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AI-Based Methods for Improving Energy Efficiency of Home Appliances through Air Quality Monitoring

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Abstract
Energy efficiency in home appliances is becoming more and more important especially with the increasing need to save electricity and move towards sustainable living. With the growing use of artificial intelligence new ways are being explored to make appliances smarter and more energy-efficient. This research work has proposed a method that uses intelligent algorithms to improve the energy efficiency of home appliances by analyzing indoor air quality (IAQ) data. Traditional methods often struggle due to small datasets, high computational requirements and poor adaptability. To tackle these issues data preprocessing techniques like SMOTE-ENN to handle class imbalance and Z-score normalization for proper feature scaling are used. This study tested several models and found that Bidirectional GRU and Stacked LSTM performed the best reaching high validation accuracies of 99.81% and 99.64% respectively. What makes this approach different is how it links indoor environmental factors like CO_2 levels, humidity and temperature with energy usage patterns. This kind of integration can lead to more efficient and eco-friendly home energy systems. Overall, this work shows how smart algorithms can help us take a step forward in building greener and smarter homes.
Keywords: *Energy efficiency, Artificial Intelligence, Sustainable Living, SMOTE, Z-Score, Energy Management Systems*

1. INTRODUCTION

With the onset of the 21st century, there has been a noticeable rise in global energy consumption across almost every region. Studies show that this growing demand for energy is largely driven by factors such as economic development, increasing population and higher electricity usage per person [1]. Among the various contributors household appliances account for a significant portion over 30% of total energy consumption in some countries making residential energy use a key area for efficiency improvements.
Improving the energy efficiency of home appliances is not only important for reducing overall electricity usage but also plays a crucial role in minimizing the environmental and economic impacts of rising power demands [2]. These efforts directly support sustainable practices and help in lowering pollution levels while also contributing to the fight against climate change on an individual level.
An energy-efficient home today is no longer just a concept. It is a practical reality that uses modern technologies and smart design principles to reduce energy consumption without compromising on safety, comfort or aesthetics [3]. Figure 1 illustrates the proportion of energy consumed by different household iances highlighting the need for intelligent energy management in day-to-day living. appl

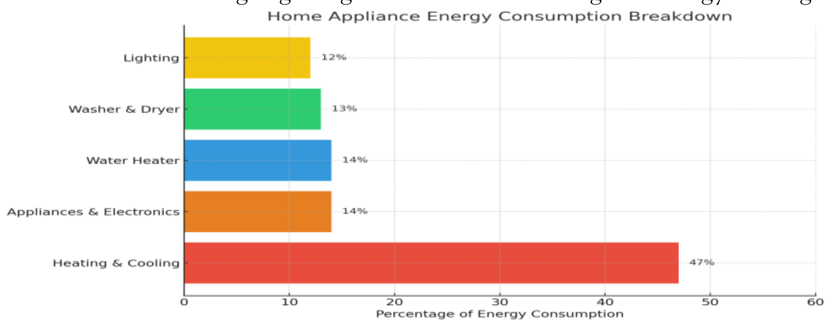

Figure 1: Energy contributions by different home appliances to highlight their share in total residential energy consumption [31]

Across the world, improving energy efficiency has brought in clear benefits not just for the environment, but also for both energy providers and everyday users. These improvements lead to better energy conservation, cost savings and even social welfare. With the increasing energy demand and expanding economies, it's become more important than ever to manage energy use wisely. This includes managing the use of household appliances controlling peak usage times and designing smarter more efficient devices [4].

Among all appliances, heating and cooling systems take up a major share of electricity in homes, so focusing on their efficiency makes a big difference. Interestingly, indoor air quality plays a key role here. For example, when there's more dust in the air devices like air purifiers and fans have to work harder which affects both their performance and energy use. Similarly, if the CO_2 levels are high like when more people are inside it indicates the need for better ventilation, heating and lighting to maintain comfort while still being energy efficient [5].

By studying past indoor air quality data one can find useful patterns and trends. This helps in making smart, personalized suggestions to improve how appliances work depending on the air quality around them. So, using indoor air quality index values not only gives us an idea of how these appliances might behave but also helps us plan ahead to keep them running well under different indoor conditions [6].

Multiple traditional approaches are employed to improve the energy efficiency of household appliances, including the enforcement of energy-efficiency standards, advancements in appliance design and the encouragement of energy-saving technologies. However, these conventional strategies encounter several obstacles such as the intricacy of appliance designs, resistance from manufacturers toward regulations and the unpredictable nature of consumer behavior [7]. To overcome these challenges, deep learning emerges as a viable alternative by leveraging data-driven insights to enhance appliance design. Moreover, deep learning models can uncover complex relationships and patterns from large-scale data involving appliance performance, energy usage and Indoor Air Quality (IAQ) which might be missed by traditional techniques. This allows for the development of smarter more energy-efficient appliances that also improve IAQ [8].

Numerous studies have highlighted the role of machine and deep learning in enhancing the energy efficiency of home appliances. For instance, [9] introduced an AI-based Energy Management Model (AI-EMM) tailored for green buildings, focusing on user safety and comfort alongside energy efficiency. Their system used a universal infrared communication interface and a Long Short-Term Memory (LSTM) network to optimize energy use, particularly by improving the airside design of HVAC systems, which resulted in measurable economic and environmental gains. The AI-EMM achieved a high-performance ratio of 94.3% reduced energy consumption by 15.7% and demonstrated prediction accuracy of 97.1% among other metrics.

In another study, [10] applied correlation analysis to eliminate redundant sensors and optimize the design of IoT systems in smart homes. Their machine learning-based intelligent service model assessed using Root Mean Square Error (RMSE), found the gradient-boosting regressor to be the most accurate with an RMSE of 22.29. Furthermore, researchers have explored several deep recurrent neural network (DRNN) architectures aimed at short and long-term energy consumption forecasting particularly for heating and electricity usage on an hourly basis. Their proposed DRNN model outperformed traditional models such as Support Vector Machines (SVMs) and Gradient Boosting (GB) with improvements of 5.4% and 7.0% respectively in forecasting accuracy.

A novel model featuring three components i.e. data smoothing using Kalman filtering, real-time cost error optimization using firefly along with genetic algorithm and fuzzy logic-based control through Mamdani systems has also been proposed [12]. This integrated system efficiently manages energy distribution for lighting and temperature demonstrating superior performance when compared to existing approaches. The authors highlighted the importance of optimization techniques and adaptive controllers in enhancing user comfort and energy efficiency while addressing the limitations of fixed PID controllers.

Shree Lakshmi et al. used a Kaggle dataset comprising 29 features to reduce energy usage applying LSTM models combined with optimization techniques like genetic algorithms and grey wolf optimization for hyper parameter tuning [13]. Their GWO-LSTM approach demonstrated outstanding predictive performance with minimal error. Similarly, Khan et al. employed a combination of 1D deep convolutional neural networks, LSTM models and scheduling algorithms to develop a smart energy

management system for homes. Their model validated using real-world datasets effectively forecasted loads and optimized appliance scheduling, eliminating the need for additional energy sources [14].
Liao et al. (2020) [32] investigated deep learning approaches for forecasting air quality using CNNs, RNNs, LSTMs and spatiotemporal networks. They addressed key challenges such as model overfitting and discussed the real-world feasibility of their methods.
Despite these advances, ongoing challenges include the significant computational resources required to train deep models, limited availability of diverse datasets and inconsistencies in data sourced from different platforms which can impact model accuracy and reliability. Overcoming these barriers is essential for developing robust and scalable solutions for energy-efficient smart environments.
While existing literature has proposed various energy optimization techniques in residential settings the incorporation of Indoor Air Quality (IAQ) metrics remains limited. This research addresses that gap by integrating IAQ factors such as CO_2 concentration, humidity and temperature into a deep learning framework to enable responsive and context-aware energy management. Leveraging advanced models like Bidirectional Gated Recurrent Units (Bi-GRU) and Stacked LSTM, the system is capable of capturing both short- and long-term temporal dependencies. To handle class imbalance the hybrid SMOTE-ENN technique is employed, enhancing the model's robustness and generalization. This innovative approach underscores the potential of harmonizing IAQ metrics with energy efficiency strategies, laying the groundwork for intelligent, adaptive and sustainable smart home systems.

Contribution of the Paper

This study aims to design an automated system leveraging deep learning algorithms to detect and classify air quality levels based on multiple environmental parameters including the Indoor Air Quality Index (IAQI). The specific contributions of this research are as follows:

- A comprehensive dataset comprising 132,007 records with seven key attributes namely CO_2 concentration, humidity, temperature, Passive Infrared (PIR) sensor data, IAQI and overall room air quality levels were collected from two distinct indoor environments, Room 415 (Data I) and Room 776 (Data II).
- The collected data underwent preprocessing to handle missing or null values, followed by graphical visualization techniques to explore and understand underlying patterns and trends.
- To address the issue of class imbalance within the dataset, the Synthetic Minority Over-sampling Technique (SMOTE) was implemented. Additionally, feature scaling was applied to standardize the dataset for improved model performance.
- Multiple Artificial Intelligence models were trained and evaluated on the processed dataset. Their performance was assessed using standard evaluation metrics including learning curves, confusion matrices and computational time analysis.

Paper Organization

The paper is organized as follows:

- Section I discusses the concept of energy efficiency and its relevance to society while also reviewing current methodologies and their limitations.
- Section II outlines the proposed methodology for developing an energy efficiency prediction model using advanced deep learning techniques.
- Section III presents the evaluation and performance analysis of the implemented classifiers using various metrics.
- Section IV concludes the paper by summarizing the key findings and discussing their practical implications and potential future work.

2. RESEARCH METHODOLOGY

This section defines the phases that have been used to predict and classify the Air Quality Level of a room using hybrid advanced deep learning techniques, as shown in Figure 2.

