INTRODUCTION

In recent times, the emergence of smart home technologies has become increasingly sophisticated and contributed to the transformations of the home from a traditional environment to a smart internet-connected one. Home Automation Systems (HAS) furnishes infrastructure and techniques to transfer all appliance information and services. A smart home is a field of Internet of Things (IoT) technology, which provides sensors, wired and wireless networks, actuators, and intelligent systems to provide electronic, sensor, software, and network connectivity within a home [1]. Smart homes are equipped with highly advanced automated systems to make home activities more convenient and comfortable for residents and potentially reduce energy consumption. Smart home technology collects and analyzes data from the domestic environment, including temperature, lighting, security systems, appliances, and sensing devices, via network communication. Along with increasing enterprise investment in the smart home industry, the academic and research community has intensified their focus on investigating the smart home concept, its technological abilities, ramifications, and effects on people's lives. The usage of smart systems in the home is increasing globally for several aspects, including energy consumption, smart home alerts, smart home appliances, entertainment and communication [2].

In the residential industry, energy efficiency has sparked a lot of research interest worldwide due to the rise of energy consumption. The residential industry tends to consume high energy; thus, smart home systems are integrated into the IoT, which is beneficial for improving energy efficiency [3]. An enormous amount of energy is wasted in the residential industry because of the ineffective human interaction with electronic appliances and devices of the smart home. Various factors influence energy consumption, including infrastructure, electricity costs, and atmospheric conditions. Moreover, insufficient energy processing and other pertinent data lead to poor performance when dealing with energy crises. IoT facilitates a vital role in generating data for identifying patterns that can be applied to design efficient systems for handling energy crises in future smart homes and buildings.

Artificial Intelligence (AI) has recently been used for smart home applications such as activity recognition, data processing, voice recognition, image recognition, decision, and prediction-making [4]. The advancement of AI technologies has led to the creation of numerous intelligent sensors and systems that are empowered with advanced data analytics supported by machine learning or deep learning for several smart home applications. In essence, the application efforts of deep learning toward smart homes have been burgeoning [5]. Owing to the learning capability of deep learning models in analyzing residents' daily data from smart home devices and delivering them the most optimal functions for the resident's needs. Deep learning algorithms have been widely used in different smart services in smart home applications such as sound recognition, user authentication, human activity recognition, activity prediction, data classifier, energy management, home security, climate control, smart lighting, predictive maintenance and personalized recommendation. To enforce the deep learning algorithm more conveniently, researchers of Google developed TensorFlow deep learning framework [6]. The TensorFlow framework significantly simplifies and facilitates the advancement and implementation of deep neural networks for several research and applications. TensorFlow is an open-source library that is flexible and scalable to perform end-to-end computation using a dataflow graph model, making it optimal for training huge-scale models. Developing a smart home with a real-time energy management system is significant for home safety, convenience and energy conservation. This work proposes an effective smart home automation system, which relies on classifying the energy consumption level using information on various environmental factors and household energy consumption. The major contributions of this work are enumerated as follows:

- This paper focuses on enhancing the decision-making in smart home automation systems under the classification of energy consumption data according to environmental parameters using a tensorflow-based deep ensemble learning technique.
- Initially, the proposed methodology performs outlier analysis for handling outliers in the raw smart home data for effective feature selection. Then, the different feature selection techniques are applied to reduce the high dimensionality of features to improve the performance of data labeling and classification using the best set of selected features.
- By incorporating the fuzzy logic system, the proposed methodology labels the selected sub-set of features based on certain weather condition information and classifies the level of energy consumption using a deep ensemble learning model.

2. LITERATURE SURVEY

With the rise of smart technology in the diverse domain, deep learning techniques and IoT achieved remarkable growth in smart technology applications. Thus, this section reviews recent deep-learning approaches for smart home applications.

2.1 DEEP LEARNING APPROACHES FOR SMART HOME AUTOMATION

An intelligent model [7] was designed for the IoT application services in a smart home to resolve energy wastage and high traffic in the smart home network with the help of an artificial TensorFlow engine for data learning. It encompasses three intelligent models, including Intelligence Awareness Target as a Service (IAT), Intelligence Energy Efficiency as a Service (IE2S), and Intelligence Service TAS (IST). These intelligent models diminish unwanted network tasks depending on the smart home's IoT usage patterns. An intelligent smart home environment platform [8] was presented for smart home automation. In this platform, a smart home controller was designed with genetic automation algorithms to control the connected systems in the smart home. This platform adopts deep neural networks as non-intrusive load monitoring and energy load forecasting to detect unusual energy consumption alterations conducive to producing energy efficiency awareness to users. An energy management system [9] was proposed to examine energy cost minimization issues for the smart home. This system exploits Deep Deterministic Policy Gradients (DDPG) based energy management algorithm to effectively deal with Heating, Ventilation, and Air Conditioning (HVAC) and energy storage systems in the smart home.

A home energy management optimization strategy [10] was proposed to schedule home energy appliances. This strategy adopts deep reinforcement methods such as Deep Q-learning Networks (DQN) and Double Deep Q-learning Networks (DDQN) to maximize energy efficiency in a dynamic environment. This strategy shows that DDQN is more suitable than DQN for minimizing energy costs in smart homes. Energy efficient autonomous smart home system [11] was developed to manage electrical energy requirements and arrange the running time of appliances. It employs a one-Dimensional Deep Convolutional Neural Network (1D-DCNN) and Long-short Term Memory (LSTM) to control the energy consumption in smart home networks automatically. In this system, 1D-DCNN extract the essential energy patterns, Bi-LSTM to predict the loads and the operational time is scheduled using a reinforcement learning algorithm with high prediction accuracy. An adaptive decision-making model [12] was proposed to improve the decision-making capability of the home automation system. By employing reinforcement learning, the multi-modal scenario information extracted from the graphic data, Deep Convolution Neural Network (DCNN) based decision model is constructed, and a simulation system was exploited to forecast the optimal times of day to adjust lighting and window blinds in the home, to update home appliance operations depend on user preferences. A smart waste management system [13] was presented based on IoT to monitor the status of the bin. It exploits LoRa communication protocol to transmit less power and long-range data and TensorFlow-based deep learning for real-time object detection and classification.

A clustering analysis-based energy consumption method [14] was proposed to classify electricity usage into several levels. This method forecasts the electric power consumption from the smart residential sensor by adopting a deep autoencoder for feature learning fine-tuned deep autoencoder with Self-Organizing Maps (SOM) for clustering and statistical analysis to establish the levels of electrical energy consumption. The energy consumption optimization technique [15] was proposed to comfort the user in smart with efficient resource management. This technique uses the comfort indices such as thermal, visual and air quality and adopts a Deep Extreme Learning Machine (DELM) for providing dynamic user preferences, bat algorithm and fuzzy logic for energy optimization and comfort index management. A two-level Deep Reinforcement Learning (DRL) framework [16] was introduced for optimal energy management in the smart home. This framework utilizes distributed DRL algorithm to reduce electricity costs by organizing the energy consumption of the user’s preferred controllable home appliances and charging and discharging an energy storage system and an electric vehicle with the user’s environmental characteristics.

An energy storage system management approach [17] was proposed to maintain energy in the home efficiently. It exploits LSTM based deep learning model to forecast energy consumption and energy storage system charge. A deep learning and IoT-based technique [18] were presented for effective energy management in smart buildings. By applying YOLOv3 advanced intelligence algorithm, this technique controls and records the operational status of the air conditioner to minimize energy loss and cost. An enhanced deep learning-based approach [19] was developed for the home appliances classification and monitoring system in smart homes, which is beneficial to identify faults and declining devices and enable automated load regulation. This approach employs DCNN architectures and transfers learning to aggregate the load behavior of the home appliances from the smart meter data. An improved intelligent home automation system [20] was recommended to control home equipment, monitor environmental aspects and recognize home movements and circumstances. This system employs Convolutional Neural Network (CNN) based deep learning model to categorize and recognize intruders in the home with the help of the Android-based mobile application.

3. PROPOSED METHOD FOR SMART HOME ENERGY MANAGEMENT SYSTEM

In this section, this work presents the proposed methodology for a smart home system. Initially, it discusses the problem statement and the proposed phases.

3.1 PROBLEM STATEMENT

The fast-paced advancement of smart applications, specifically in the smart home system, has confronted several challenges, such as security and privacy issues, insufficient data, energy consumption, ineffective operating system, network traffic and compatibility. One of the main problems in smart home systems is energy consumption. Increasing demand createsa significant discrepancy between energy and supply, resulting in higher utility costs. Recently, energy consumption predicting systems have become increasingly essential owing to the persistent expansion in population and the increased demand for energy. The variation in electricity usage mainly relies on the number of electrical appliances in households and the habits of residents. Difficulties of energy management in smart home systems are divergence of residential electrical appliances, complex and varied purposes of the household environment and indeterminate nature of future consumption. Existing smart home automation systems have applied machine learning and deep learning techniques to impart automated service with increased convenience and a superior level of satisfaction. Despite its potential benefits in the smart home automation system, the energy waste may result in high energy bills and environmental effects. However, reduced energy efficiency in deep learning and machine learning-based smart home automation system is due to inadequate data, imprecise sensor data, inadaptable to changing home environments and lack of user preferences. Therefore, it is necessary to address the energy consumption problem in smart home automation systems to attain energy efficiency and environmental sustainability.

3.2 AN OVERVIEW OF THE PROPOSED METHODOLOGY

Energy consumption is a critical factor in the smart home setting, as the smart home relies on several interconnected devices and technologies that use energy. The proposed methodology aims to predict the energy usage of the residents or occupants, beneficial to accomplish cost savings, reduction of environmental effects, enhance system efficacy and improve user control. Owing to the importance of energy consumption in the smart home system, this work focuses on classifying the energy consumption level concerning weather information. Throughout the day, residents interact with several home electronic appliances and produce a sequence of energy consumption values. The energy consumption values lack sufficient information apart from the energy load of the entire home. Therefore, extracting essential features and categorizing them according to energy consumption is significant. The proposed methodology aims to analyze the weather information, as it directly influences the energy consumption of homes. By identifying the level of energy usage using weather information, the smart home management system benefits from predicting data with minimum energy consumption and high user comfort. Figure 1 presents the workflow of the proposed methodology.

This research work contributes to the enhancement of the decision-making ability to forecast future energy consumption based on the energy usage of household appliances and with the weather information through four major phases, which are described as follows:

3.2.1 Data Preprocessing:

In this phase, the proposed methodology aims to perform outlier analysis and normalization through preprocessing procedures to avoid ambiguous prediction, the abnormalities and redundancies in the raw smart home data towards effective attributes identification and selection for classification.

3.2.2 Feature Selection:

This feature selection phase tends to extract and select the most prominent features using the feature reduction technique from the large data set to reduce the computational complexity. The Feature reduction methods such as Principal Component Analysis (PCA), Chi-squared (CHI) (X^2) and Information Gain (IG) are exploited in the proposed scheme. Among them, PCA helps to simplify the analysis of complex datasets by recognizing the most important features that contribute most to the variation in the data while reducing the dimensionality of the dataset and the loss of information. CHI is applied to determine the significance of the interconnection between two categorical variables by measuring the degree of dependence between each feature and the target variable. IG method quantifies the amount of information that a feature provides about the class variable and selects a subset of features that can best denote the original data while minimizing the dimensionality of the data.