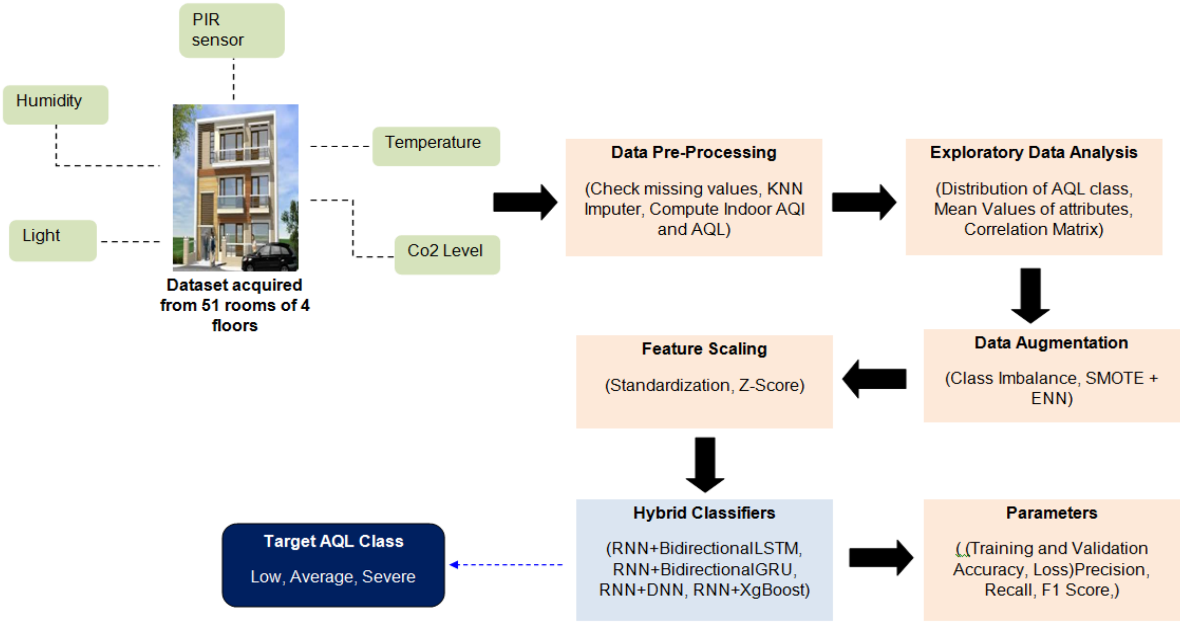

Figure 2: Proposed system for air quality assessment using deep learning classifiers

Dataset Description

The dataset utilized in this study comprises time-series data collected from 255 environmental sensors installed across 51 rooms spanning four floors of Sutardja Dai Hall, University of California, Berkeley. The sensors recorded various environmental parameters such as Passive Infrared (PIR) motion detection, Carbon Dioxide (CO_2) concentration, humidity, temperature and luminosity. Sensor readings were logged at a high temporal resolution of every five seconds with timestamps formatted in UNIX EPOCH time [15, 33].

Data Preprocessing

A meticulous data preprocessing phase was undertaken to ensure data quality and reliability. Initially, all attributes from the 51 rooms were examined for null or missing values as summarized in Table 1. To handle the missing data effectively, the K-Nearest Neighbour (KNN) imputation technique was employed. This method estimates missing values based on the proximity of similar data points in the feature space thereby preserving the statistical structure and inherent patterns of the dataset [16].

Following data cleaning, Air Quality Index (AQI) values were computed for each room using the available sensor readings. These AQI values served as a composite measure representing the overall air quality of each indoor space. During this process, it was observed that some computed AQI values were negative which are scientifically invalid and hinder meaningful analysis. Therefore, records containing negative AQI values were excluded from further analysis.

To maintain consistency and focus the study concentrated on data extracted from two randomly selected rooms, Room 415 (referred to as Data-I) and Room 776 (Data-II). Using the valid AQI data the corresponding Air Quality Level (AQL) classes were categorized as follows:

- **Low:** AQI 0–50
- **Average:** AQI 51–100
- **Severe:** AQI 101–500

These class labels facilitated the classification task for model training and evaluation [35].

Exploratory Data Analysis (EDA)

Exploratory Data Analysis was performed to extract meaningful insights and understand the interdependence between indoor environmental factors and energy-related patterns [34, 44]. The EDA specifically focused on the distribution and correlation of computed AQI values with the corresponding air quality level classes (Low, Average, Severe).

Figure 3 illustrates the correlation between indoor AQI measurements and their respective classifications for both Room 415 and Room 776. This analysis was instrumental in identifying the minimum and maximum AQI values observed across the selected rooms, which helped refine the classification thresholds.

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By performing EDA, this study enhances interpretability of the data provides a deeper understanding of the environmental context and contributes to the development of a robust classification model for efficient indoor air quality management.

Table 1: Comparison of missing values across attributes in Data-I and Data-II to emphasize the significance of imputing missing data for accurate analysis

Sensor Attribute	Missing Values (Data-I: Room 415)	Missing Values (Data-II: Room 776)
CO_2	0	1095
Humidity	1113	1
Light	1113	1
PIR (Motion)	55875	59171
Temperature	1114	0

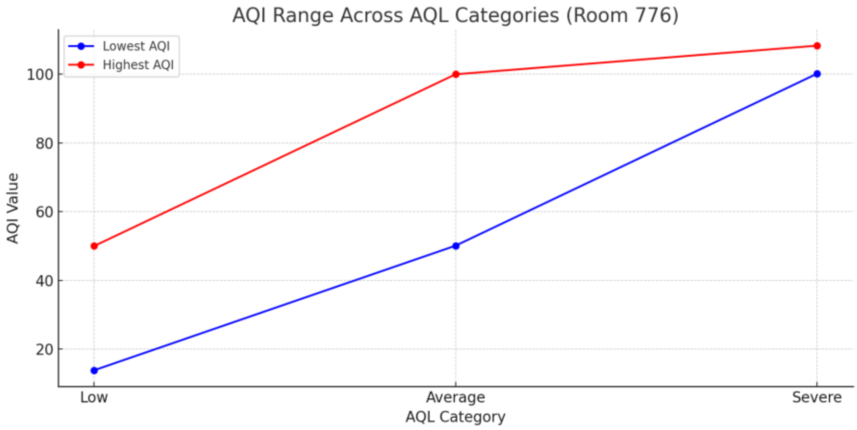


Figure 3: AQI values of Data I and Data II for different categories of AQL

Figure 4 presents a comprehensive graphical analysis of various environmental parameters across different air quality levels - low, average and severe. The data visualization encompasses CO2 concentration, PIR readings, light intensity, humidity and temperature measurements.

Delving into Room 415's data patterns as shown in Figure 4(a), it is observed that low air quality conditions predominantly occur when CO2 levels fall between 450-500 ppm, temperature ranges from 23.0-23.5°C, humidity stays between 58-60% and light intensity remains within 0-25 units.

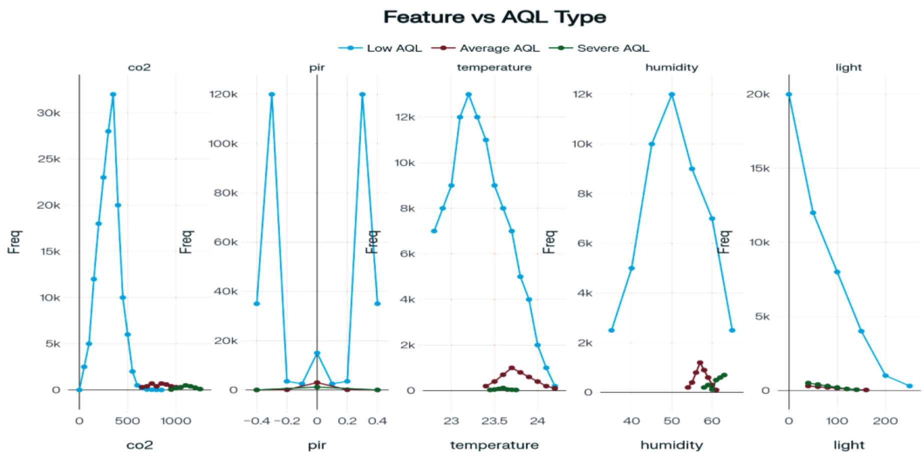


Figure 4(a): Distribution of values of Data I features across various classes of AQL

For average air quality conditions, the peak frequencies are recorded at CO2 levels of 690-700 ppm, temperature between 23.5-23.9°C, humidity at two distinct ranges of 54-55% and 58-58.5% and light intensity varying from 40-80 units.

In cases of severe air quality, the predominant measurements show CO2 concentration hovering between 1050-1100 ppm, temperature maintaining 23.65-23.70°C, humidity dropping below 58% (specifically around 57.84%) and light intensity ranging from 40-50 units. It is important to note that these values represent approximate ranges rather than fixed constants [45].

Following a similar analytical approach the data patterns for Room 776 were examined as depicted in Figure 4(b). The analysis reveals distinct patterns across different air quality levels.

For low air quality conditions, the maximum frequency of occurrences is observed when CO2 levels range between 450-500 ppm, temperature stays within 23.0-23.5°C, humidity fluctuates between 57-58% and light intensity remains low at 0-10 units.

In the average air quality category, the peak frequencies are recorded at CO2 levels of 700-720 ppm, temperature hovering around 25.0°C, humidity maintaining 54-55% and light intensity showing two distinct ranges of 60 units and 90-100 units [46].

The severe air quality conditions present a different pattern with CO2 concentration stabilizing around 700 ppm, temperature rising to approximately 25.2°C, humidity settling at 54.5% and light intensity ranging from 80-100 units. An interesting observation is the presence of non-zero PIR (Passive Infrared) values across various attributes indicating occasional movement detection.