3.2.3 Fuzzy Logic-based Data Labeling:

The third phase comprises the smart home data labeling based on the fuzzy logic system. The proposed methodology designs the fuzzy rule and generates the data labeling using environmental parameters such as temperature, Wind, and others that aid in classifying energy consumption. A fuzzy logic system permits imprecision and uncertainty in decision-making. In the proposed approach, fuzzy logic helps label temperature and weather-related data from smart homes as it can handle uncertain or ambiguous data. These annotations provide contextual information about the smart home data, which can be exploited to extract meaningful insights and generates informed energy consumption forecasting.

3.2.4 Classification of Energy Consumption using Tensorflow-based Deep Ensemble Learning Technique:

After labeling the features of the smart home data by utilizing the fuzzy logic system, the proposed methodology incorporates the tensorflow framework and deep ensemble learning model to classify the energy consumption level of the household appliances and also, obtaining the effective energy management in smart home systems.

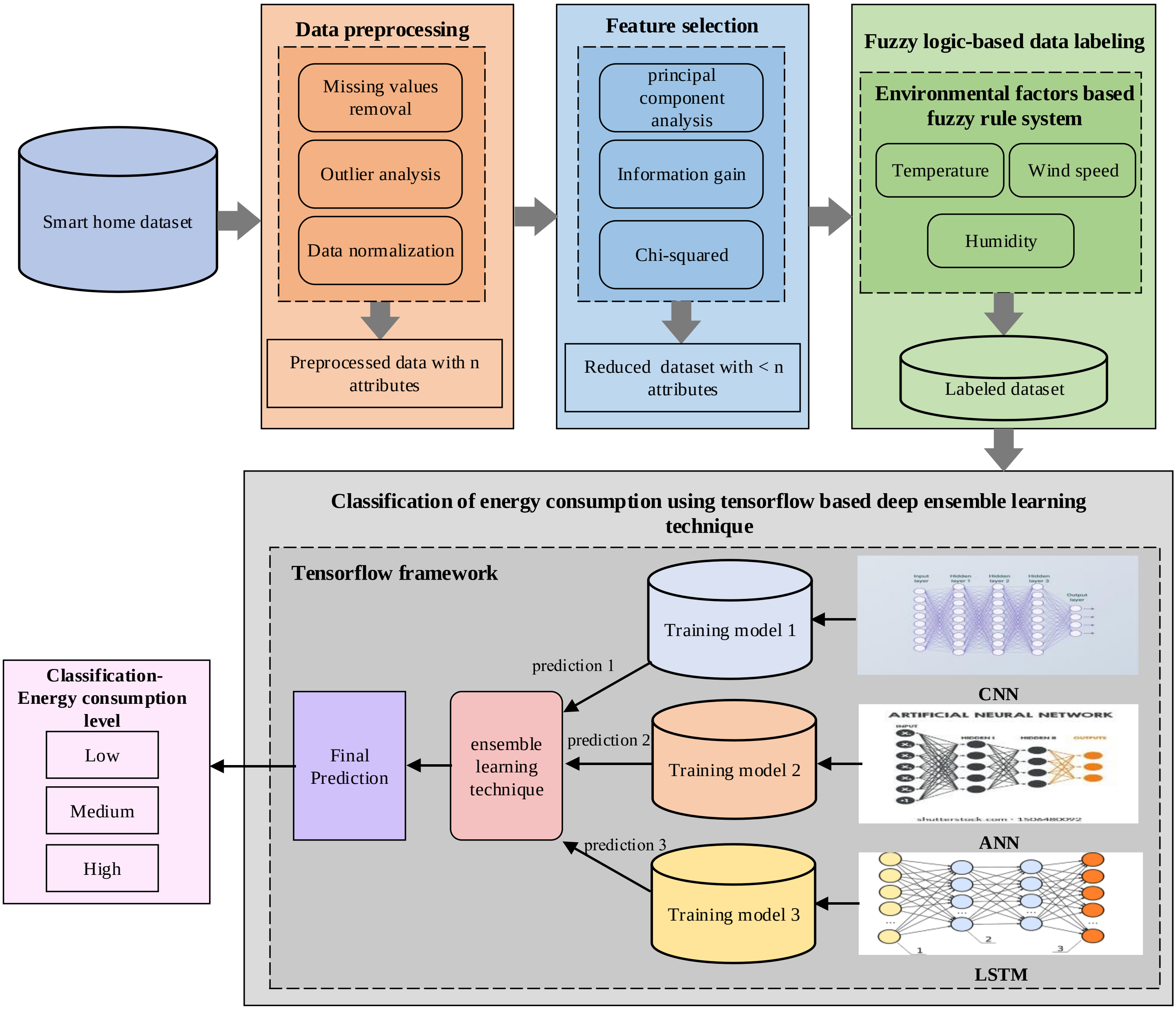

Fig.1. An Overall process of the proposed methodology

3.3 DATA PREPROCESSING

As the energy consumption data are acquired from the sensors, which are fixed to several home appliances, there is a possibility that the data comprises inconsistencies, uncertainties and errors since climate change or malfunctioning meters. Hence, it is essential to prevent data corruption through data preprocessing, which aidsin achieving data quality and improving performance. The proposed methodology applies preprocessing procedures involving outlier removal and normalization of the raw energy consumption data. Outliers are the data points that differ from the other data points due to the home equipment malfunctions, user behavior or environmental factors in the smart home system. Handling and removing outliers improve the learning model from poor performance and over-fitting data. Therefore, applying the three-sigma rule of thumb technique [21], the proposed methodology eliminates the outliers effectively in the input energy consumption data (X). The three-sigma rule of thumb technique is defined as follows,