It is crucial to emphasize that these measurements represent approximate ranges rather than fixed values as environmental conditions tend to fluctuate based on various factors.

These visualizations were developed with the primary aim of enhancing energy efficiency. By optimizing the detection and management systems based on the identified thresholds, it can implement proactive interventions that ensure resource allocation aligns with actual environmental conditions [35, 38]. This approach would help minimize energy consumption while maintaining required air quality standards.

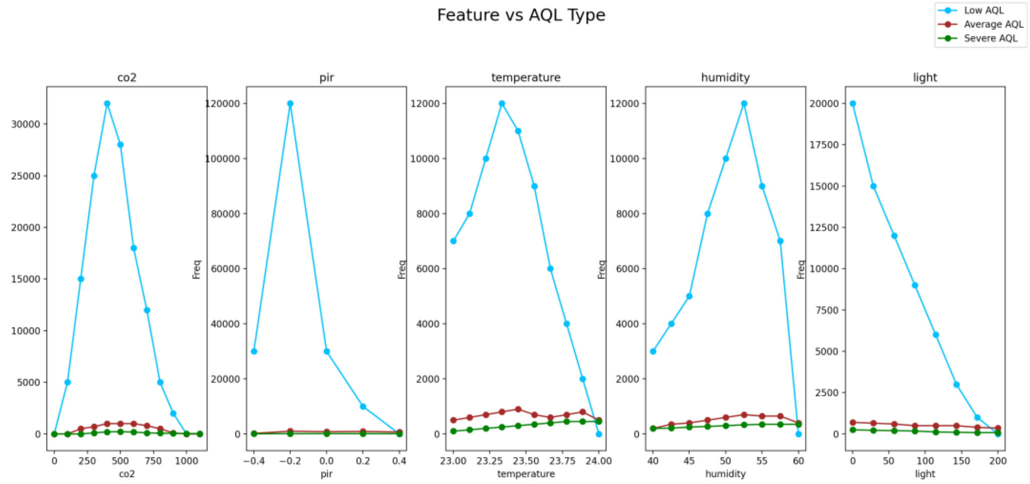


Figure 4(b): Distribution of values of Data II features across various classes of AQL

Data Augmentation

To address the critical issue of class imbalance in this dataset, a hybrid approach combining SMOTE (Synthetic Minority Over-sampling Technique) and ENN (Edited Nearest Neighbors) is implemented as illustrated in Figure 5 [37]. This innovative combination offers a two-fold advantage: SMOTE enhances the representation of minority classes by creating synthetic instances while ENN systematically eliminates noisy data points from both minority and majority classes resulting in a more balanced and refined dataset [17].

The mathematical representation of SMOTE-ENN approach can be expressed as:

$$SMOTE + ENN\ (X, y) = ENN(SMOTE(X_{minority}), y_{minority}, k) \qquad \text{(i)}$$

Where:

X represents the feature matrix of dataset

y denotes the target vector containing class labels

k indicates the number of nearest neighbors utilized in both SMOTE and ENN algorithms

While conventional oversampling techniques such as standalone SMOTE effectively increase minority class representation through synthetic sample generation, they often introduce noise by creating samples near outliers or class boundaries, potentially compromising model performance. Similarly, traditional undersampling methods, which primarily focus on reducing majority class samples to achieve balance frequently lead to the loss of crucial information that could be valuable for model training.

Hybrid SMOTE-ENN approach effectively mitigates these limitations by simultaneously addressing class imbalance and noise reduction thereby enhancing the overall performance of learning models

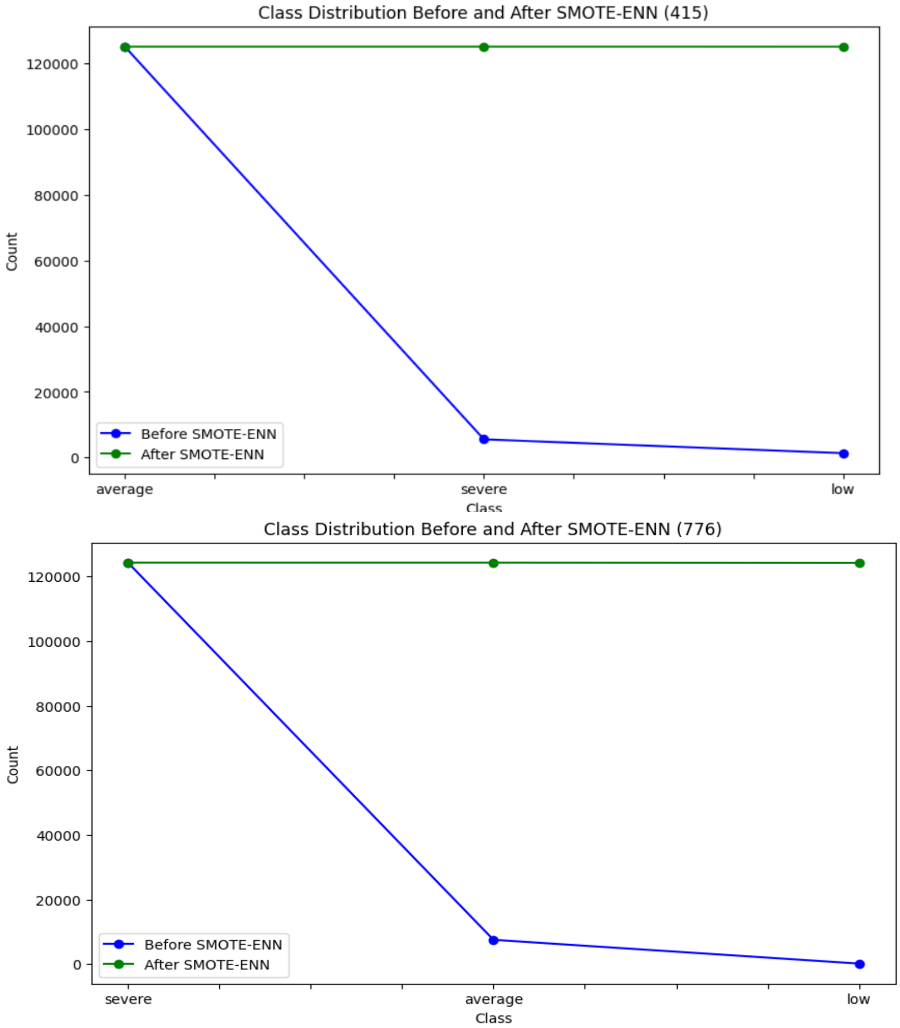


Figure 5: Class balancing achieved using the SMOTE-ENN technique to improve distribution of air quality levels in Data-I and Data-II

Feature Scaling: In the analysis, Z-score standardization has been employed as a robust method for outlier detection and data normalization [48]. This approach proves particularly valuable as it enables us to identify data points that exhibit significant deviations from the dataset's central tendency. When Z-scores deviate substantially from zero either in the positive or negative direction, these points are flagged as potential outliers indicating their statistical significance in the context of the overall distribution.

The mathematical formulation of Z-score standardization is expressed as:

$$z = \frac{x-\mu}{\sigma} \tag{ii}$$

Where:

x represents the individual data point value

μ denotes the population mean

σ signifies the population standard deviation

This standardization technique offers several advantages in analysis. Primarily, it facilitates the identification and interpretation of outliers by transforming the data into a standardized scale. Furthermore, it enables meaningful comparisons across different datasets that may have varying means and standard deviations [18]. This is particularly crucial in this study as it deals with multiple environmental parameters that operate on different scales.

Classifiers

This study employs several sophisticated neural network architectures to analyze indoor energy efficiency parameters [36]. Let us examine each approach in detail:

Multi-Layer Perceptron (MLP):

The MLP architecture in this study is specifically designed to process environmental parameters including temperature, humidity, occupancy and lighting conditions from building sensors [49]. The network comprises an input layer for environmental data ingestion, multiple hidden layers for nonlinear transformations and feature extraction and an output layer for energy efficiency predictions [19]. The mathematical formulation is expressed as:

$$z_j^{(l)} = \sum_{i=1}^{n} w_{ij}^{l}\, x_i + b_j^{l} \quad \text{(iii)}$$

$$a_j^{(l)} = f\left(z_j^{(l)}\right) \quad \text{(iv)}$$

Where:

n represents the number of input features

w_{ij}^{l} denotes the weight for the jth neuron

b_j^{l} represents the bias term

x_i indicates the input feature

$f(.)$ represents the activation function

$a_j^{(l)}$ signifies the output of the jth neuron

Recurrent Neural Networks (RNNs):

RNNs are particularly effective for processing sequential data in indoor energy optimization [43]. Their architecture features input, hidden and output layers with recurrent connections, enabling memory retention of previous data points [20]. The hidden state is defined as:

$$h_t = \sigma\,(W_{hx}x_t + W_{hh}h_{t-1} + b_h) \quad \text{(v)}$$

Where:

W_{hx} and W_{hh} represent weight matrices

σ denotes the activation function

b_h indicates the bias vector

Long Short-Term Memory (LSTM):

LSTM networks, a specialized RNN variant, excel at handling long-term dependencies in sequential data while addressing vanishing gradient issues [21]. The architecture employs memory cells with three gates (input, forget and output) that regulate information flow. The mathematical expressions for these gates are:

$$Forget\ gate\ (f_t) = \sigma\big(W_f.[h_{t-1}, x_t] + b_f\big) \quad \text{(vi)}$$

$$Input\ gate\ (i_t) = \sigma(W_i.[h_{t-1}, x_t] + b_i) \quad \text{(vii)}$$

$$Output\ gate\ (o_t) = \sigma(W_o.[h_{t-1}, x_t] + b_o) \quad \text{(viii)}$$

$$Candidate\ cell\ state\ (\tilde{c}_t) = tanh(W_c.[h_{t-1}, x_t] + b_c) \quad \text{(ix)}$$

$$Cell\ state\ update(c_t) = f_t.c_{t-1} + i_t.\tilde{c}_t \quad \text{(x)}$$

$$Hidden\ state\ update\ (h_t) = o_t\,.tanh\,(c_t) \quad \text{(xi)}$$

Gated Recurrent Unit (GRU):