$$F(X_i) = f(x)$$
$$= \begin{cases} Avg(x) + 2 \cdot std(x) & \text{if } x_i > avg(x) + std(x) \\ x_i & \text{otherwise} \end{cases} \quad (1)$$

where $Avg(X)$ is the average of 'X,' and $Std(X)$ indicates the standard deviation of 'X'. After eliminating the outliers, the proposed methodology applies the min-max normalization method [22] to scale and standardize the attributes in the input data, as it contains different attributes that measure several factors of the home setting, including temperature, humidity, light levels and power consumption. By normalizing the data using the min-max method, the proposed methodology minimizes the variances of the dataset and biases. It is formulated as follows,

$$Z = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{2}$$

where 'x' defines the actual feature, minimum (x) and maximum (x) denote the minimum and maximum values of the feature 'x' and 'Z' denotes the normalized feature.

These preprocessing methods are applied to all data fields of the smart home dataset, which is beneficial for analyzing the outliers and distribution. In the subsequence of data preprocessing, the proposed methodology examines the most significant features relevant to energy consumption. An effective set of features greatly enhances the performance of energy consumption level classification across the multiple features. The proposed methodology applies a dimensionality-reduction algorithm to reduce the dimensionality of features in terms of discarding redundant, irrelevant and noisy features. Moreover, selecting many features from the linear and nonlinear data makes feature reduction essential for a high-dimensional dataset. Hence, by adopting the feature selection method, the proposed method reduces the computational cost and increases the efficiency while energy consumption level classification.

The exponentially growing complexity of energy systems with the enormous increase of smart home data poses a highly challenging way of analyzing data quality towards effective feature extraction. The feature selection method focuses on selecting the most representative attributes based on computing the significance of each one of the attributes in the large set of data. To classify the energy consumption level in smart home systems, the proposed methodology employs the smart home with a weather information dataset [23]. This dataset comprised 32 attributes, each of a 1-minute duration of various house appliances in kW. The data fields containing time, use [kW], gen [kW], House overall [kW], Dishwasher, Furnace 1, Furnace 2, Home office, Fridge, Wine cellar, Garage door, Kitchen 12, Kitchen 14, Kitchen 38, Barn, Well, Microwave, Living room, Solar, temperature, humidity, visibility, summary, apparent Temperature, windSpeed, cloud cover, wind bearing, precipIntensity, dewPoint, and precipProbability.

Before annotating the smart home data using a fuzzy rule system, the proposed methodology focuses on applying the three different feature selection methods and reduces the number of attributes in a high-dimensional dataset. In essence, it employs PCA, IG and CHI methods [24] and automatically selects the best subset of features which are the greatest impact on the prediction of energy consumption in the smart home system. Applying these feature selection algorithms, the proposed methodology compares and evaluates these methods' performance in reducing the number of features in a high-dimensional Smart home dataset.

3.3.1 Principal Component Analysis (PCA)-based Method:

Principal Component Analysis (PCA) based dimensionality-reduction algorithm to reduce the complexity of large dataset and understand the influence of the various attributes on the overall energy detection patterns. PCA transforms a group of correlated variables into a reduced set of uncorrelated variables as principal components. As the efficient factor analysis method, PCA discovers wide applications in depleting the number of variables and facilitating the ranking and analysis of decision-making units. By applying the PCA model, the proposed methodology decomposes the high-dimensionality data matrix $\hat{X}$ into a structured data $M_{\hat{X}}$ and a noise error part, $N_{E(\hat{X})}$. It is modeled as follows, $\hat{X} = M_{\hat{X}} + N_{E(\hat{X})}$. The modeled part of $\hat{X}$ defines a subspace with 'D' dimensionality, where 'D' implies the number of principal components used to reduce the features into a small number of features. The error content changes while the learning model dimensionality 'D' changes. Then, the dimensionality reduction processes are performed through the PCA loading plot of principal components.

3.3.2 Chi-squared (CHI)-based Method (X^2):

CHI is a statistical test-based method that assesses the relative dependence between the two categorical variables. It is used to measure the goodness of a feature. CHI score of a feature based on computing the chi-squared statistic between the class variable and the feature variable in the data.

3.3.3 Information Gain (IG)-based Method:

This method is based on the concept of entropy and is used to show the relevance of features with respect to the class. IG defines the changes in class entropy from a previous state to a state when the feature value is known. An effective three-step feature selection algorithm is used to determine the optimal feature subset to improve classification performance accuracy and scalability. By employing this method, the proposed methodology initially computes the IG score of the features based on the mutual information that is gained between the class label and the feature, which is represented as Gain(C,F)=H(C)-H(C|P), where H(), C and P denote the entropy, class variable and feature variable, respectively. After computing the IG scores of all the features, this methodology ranks each feature based on importance. Finally, the higher the IG gain score is selected as the most contributive feature to the target variable.

To test the performance of the three different feature selection methods, the proposed methodology employs the Linear regression (LR) model and validates the performance of different reduced sub-set of features highly correlated to the input energy consumption data according to a performance metric. Generally, Linear regression is a predictive model which examines the best-fitting straight line through the points. Hence, by employing the different sub-set of features obtained from the feature selection methods, the proposed methodology identifies and selects the final best sub-set of features that meets the high performance in regression evaluation metric on the LR model. Accordingly, it was observed that the CHI method significantly minimizes irrelevant features and yields better performance than the other feature selection methods when evaluating the combination of reduced feature sets on a specific regression metric. Therefore, comparing these feature selection techniques, the CHI-based reduced dataset with attributes isthe best method for classifying energy consumption.

3.4 FUZZY LOGIC-BASED DATA LABELING

The proposed methodology labels the best subset of features acquired from the CHI-based feature selection approach to classify the energy consumption values based on environmental factors. The definition of a similar label differs between two environments or from one annotator to another annotator. Hence, labeling a dataset is an imperative and error-prone task that aids in overcoming deterioration while the prediction process.

In the labeling phase, the proposed methodology adopts the fuzzy logic system [25] to label the consumption of household appliances as Low, Medium and High to build the training dataset for TensorFlow-based deep learning technique for classification of the energy consumption values with the labeled data samples effectively. The fuzzy rule, defined as the multi-valued logical system, dealt with the imprecision and ambiguity in knowledge representation through fuzzy sets and fuzzy numbers represented in linguistic terms such as 'small, 'medium,' and 'high'. The fuzzy rule employs the linguistic IF-THEN condition to model the linear relationships between the input and output values in a fuzzy way. In a fuzzy logic system, input as crisp values and output as a fuzzy set, a set of membership degrees for each possible output value representing the different classes in smart home data. The fuzzy logic system involves rule-based, fuzzification, inference engine and defuzzification phase in which rule-based comprises the IF-THEN condition to govern decision making, fuzzification performs the input membership functions, inference engine performs the decision making to form control actions based on the designed rule, and finally, defuzzification phase performs output membership functions of the system. The membership functions identify the similarity between the two feature values based on the different levels of fuzzy rule.

Table.1. Input- membership functions and their range

Rule	Temperature (°C)	Humidity (%)	Wind Speed (m/s)	Energy Consumption (kWh)
1.	(-20 -50) Poor	(0.5-0.8) Average	(0-7) Poor	(0-0.5) Low
2.	(50-90) Average	(0-0.5) Poor	(10-25) Good	(0.5-1.5) Medium
3.	(90-100) Good	(0.8-1) Good	(7-10) Average	(1.5-2.5) High

The proposed methodology designs the member functions using temperature, wind speed and humidity as input component planes and computing the clustering averages of the planes into three classes involving the 'Low', 'Medium' and 'High'. Then, the fuzzy IF-THEN rule is designed with the assistance of membership functions of the input variables as temperature, wind speed and humidity. The input variables-membership functions are defined in Table.1. A total of 27 fuzzy rules are developed using the membership functions of the input variables for classifying the energy consumption level under three low, medium and high classes. Among them, some of the basic criteria are illustrated in Table.2.

Table.2. The proposed fuzzy-rule system

Rules	Proposed fuzzy-rule system
Rule 1	IF Temperature is Poor condition (-20-50) AND Humidity is average (0.5-0.8) AND Wind is poor (0-7) THEN Energy consumption level under low class (0-0.5)
Rule 2	IF Temperature is average condition (50-90) AND Humidity is poor (0-0.5) AND Wind is good (0-7), THEN Energy consumption level is under Medium class (0.5-1.5)
Rule 3	IF Temperature is good condition (90-100) AND Humidity is good condition (0.8-1) AND Wind is in average condition (7-10) THEN Energy consumption level under High class (1.5-2.5)

According to Table.2, the proposed methodology annotates each input smart data to make the training dataset for the deep ensemble learning model predict and classify the energy consumption levels. The proposed methodology utilizes the deep ensemble learning model and predicts the final prediction outcome based on combining the prediction outcomes from the multiple learning models.

3.5 CLASSIFICATION OF ENERGY CONSUMPTION USING A TENSORFLOW-BASED DEEP ENSEMBLE LEARNING TECHNIQUE

In the subsequence of labeling the energy consumption data using the fuzzy logic system, the proposed methodology employs a TensorFlow framework to train a deep ensemble learning model for classifying the energy consumption values according to the environmental factors information. The tensorFlow framework is a deep learning library in which learning models are trained for recognition and classification performance. Internally, TensorFlow translates the learning model into a data flow graph structure where the nodes represent the mathematical operations, while the edges denote the tensors, the multidimensional data arrays. For classifying the energy consumption values of household appliances, this proposed methodology employs the TensorFlow framework and deep ensemble learning-based classification model to learn the selected set of features and classifies the overall electrical consumption through the information of environmental conditions. Traditionally, a deep ensemble learning technique employs multiple classifier models and makes a final prediction based on combining the prediction outcomes of the individual learning models via different ensemble techniques. In this work, the proposed methodology employs a deep ensemble learning model as Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) model to inherently learn the multiple smart home data features and classifies the energy consumption values from the labeled knowledge of environmental factors.

In the deep ensemble learning model, the CNN model is widely used as a feature extractor model, consisting of multiple layers that extract the set of features from the reduced smart home dataset and predict the output through multiple convolution layers. ANN model is employed, which can model the non-linear data according to the different input conditions. This proposed methodology employed the ANN model to learn and classifies the energy consumption values based on estimating the non-linear relationship between the different input factors in estimating the consumption values. The LSTM model consists of an input gate, forget gate and an output gate used to learn the long-term temporal dependency among the data sequentially. Hence, by employing the CNN, ANN and LSTM models, the proposed methodology generates different prediction outcomes for the energy consumption values.

For acquiring the final disease prediction outcome, the prediction outcomes from the CNN, ANN and LSTM models are combined via an ensemble learning technique, and the proposed methodology employs an advanced ensemble technique that builds a new model and generates the final prediction outcome by combining multiple decisions from the individual learning models. Among the deep ensemble learning techniques [26], the stacking technique utilizes the meta-learning algorithm and produces predictions from the multiple models, which as the first-level learners using the original training data and then the final prediction is generated by meta-learner algorithm based on the input of first level learners' prediction outcomes. Boosting technique generates the final output based on the weighted scores from all the sequential trained models. At the same time, the bagging technique adopts the major voting method for predicting the final output by combining the predictions of the individual learning models. Considering the prediction outcomes of CNN, ANN and LSTM models (p_1,p_2,p_3), the proposed methodology combines these prediction outcomes into a new model and generates the final prediction output using the multiple prediction outcome. Thus, by adopting the deep ensemble learning technique, this work improves the energy consumption prediction performance via multiple prediction outcomes.