GRU architecture, while similar to LSTM, offers a more streamlined approach to handling sequential data. It employs reset and update gates to selectively retain or discard information from previous time steps [22]. The mathematical formulation is:

$$Update\ gate\ (z_t) = \sigma(W_z.[h_{t-1}, x_t] + b_z) \quad \text{(xii)}$$

$$Reset\ gate\ (r_t) = \sigma(W_r.[h_{t-1}, x_t] + b_r) \quad \text{(xiii)}$$

$$Candidate\ hidden\ state\ \big(\tilde{h}_t\big) = tanh(W_h.[r_t \odot h_{t-1}, x_t] + b_h) \quad \text{(xiv)}$$

$$Hidden\ state\ update\ (h_t) = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad \text{(xv)}$$

Where:
W_z, W_r, W_h represent weight matrices
$\odot$ indicates element-wise multiplication
h_t denotes the current hidden state
These architectures collectively enable sophisticated analysis of indoor environmental patterns facilitating real-time energy management and optimization strategies.
Bidirectional Neural Networks: The study incorporates two sophisticated bidirectional architectures for enhanced temporal data processing [40].
Bidirectional Long Short-Term Memory (Bi-LSTM):
The Bi-LSTM architecture represents a significant advancement in sequence processing, utilizing two parallel LSTM layers to process input data in both forward and backward directions [50]. This dual-directional approach enables the network to capture contextual information from both past and future time steps thereby enhancing its ability to understand complex temporal patterns in indoor environmental data.
The mathematical formulation for Bi-LSTM is expressed in two parts:
Forward LSTM : (xvi)

$$Forget\ gate\ \left(f_t{}^{(f)}\right) = \sigma(W_f{}^{(f)}.\left[h_{t-1}{}^{(f)}, x_t\right] + b_f{}^{(f)})$$
$$Input\ gate\ \left(i_t{}^{(f)}\right) = \sigma(W_i{}^{(f)}.\left[h_{t-1}{}^{(f)}, x_t\right] + b_i{}^{(f)})$$
$$Output\ gate\ \left(o_t{}^{(f)}\right) = \sigma(W_o{}^{(f)}.\left[h_{t-1}{}^{(f)}, x_t\right] + b_o{}^{(f)})$$
$$Candidate\ cell\ state\ \left(\tilde{c}_t{}^{(f)}\right) = tanh(W_c{}^{(f)}.\left[h_{t-1}{}^{(f)}, x_t\right] + b_c{}^{(f)})$$
$$Cell\ state\ update\left(c_t{}^{(f)}\right) = f_t{}^{(f)}.c_{t-1}{}^{(f)} + i_t{}^{(f)}.\tilde{c}_t{}^{(f)}$$
$$Hidden\ state\ update\ \left(h_t{}^{(f)}\right) = o_t{}^{(f)}.tanh\ (c_t{}^{(f)})$$

Backward LSTM : (xvii)

$$Forget\ gate\ \left(f_t{}^{(b)}\right) = \sigma(W_f{}^{(b)}.\left[h_{t-1}{}^{(b)}, x_t\right] + b_f{}^{(b)})$$
$$Input\ gate\ \left(i_t{}^{(b)}\right) = \sigma(W_i{}^{(b)}.\left[h_{t-1}{}^{(b)}, x_t\right] + b_i{}^{(b)})$$
$$Output\ gate\ \left(o_t{}^{(b)}\right) = \sigma(W_o{}^{(b)}.\left[h_{t-1}{}^{(b)}, x_t\right] + b_o{}^{(b)})$$
$$Candidate\ cell\ state\ \left(\tilde{c}_t{}^{(b)}\right) = tanh(W_c{}^{(b)}.\left[h_{t-1}{}^{(b)}, x_t\right] + b_c{}^{(b)})$$
$$Cell\ state\ update\left(c_t{}^{(b)}\right) = f_t{}^{(b)}.c_{t-1}{}^{(b)} + i_t{}^{(b)}.\tilde{c}_t{}^{(b)}$$
$$Hidden\ state\ update\ \left(h_t{}^{(b)}\right) = o_t{}^{(b)}.tanh\ (c_t{}^{(b)})$$

Bidirectional Gated Recurrent Unit (Bi-GRU):
Similar to Bi-LSTM, the Bi-GRU architecture employs two GRU layers processing data in opposite directions enabling comprehensive temporal pattern recognition [23,24]. The mathematical formulation is expressed as:
Forward GRU : (xviii)

$$Update\ gate\ \left(z_t{}^f\right) = \sigma(W_z{}^f.\left[h_{t-1}{}^f, x_t\right] + b_z{}^f)$$
$$Reset\ gate\ \left(r_t{}^f\right) = \sigma(W_r{}^f.\left[h_{t-1}{}^f, x_t\right] + b_r{}^f)$$
$$Candidate\ hidden\ state\ \left(\tilde{h}_t{}^f\right) = tanh(W_h{}^f.\left[r_t{}^f \odot h_{t-1}{}^f, x_t\right] + b_h{}^f)$$
$$Hidden\ state\ update\ \left(h_t{}^f\right) = \left(1 - z_t{}^f\right) \odot h_{t-1}{}^f + z_t{}^f \odot \tilde{h}_t{}^f$$

Backward GRU : (xix)

$$Update\ gate\ \left(z_t{}^b\right) = \sigma(W_z{}^b.\left[h_{t-1}{}^b, x_t\right] + b_z{}^b)$$
$$Reset\ gate\ \left(r_t{}^b\right) = \sigma(W_r{}^b.\left[h_{t-1}{}^b, x_t\right] + b_r{}^b)$$
$$Candidate\ hidden\ state\ \left(\tilde{h}_t{}^b\right) = tanh(W_h{}^b.\left[r_t{}^b \odot h_{t-1}{}^b, x_t\right] + b_h{}^b)$$
$$Hidden\ state\ update\ \left(h_t{}^b\right) = \left(1 - z_t{}^b\right) \odot h_{t-1}{}^b + z_t{}^b \odot \tilde{h}_t{}^b$$

The final output at time step t is computed by concatenating the forward and backward hidden states:

$$h_t = [h_t^{(f)}, h_t^{(b)}] \quad \text{(xx)}$$

These bidirectional architectures significantly enhance the network's ability to capture complex temporal dependencies in indoor environmental data leading to more accurate predictions and better understanding of energy consumption patterns [41, 51].

Stacked Neural Network Architectures: The study employs two sophisticated stacked architectures for enhanced temporal data processing [39]:

Stacked Long Short-Term Memory (LSTM):

The Stacked LSTM architecture represents a hierarchical approach to sequence processing, comprising multiple LSTM layers arranged in a vertical configuration [49]. In this architecture, each LSTM layer processes the input data sequentially, with the output of one layer serving as the input for the subsequent layer. This layered structure enables the network to capture both short-term and long-term dependencies in the data thereby enhancing its ability to model complex temporal patterns in indoor environmental variables.

Stacked Gated Recurrent Unit (GRU):

The Stacked GRU architecture follows a similar hierarchical principle as the Stacked LSTM but utilizes GRU units instead of LSTM cells [42]. This architecture consists of multiple GRU layers stacked vertically creating a deep network structure. Each layer contains a series of GRU units and each equipped with its own set of parameters for analyzing input data patterns and relationships. The hierarchical nature of this architecture allows the network to learn representations at multiple levels of abstraction as information flows from one layer to the next [25, 26].

The effectiveness of these stacked architectures in modeling indoor environmental variables is further enhanced by carefully selected hyperparameter values which are detailed in Table 2. These hyper parameters play a crucial role in determining the network's learning capacity and overall performance

Performance Metrics: This study employs a comprehensive set of evaluation metrics to assess the performance of classification models in the context of energy efficiency for smart home appliances, specifically focusing on indoor air quality index and air quality level predictions [47].

The primary metrics used in this analysis are:

Accuracy:

Accuracy serves as a fundamental measure of model performance representing the proportion of correctly classified instances across all classes [27]. It is calculated as:

$$Acc = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \qquad \text{(xxi)}$$

Loss:

Loss function quantifies the discrepancy between predicted and actual values with cross-entropy serving as a crucial metric for model optimization and convergence [28, 47]. The mathematical expression is:

$$Loss = \frac{(Actual\ Value - Predicted\ Value)^2}{Number\ of\ observations} \qquad \text{(xxii)}$$

Precision:

Precision is particularly important in this context as it measures the model's ability to accurately identify equipment responsible for poor air quality while minimizing false positives [51]. It is expressed as:

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \qquad \text{(xxiii)}$$

Recall:

Recall evaluates the model's capability to correctly identify all actual positive cases which is crucial for comprehensive air quality monitoring. The formula is:

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \qquad \text{(xxiv)}$$

F1 Score:

The F1 score provides a balanced measure of model performance, especially useful when dealing with imbalanced positive and negative instances [29, 30]. It is calculated as:

$$F1\ score = 2\frac{Precision * Recall}{Recall + Precision} \qquad \text{(xxv)}$$

To ensure optimal model performance, very carefully hyperparameters were selected for model training as detailed in Table 2:

Table 2: Hyperparameters and their selected values for model training

Hyperparameter	**Value**
Learning Rate	0.001

Batch Size	16
Epochs	15
Optimizer	Adam
Dropout Rate	0.5
Activation Layer	ReLU in hidden, Softmax in output

These metrics and hyperparameters collectively provide a robust framework for evaluating and optimizing the models' performance in predicting indoor air quality and energy efficiency.