4. EXPERIMENTS AND RESULTS

This section discusses the performance results of the proposed ensemble deep learning model and the individual deep learning classifiers such as ANN, CNN and LSTM on smart home data, including the details of experiments, the dataset used and followed by the evaluation metrics used for validation.

4.1 DATASET DESCRIPTION

The experimental framework implements the proposed deep ensemble learning model and the existing deep learning classifiers using the tensorflow framework on the smart home dataset. To validate the performance of the proposed system, the experimental framework employs Smart Home Dataset with weather information [21]. This dataset provides a desirable resource for researchers and practitioners intrigued in smart home energy management and relevant applications. It consists of one week's historical electrical data and comprises time series data with 503,910 readings on electricity and weather information. In this dataset, data was collected with a time interval of one minute of home appliances from a smart meter, resulting in a large dataset compatible with time-series analysis and forecasting in smart grids or smart homes. The Table.3 depicts the details of attributes and their description in the smart home with the weather information dataset.

Table.3. Attributes Description

S.No	Attribute	Description
1.	use [kW]	Overall energy consumption
2.	gen [kW]	Overall energy generated by solar or other resources
3.	House overall [kW]	Overall household energy usage
4.	Dishwasher [kW]	Electricity consumed by the dishwasher
5.	Furnace 1 [kW]	Electricity consumed by furnace 1
6.	Furnace 2 [kW]	Electricity consumed by furnace 2
7.	Home office [kW]	Electricity consumed in the home office
8.	Fridge [kW]	Electricity consumed by the fridge
9.	Wine cellar [kW]	Electricity consumed by wine cellar
10.	Garage door [kW]	Electricity consumed by garage door
11.	Kitchen 12 [kW]	Electricity consumed in kitchen 1
12.	Kitchen 14 [kW]	Electricity consumed in kitchen 2
13.	Kitchen 38 [kW]	Electricity consumed in kitchen 3
14.	Barn [kW]	Electricity consumed by the barn
15.	Well [kW]	Electricity consumed by well
16.	Microwave [kW]	Electricity consumed by microwave
17.	Living room [kW]	Electricity consumed in the living room
18.	Solar [kW]	Solar energy production
19.	Temperature	Physical measure denoting the level of hotness and coldness
20.	Humidity	The concentration of water vapor in the air
21.	Visibility	Meteorological optical range
22.	ApparentTemperature	The temperature that humans perceive is determined by the combined effect of air temperature, relative humidity, and wind speed.
24.	Pressure	Falling air pressure denotes bad weather, whereas rising air pressure denotes good weather.
25.	cloudCover	The proportion of the sky that exhibits covered by clouds when viewed from a particular position
26.	windSpeed	Essential atmospheric quantity
27.	windBearing	Representing the direction of Wind
28.	precipIntensity	Quantity of rain that falls over time
29.	dewPoint	Atmospheric temperature below which water droplets start to compress, and dew can form
30.	precipProbability	Quantify the probability of experiencing a minimum amount of precipitation during a specific predicted period and location

4.2 EVALUATION METRICS

The experimental framework utilizes the standard evaluation metrics such as precision, recall, F1-score, accuracy, specificity, false positive rate and AUC score to exemplify the performance of the proposed ensemble model against the different baseline models.

- **Precision:** The ratio between the number of accurately forecasted activities and the number of activities forecasted by the automation system for the smart home.

Precision= (True Positive)/(True Positive+False Positive)

- **Recall:** The ratio between the number of accurately forecasted activities and the total number of activities given to the smart home.

Recall= (True Positive)/(True Positive+False Negative)

- **F1-score:** It is the measure of accuracy based upon precision and recall.

F1-score= (2*Precision*Recall)/(Precision+Recall)

- **Accuracy:** Accuracy is the evaluation ratio metric appropriate for assessing the system's classification performance. The ratio between the number of accurately forecasted activities and the total number of activities forecasted by the automation system.

Accuracy= (True Positive+True Negative)/(True Positive+True Negative+False Positive+False Negative)

- **Specificity:** The ratio between the number of inaccurately forecasted activities and the total number of activities in the smart home system.

Specificity = (True Negative)/(True Negative+False Positive)

- **False Positive Rate:** The ratio between the positive instances that are incorrectly forecasted as negative with all negative instances.

False Positive Rate= (False Positive)/(False Positive+True Negative)

- **AUC Score:** The area under the ROC curve measures the overall performance and efficiency of the smart home system.

where,

- True Positive: Number of correctly forecasted activity by the proposed algorithm
- False Positive: Number of incorrectly forecasted activities by the proposed algorithm
- False Negative: Number of incorrectly unforecasted activities by the proposed algorithm.
- True Negative: Number of correctly unforecasted activities by the proposed algorithm.

4.3 RESULTS AND DISCUSSION

The experimental framework conducts and evaluates the performance of the proposed methodology for energy consumption level classification on the proposed deep ensemble learning-based classification model, and the baseline models such as ANN, CNN, LSTM**,** boosting technique, and stacking technique through the different evaluation metrics are depicted in Table.4.