3. RESULTS AND DISCUSSIONS

This section presents a comprehensive analysis of the performance of various neural network models trained on data collected from both rooms. Let us begin with the analysis of Data I from Room 415.

Analysis of Models for Data I of Room 415

This research evaluated the performance of eight different neural network architectures including MLP, RNN, GRU, LSTM and their various combinations using both training and validation datasets. The evaluation metrics focused on accuracy and loss where higher accuracy and lower loss values indicate superior model performance.

Table 3 presents the detailed performance metrics for each model:

Table 3: Accuracy and Loss Metrics for Training and Validation Phases of Various Models Applied to Data-I

Models	**Training**		**Validation**	
	Acc	Loss	Acc	Loss
MLP	99.53	0.0146	99.16	0.0200
RNN	99.44	0.0169	99.75	0.0061
Bidirectional GRU	99.46	0.0152	99.81	0.0081
Bidirectional LSTM	99.47	0.0148	99.72	0.0066
LSTM	99.41	0.0166	99.57	0.0104
GRU	99.49	0.0149	99.79	0.0082
Stacked LSTM	99.40	0.0173	99.56	0.0102
Stacked GRU	99.45	0.0162	99.51	0.0156

The results reveal several interesting patterns in model performance. The MLP model achieved the highest training accuracy (99.53%) but showed slightly lower validation accuracy (99.16%). In contrast, the Bidirectional GRU model demonstrated the highest validation accuracy (99.81%) while maintaining a strong training accuracy (99.46%). The RNN model showed remarkable validation performance with the lowest validation loss (0.0061) indicating excellent generalization capabilities.

Analysis of Model Performance:

The MLP model demonstrated superior performance during the training phase achieving the highest accuracy of 99.53% with the lowest loss of 0.0146. This performance establishes MLP as the most effective model in terms of training metrics among all evaluated architectures.

The bidirectional architectures, particularly Bidirectional LSTM and Bidirectional GRU showed commendable performance. Bidirectional LSTM slightly outperformed Bidirectional GRU with a marginally lower loss (0.0148 versus 0.0152) and slightly higher accuracy (99.47% versus 99.46%). This superior performance can be attributed to their ability to capture temporal dependencies in both forward and backward directions thereby enhancing their learning capabilities.

The stacked architectures (Stacked LSTM and Stacked GRU) achieved respectable accuracies of 99.40% and 99.45% respectively. However, these performances were slightly inferior to their non-stacked counterparts (LSTM: 99.41% and GRU: 99.49%) suggesting that increased network depth does not necessarily translate to improved performance for this particular dataset.

In the validation phase, Bidirectional GRU and Bidirectional LSTM models exhibited exceptional performance, achieving validation accuracies of 99.81% and 99.72% respectively coupled with low loss values of 0.0081 and 0.0066. These results highlight their strong generalization capabilities primarily due to their ability to process temporal dependencies bidirectionally.

The MLP model maintained good performance with a validation accuracy of 99.16% and a loss of 0.0200. However, it was slightly outperformed by RNN-based models likely due to its inherent limitations in capturing sequential dependencies.

Standard LSTM and GRU models demonstrated robust performance with accuracies of 99.57% and 99.79% and losses of 0.0104 and 0.0082 respectively reaffirming their effectiveness in processing sequential data.

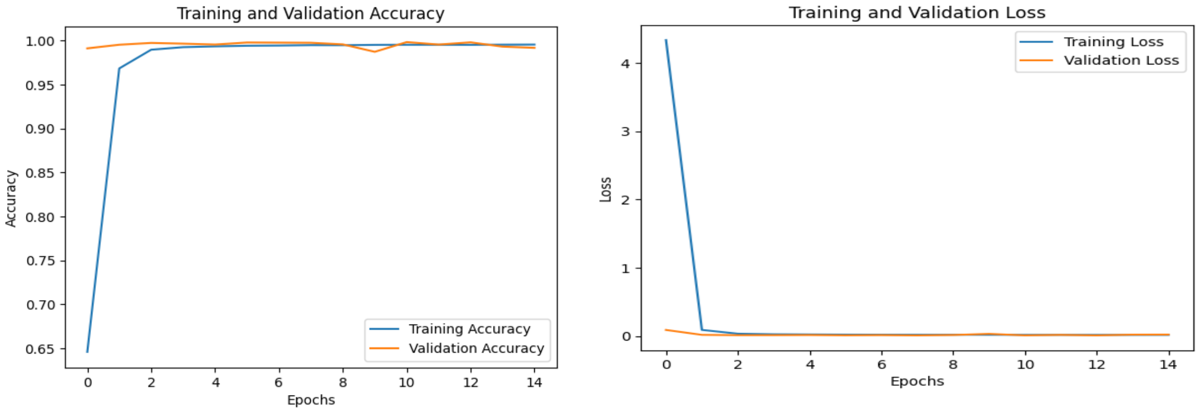
The stacked architectures (Stacked LSTM and Stacked GRU) showed solid performance with accuracies of 99.56% and 99.51% respectively but failed to significantly outperform their single-layer counterparts further supporting the observation that increased network complexity does not necessarily yield better results for this dataset.

Figure 6 illustrates the learning curves of various models depicting training and validation accuracy as well as loss over 15 epochs. The analysis reveals distinct patterns in model behavior:

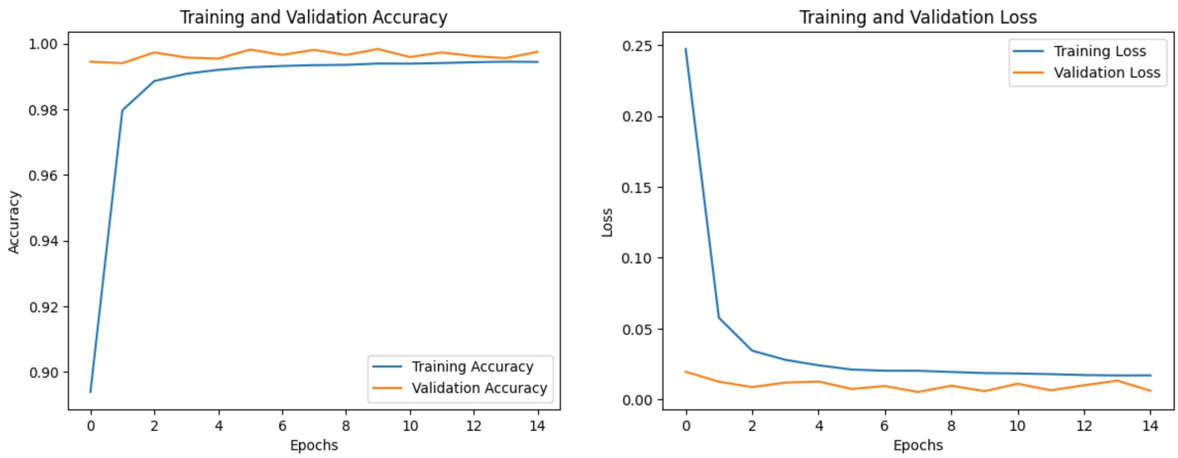
The MLP and RNN models demonstrate particularly stable learning curves, indicating consistent performance throughout the training process. In contrast, the remaining models exhibit slight zig-zag patterns in their curves suggesting minor fluctuations in their performance metrics.

An interesting observation emerges from the loss curves that the validation loss consistently remains lower than the training loss across all models. This pattern suggests that the validation dataset might present a simpler prediction task compared to the training dataset.

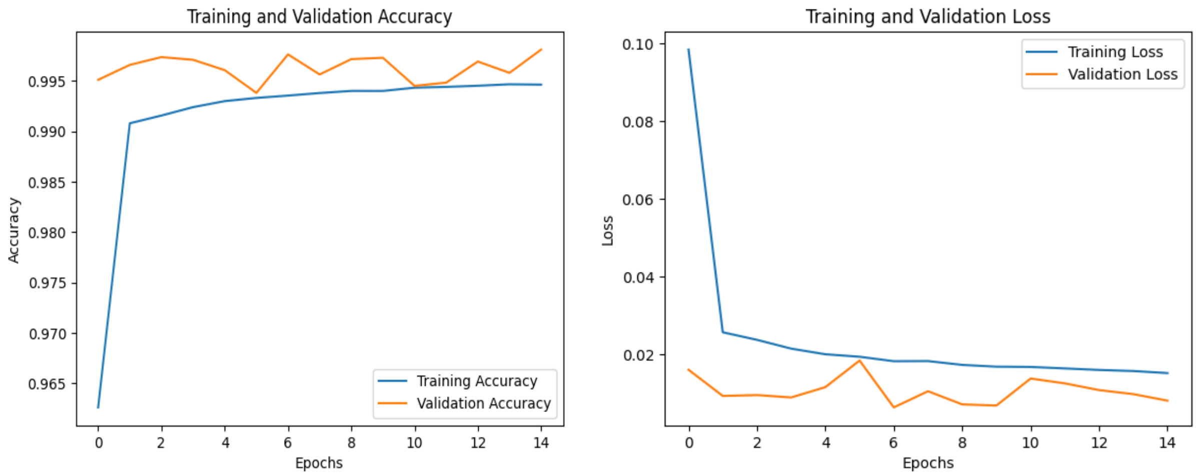
Similarly, the accuracy curves reveal that validation accuracy consistently outperforms training accuracy from the initial epochs. This phenomenon could be attributed to either the validation dataset being inherently easier to predict or having a different distribution compared to the training set leading to superior performance on the validation data.



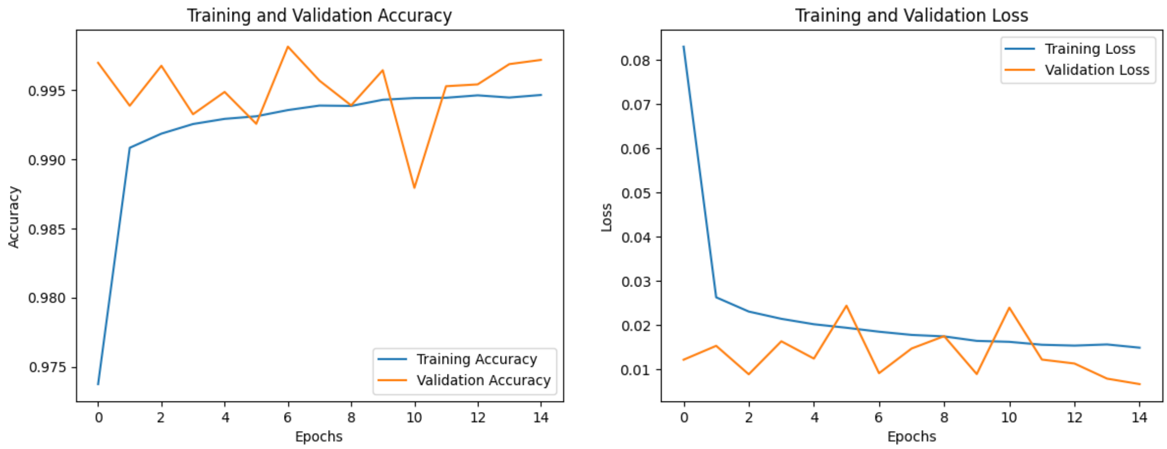
MLP



RNN



Bidirectional GRU



Bidirectional LSTM

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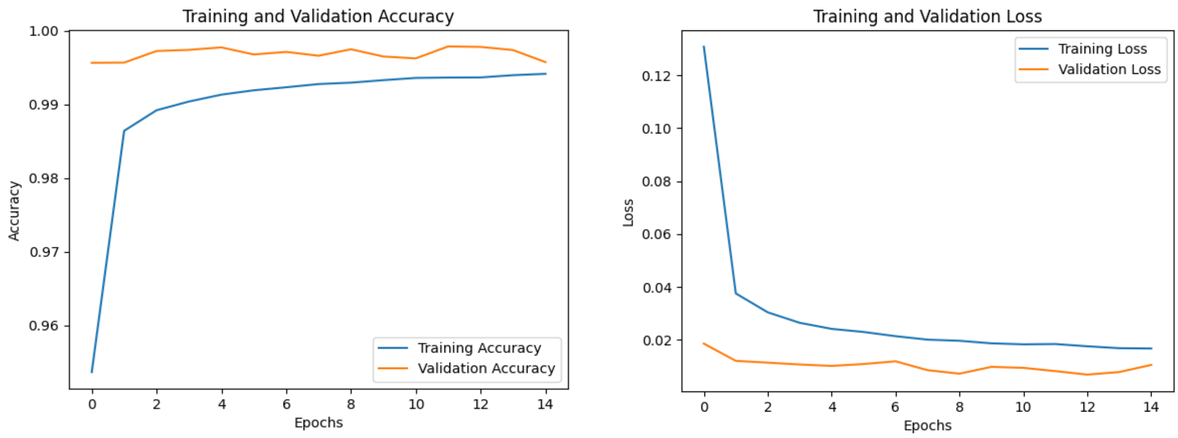
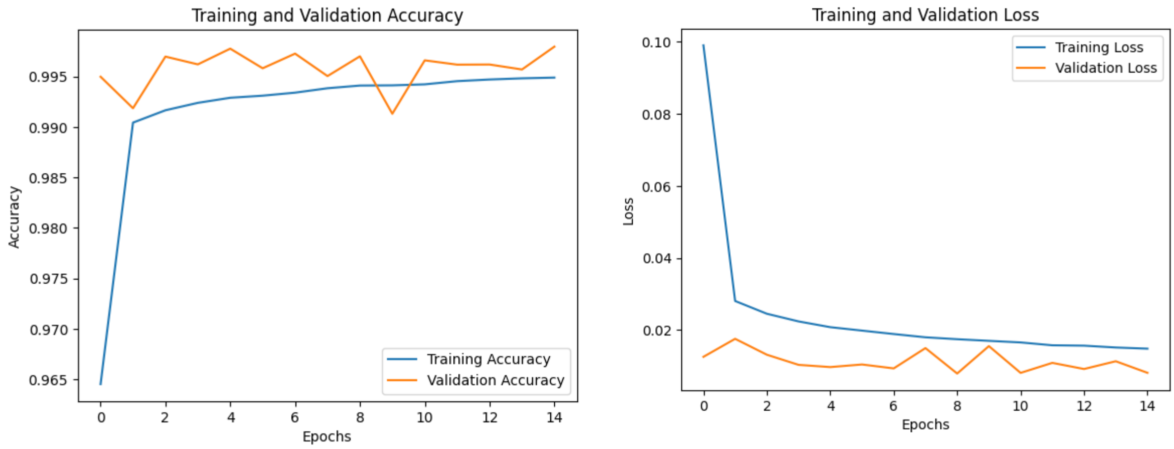
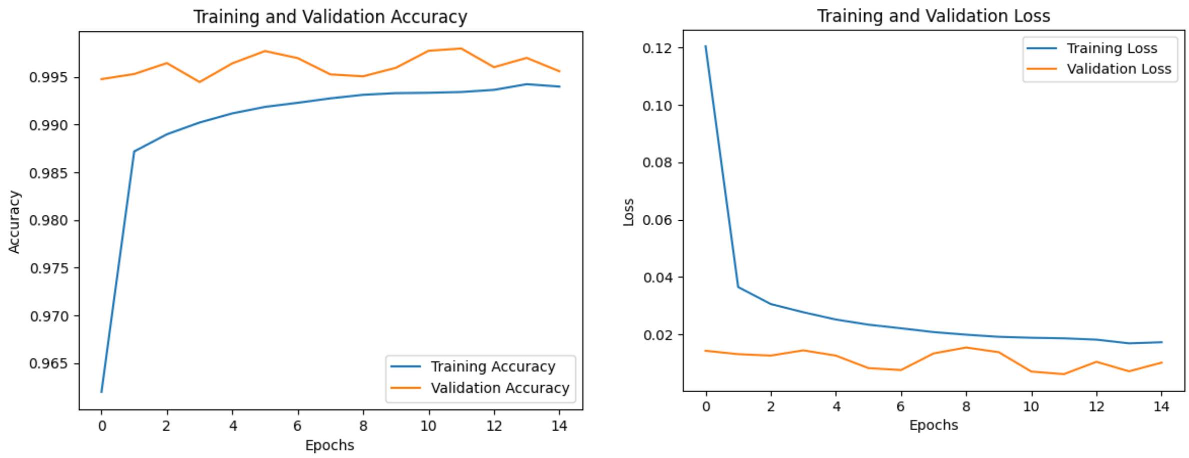


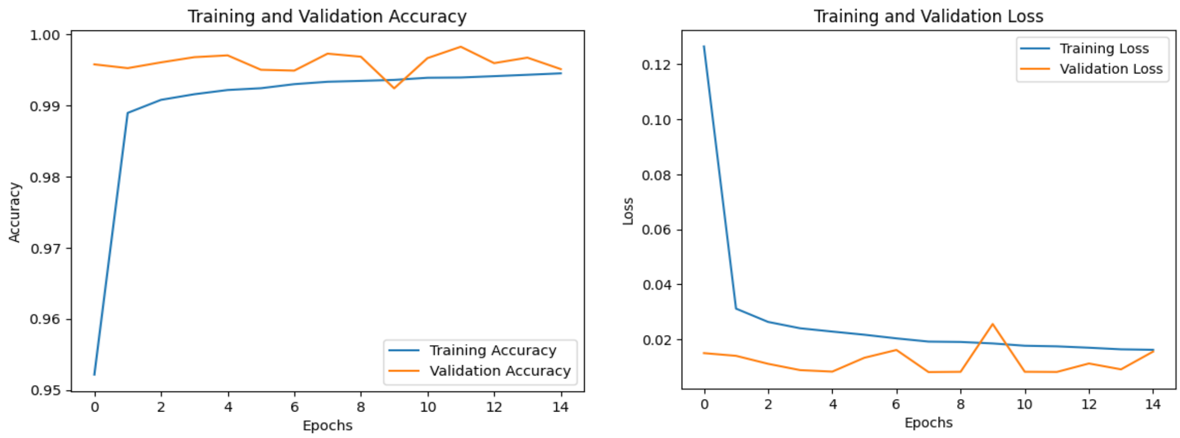
LSTM



GRU



Stacked LSTM



Stacked GRU

Figure 6: Learning curves depicting training/validation accuracy and loss for models applied to Data-I to indicate convergence and generalization trends.

Table 4 presents a comprehensive evaluation of various neural network models through precision, recall and F1 scores for energy efficient home appliances for Data-I:

Table 4: Analysis of models for the energy efficient home appliances Data-I

Models	**Precision**	**Recall**	**F1score**
MLP	0.9971	0.9915	0.9914
RNN	0.9975	0.9975	0.9974
Bidirectional GRU	0.9980	0.9982	0.9979
Bidirectional LSTM	0.9972	0.9972	0.9972
LSTM	0.9957	0.9957	0.9956
GRU	0.9979	0.9980	0.9979
Stacked LSTM	0.9955	0.9955	0.9954
Stacked GRU	0.9951	0.9950	0.9950

The analysis shows Bidirectional GRU as the top performer with precision (0.9980), recall (0.9982) and F1 score (0.9979). The standard GRU model followed closely with similar metrics (precision: 0.9979, recall: 0.9980, F1: 0.9979).