Table.4. Comparative Results of different models

Classifier	Precision	Recall	F1	Accuracy	Specificity	FPR	AUC
ANN	0.74	0.75	0.74	0.75	0.8079	0.1920	0.8108
CNN	0.67	0.65	0.65	0.66	0.7657	0.2356	0.7424
LSTM	0.84	0.83	0.83	0.83	0.8734	0.1265	0.8698
Deep ensemble	0.86	0.86	0.86	0.86	0.8876	0.1126	0.8950
Boosting technique	0.91	0.90	0.90	0.91	0.9148	0.0851	0.9277
Stacking technique	0.86	0.85	0.85	0.86	0.8850	0.1149	0.8906

4.4 PERFORMANCE OF PRECISION, RECALL AND F1-SCORE

The comparative performance of the proposed ensemble deep learning model and the baseline models includes ANN, CNN, LSTM, boosting technique, and stacking technique while testing on the smart home dataset for energy consumption classification in terms of precision, recall and f1-score is illustrated in Fig.2.

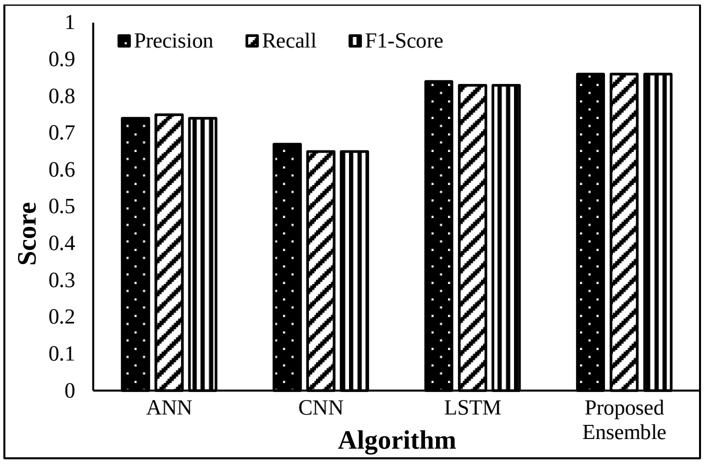

Fig.2. Comparative Performance results

Initially, in the context of the precision metric, it was found that the CNN model obtained a low precision score of 0.67 while testing on the smart home dataset. Even though the CNN model facilitates extracting the time-invariant features, it attained the lowest score against the other baseline models and the proposed deep ensemble learning model. In contrast, the precision of the proposed ensemble model is 0.86, which is the considerably highest score among the other baseline models while testing on the smart home dataset. The proposed deep ensemble model surpassed all other baseline models because it employs the ensemble stacking technique, which generates the final output from the combination of prediction outcomes of the individual learning models. It is found that the LSTM model attained a precision score equal to 0.84, implying that it is the second-highest score compared to the other models. The LSTM is a sequential model that can learn the long-term dependency, thereby improving prediction performance.

Next, regarding recall performance, the proposed ensemble model yields better results with a score of 0.86 than the other baseline models. Among all the baseline models, the LSTM model gained a recall score of around 0.02, different from the proposed ensemble deep learning model. The prediction score of the ANN and CNN model is equal to 0.75 and 0.65, respectively, while testing on the same smart home dataset. Although the ANN model has the noise tolerance ability and analyzes the relationship among the data effectively, it has acquired a low-performance score compared to LSTM and the proposed model, but in contrast with the CNN model. Thus, the results reveal that the ensemble learning model exceeds the individual learning models, leading to improvised prediction outcomes.

Regarding the F1-score, the ANN, CNN, LSTM and the proposed ensemble deep learning model were obtained as 0.74, 0.65, 0.83 and 0.86, respectively. It showed that the ensemble model achieved the first highest score, the second achieved by LSTM, the third by ANN and finally, the minimal score produced by the CNN model. Furthermore, the results showed that the LSTM obtained an identical recall and F1-score of 0.86. The proposed system designed the fuzzy rule with the assistance of certain weather information and household appliances for annotating the smart home data, which highly facilitated the accurate classification of the energy consumption level.

4.4.1 Performance of Accuracy

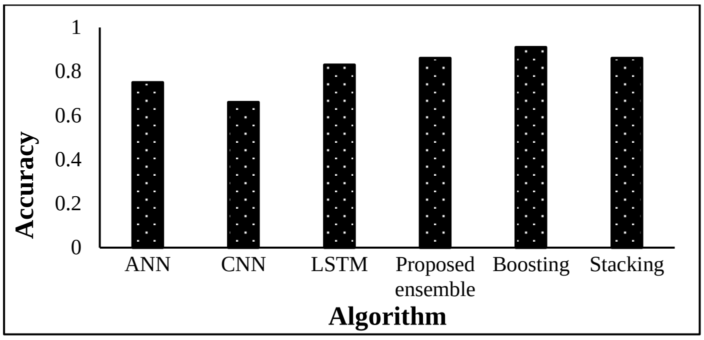

Fig.3. Performance of Accuracy

Fig.3 represents the comparative accuracy performance score for ANN, CNN, LSTM, the proposed ensemble model, and boosting and stacking technique while testing on the smart home dataset. The result demonstrated that the boosting technique achieves the highest accuracy score of 0.91 in classifying the energy consumption data. Although the proposed ensemble deep learning model employed the ensemble stacking technique, it has attained a minimal performance score with a difference of 0.05 compared to the boosting technique. The boosting technique generates the final output through the weighted average scores from the sequentially trained learning models such as ANN, CNN and LSTM. The results also show that the LSTM model outperforms the other baseline models since it can capture the long-term temporal dependency, which tends to classify the energy consumption data more accurately. Thus, the results confirm that the boosting technique performs as the best ensemble technique, providing overall better results than the other techniques.