RNN, LSTM and Bidirectional LSTM demonstrated consistent performance with RNN achieving precision, recall and F1 score of 0.9975, 0.9975 and 0.9974 respectively. The stacked architectures (Stacked LSTM and Stacked GRU) showed slightly lower performance than their non-stacked versions. MLP model performed the weakest with recall (0.9915) and F1 score (0.9914).

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A 3x3 confusion matrix (Figure 7) provides detailed insights into the models' prediction patterns across different classification categories.

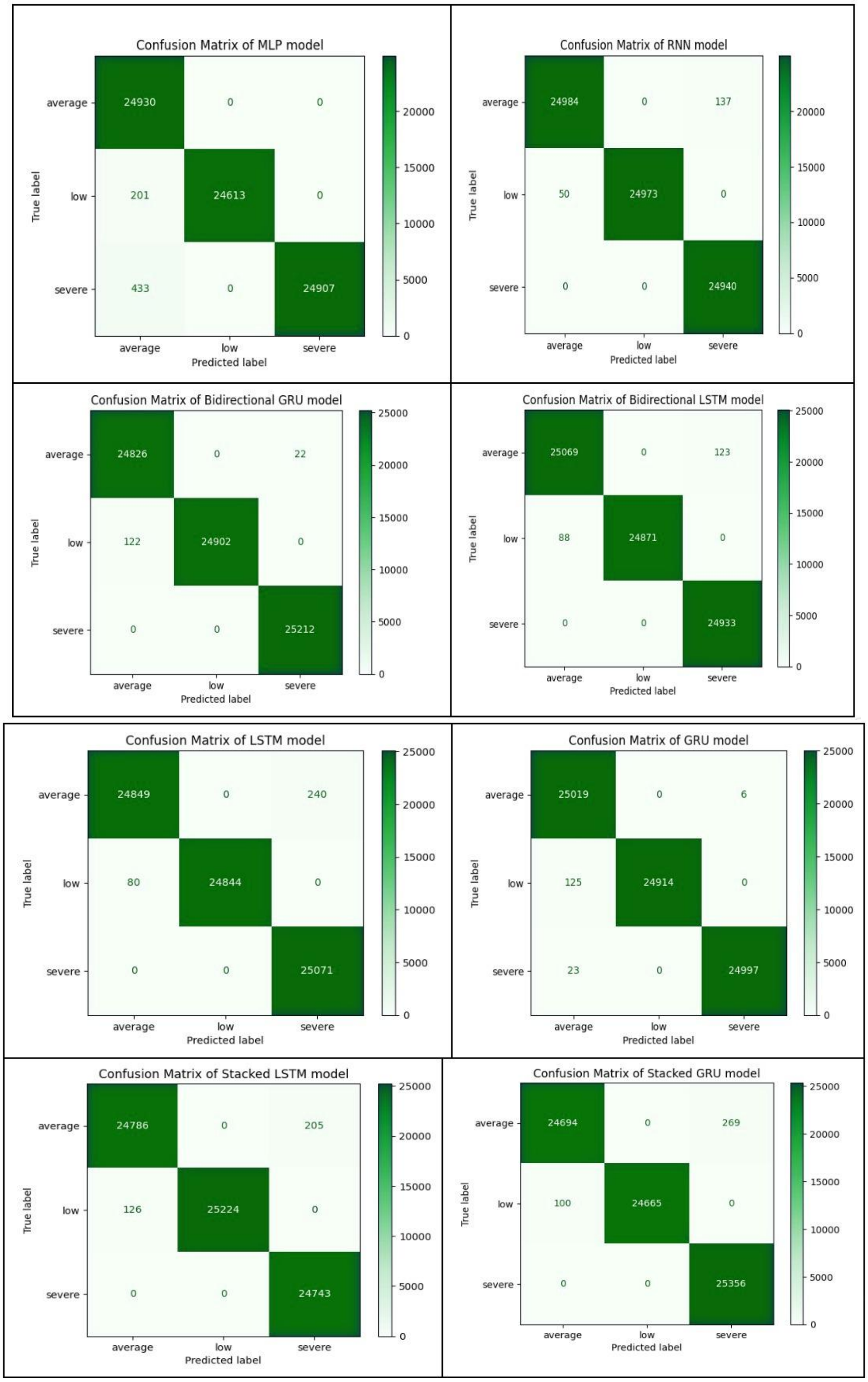

Figure 7: Confusion matrix depicting the performance of models on Data-I for three air quality classes: Low, Average and Severe

Table 5 presents a detailed class-wise analysis of model performance across three air quality categories (Low, Average and Severe) using precision, recall and F1-score metrics.

Table 5: Class-wise analysis of models for Data-I to show their precision, recall and F1-scores across Low, Average and Severe air quality classes

Models	**Class**	**Precision**	**Recall**	**F1score**
MLP	Low	1.00	0.9918	0.9958
	Average	0.9751	1.00	0.9873
	Severe	1.00	0.9829	0.9913
RNN	Low	1.00	0.9980	0.9989
	Average	0.9980	0.9946	0.9962
	Severe	0.9945	1.00	0.9972
Bidirectional GRU	Low	1.00	0.9951	0.9975
	Average	0.9951	0.9995	0.9972
	Severe	0.9991	1.00	0.999
Bidirectional LSTM	Low	1.0	0.9965	0.9982
	Average	0.9965	0.9951	0.9958
	Severe	0.9951	1.0	0.9975
LSTM	Low	1.00	0.9967	0.9983
	Average	0.9967	0.9904	0.9935
	Severe	0.9905	1.00	0.9952
GRU	Low	1.00	0.9948	0.9973
	Average	0.9941	0.9997	0.9968
	Severe	0.9997	0.9997	0.9997
Stacked LSTM	Low	1.00	0.9950	0.9974
	Average	0.9949	0.9917	0.9932
	Severe	0.9917	1.00	0.9958
Stacked GRU	Low	1.00	0.9959	0.9979
	Average	0.9959	0.9892	0.9925
	Severe	0.9895	1.00	0.9947

Analysis of model performance across different classes reveals several interesting patterns:

Low Air Quality Class:

All models achieved perfect precision scores of 1.00 indicating accurate positive predictions. However, variations in recall and F1 scores suggest differences in their ability to identify true positives. The RNN model outperformed others with the highest recall (0.9980) and F1 score (0.9989) followed by LSTM and Bidirectional LSTM with recall values of 0.9967 and 0.9965 and F1 scores of 0.9983 and 0.9982 respectively. The MLP model showed the lowest performance in this category with recall and F1 score values of 0.9918 and 0.9958 respectively, indicating a higher number of false negatives.

Average Air Quality Class:

The MLP model achieved perfect recall (1.00) demonstrating its ability to identify all true positive cases. For precision, RNN led with 0.9980 followed by LSTM (0.9967) and Bidirectional LSTM (0.9965). In terms of recall and F1 score, GRU and Bidirectional GRU showed superior performance with values of 0.9997 and 0.9968 and 0.9995 and 0.9972 respectively. The lowest performance metrics were observed in GRU's precision (0.9941) and Stacked GRU's recall and F1 score (0.9892 and 0.9925 respectively).

Severe Air Quality Class:

The MLP model maintained perfect precision while other models (RNN, Bidirectional GRU, Bidirectional LSTM, LSTM, Stacked LSTM and Stacked GRU) achieved perfect recall scores. The GRU model demonstrated balanced performance across all metrics with consistent values of 0.9997, indicating minimal false positives and false negatives. The Stacked GRU showed the lowest precision (0.9895) while the MLP recorded the lowest recall and F1 score values suggesting areas for potential improvement.

Analysis of models for the Data II of Room 776

Table 6 presents a comparative analysis of various deep learning models based on their training and validation performance metrics for data collected from room 776 for Data-II.

Table 6: Accuracy and loss values for training and validation phases of neural network models applied to Data-II

Models	Training		Validation	
	Acc	Loss	Acc	Loss
MLP	99.17	0.0276	99.58	0.0140
RNN	99.26	0.0240	99.43	0.0158
Bidirectional GRU	99.27	0.0238	99.41	0.0151
Bidirectional LSTM	99.14	0.0273	99.45	0.0130
LSTM	99.20	0.0255	99.47	0.0143
GRU	99.24	0.0247	99.63	0.0118
Stacked LSTM	99.13	0.0281	99.64	0.0117
Stacked GRU	99.16	0.0264	99.34	0.0177

Training Phase Analysis:

The Bidirectional GRU model demonstrated superior performance during training achieving the highest accuracy of 99.27% with the lowest loss of 0.0238. This was closely followed by RNN (99.26% accuracy, 0.0240 loss) and GRU (99.24% accuracy, 0.0247 loss) indicating the effectiveness of recurrent-based models in capturing training data patterns. The low loss values coupled with high accuracies suggest these models learn effectively without overfitting.

The stacked architectures (Stacked LSTM and Stacked GRU) achieved respectable accuracies of 99.13% and 99.16% respectively, but showed higher loss values (0.0281 and 0.0264), suggesting that increased network complexity did not necessarily improve performance on the training data.

Validation Phase Analysis:

All models demonstrated strong validation performance with accuracies ranging from 99.34% to 99.64% and loss values between 0.0117 and 0.0177. The Stacked LSTM model achieved the highest validation accuracy (99.64%) with the lowest loss (0.0117) followed closely by GRU (99.63% accuracy, 0.0118 loss) indicating their superior generalization capabilities.