4.4.2 Performance of Specificity and False Positive Rate:

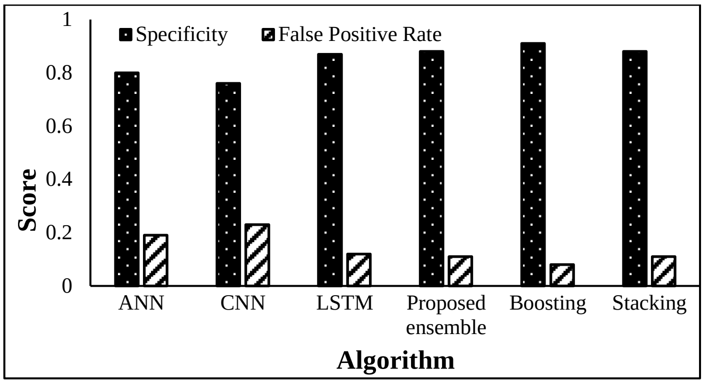

Fig.4. Performance of Specificity and False Positive Rate

The specificity and false positive rate achieved by ANN, CNN, LSTM, proposed ensemble, boosting and stacking technique on the smart home dataset are presented in Fig.4. The specificity of CNN is inferior in contrast to other baseline models and the proposed ensemble model. Among all the models, superior specificity attained by LSTM, proposed ensemble, boosting and stacking techniques, and their values are 0.87, 0.88, 0.91, 0.88, respectively. Boosting technique attains a high specificity rate which is equal to 0.91, and thereby improves the efficiency. Although the proposed model adopted the ensemble stacking technique, it obtained a minimal performance score regarding energy consumption classification compared to the boosting technique.

Regarding the false positive rate results, the proposed ensemble model, boosting, and stacking technique achieves performance scores equal to 0.11, 0.08 and 0.11, respectively. The lower the value of the false positive rate, the more models predict more positive the samples. Hence, it is observed that the ANN and CNN secure a high false positive rate. In contrast, LSTM, proposed ensemble learning model, boosting and boosting stacking achieves comparatively minimal false positive rate, nearly at 0.1. Particularly, the proposed ensemble model obtains the false positive rate of 0.11, which indicates better performance in classifying the energy consumption data.

4.4.3 Performance of AUC

The Fig.5 shows the comparative performance of the AUC over the proposed ensemble deep learning model and the baseline model such as ANN, CNN, LSTM and the boosting and stacking techniques for the classification of energy consumption on the smart home dataset.

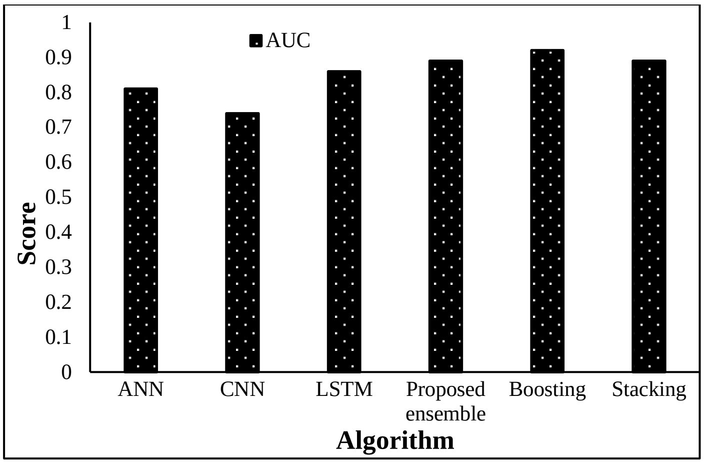

Fig.5. Performance of AUC

The AUC score obtained by the proposed ensemble deep learning model is 0.89, higher than all the baseline models and lower than the boosting-based ensemble learning technique. From the results of experiments, the AUC score of ANN is 0. 81, CNN is 0.74, LSTM is 0.86, the proposed deep ensemble learning model is 0.89, the ensemble boosting technique is 0.92, and the ensemble stacking technique is 0.89, respectively. Also, the AUC score of LSTM, proposed ensemble deep learning model, boosting technique and stacking technique are nearly similar scores ata superior level. Although, the proposed ensemble deep learning model achieves a lower score of 0.89 compared to the boosting technique, equal to 0.92 by using the same smart home dataset. These 0.02 variations depend upon the ensemble technique used for final-decision making. Boosting employs a weighted majority voting method for the final decision-making process, which facilitates minimizing bias and ensures the best performance results. Based on the experimental results, it is concluded that the proposed model outperforms the other models considered. Therefore, the proposed method leads to the best method to show a satisfactory outcome compared to other classifiers for energy consumption classification.

5. CONCLUSION

To forecast the future energy consumption of household appliances using the weather condition information, this research presented an enhanced decision-making process that depends on the classification of energy consumption level using a tensor flow-based deep ensemble learning model. The proposed scheme has worked in four major phases, i.e., data preprocessing, feature selection, fuzzy logic-based data labeling, and energy consumption classification using a tensorflow-based deep ensemble learning technique. Raw smart home data is preprocessed in the initial phase of the proposed scheme, where outlier removal and normalization are applied over raw data and make it clean for efficient training. Secondly, different feature extraction techniques such as PCA, CHI and IG are applied to reduce complexity and better feature ranking. Eventually, the fuzzy logic system was applied to annotate the smart home data of household appliances based on weather climate information. Finally, the proposed work employed a TensorFlow base deep learning algorithm to classify the energy consumption level of smart home data. The experimental model exemplifies that the deep ensemble learning technique outperforms the baseline models while testing on the smart home dataset by resulting high accuracy of 0.86, precision of 0.86, recall of 0.86, F1-Score of 0.86, specificity of 0.8876, AUC score of 0.8950 and low false positive rate of 0.1126, correspondingly. Thus, the proposed method effectively minimizes energy wastage in smart homes with less impact on the resident's comfort, making it fit for adoption by electricity firms and companies seeking to fulfill energy demands by innovative means of generation.

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