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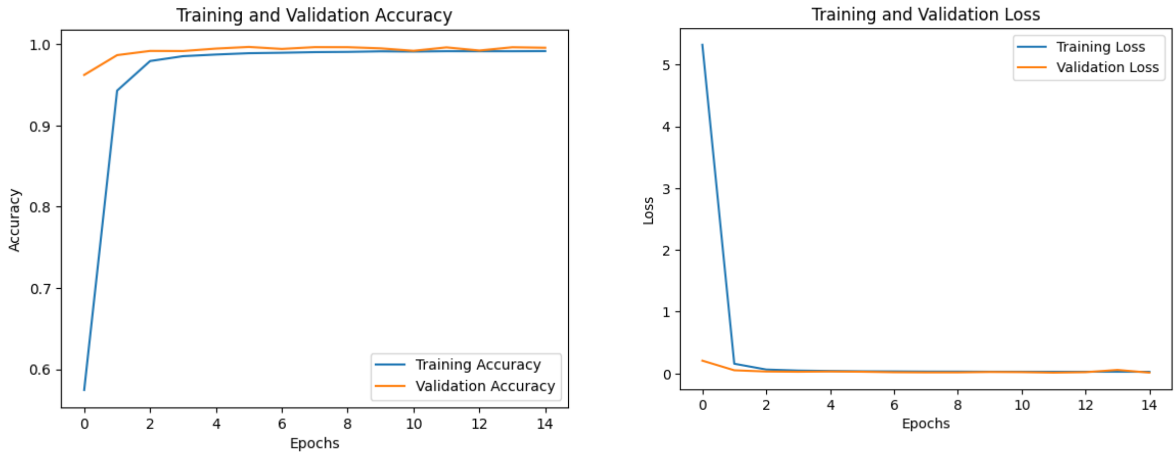
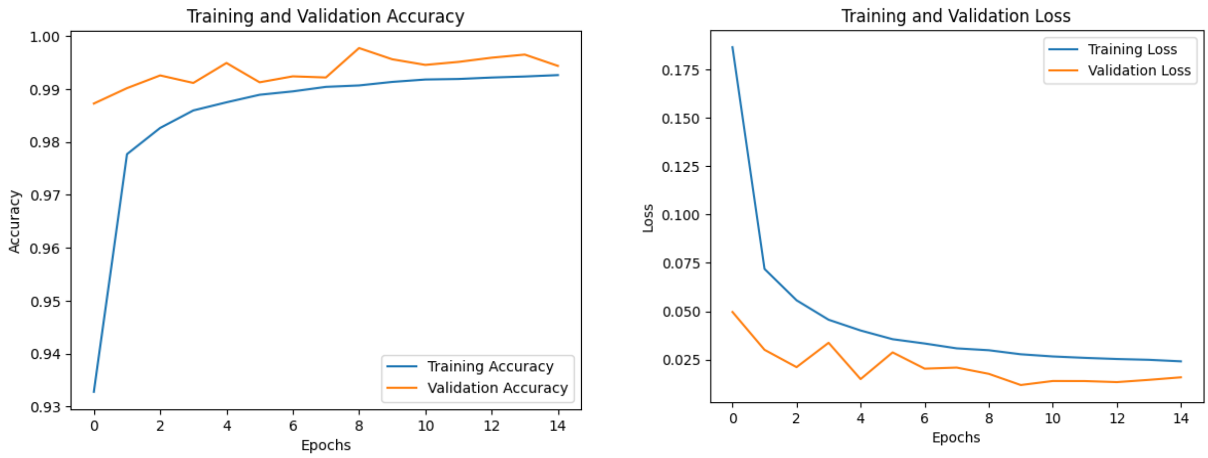
The MLP model, despite its simpler architecture, showed competitive performance with 99.58% validation accuracy and 0.0140 loss. The RNN, Bidirectional GRU and Bidirectional LSTM models showed slightly lower validation accuracies (99.43%, 99.41% and 99.45% respectively) with higher losses (0.0158, 0.0151 and 0.0130 respectively).
The Stacked GRU model showed the lowest validation accuracy (99.34%) with the highest loss (0.0177) suggesting potential overfitting issues or challenges in training the deeper architecture.

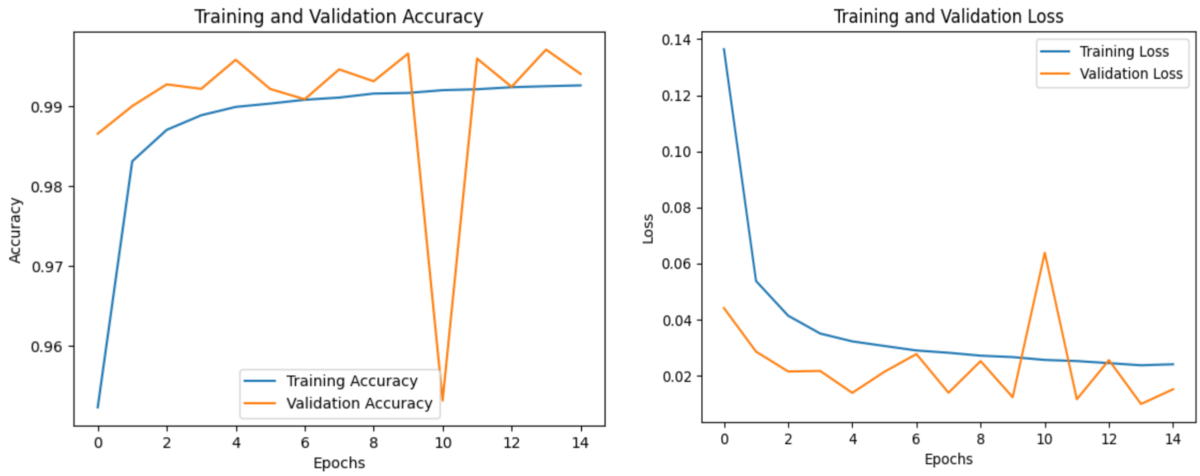
Learning Curve Analysis:
Figure 8 illustrates the learning curves for training and validation accuracy and loss over 15 epochs. Similar to Data-I, the MLP and RNN models exhibited stable learning curves. However, the Bidirectional GRU model showed an initial peak in its learning curve indicating a period of adjustment before achieving improved performance as training progressed.



MLP



RNN



Bidirectional GRU

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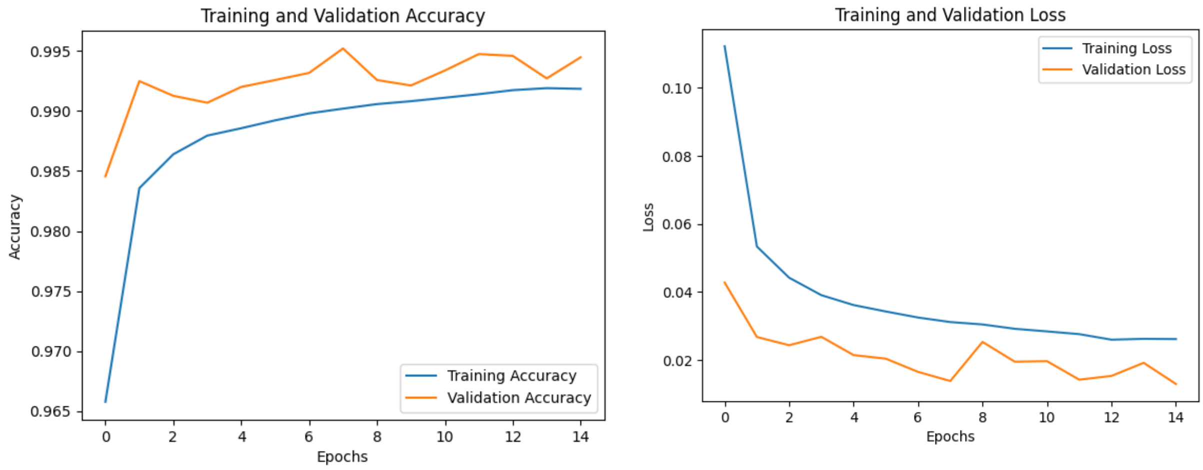
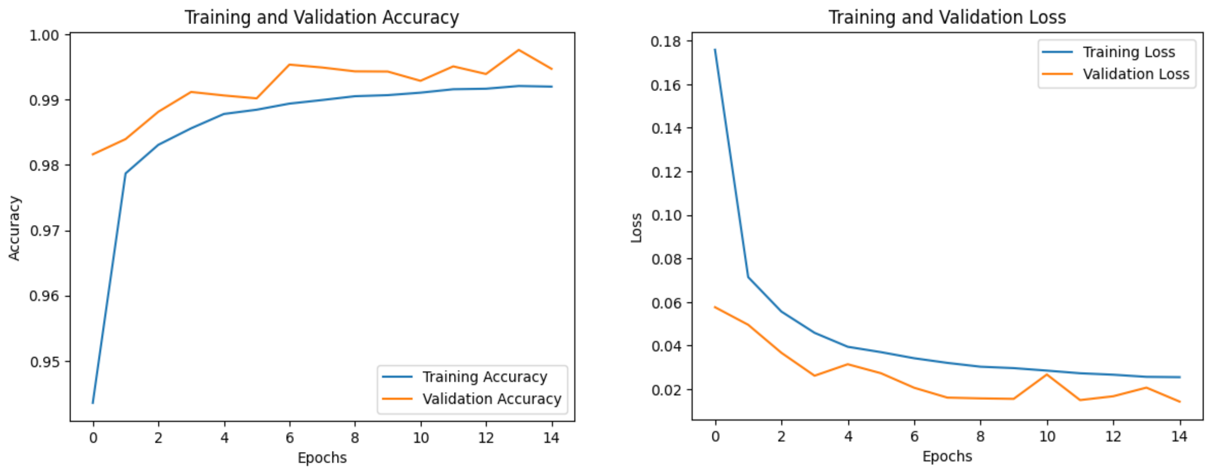
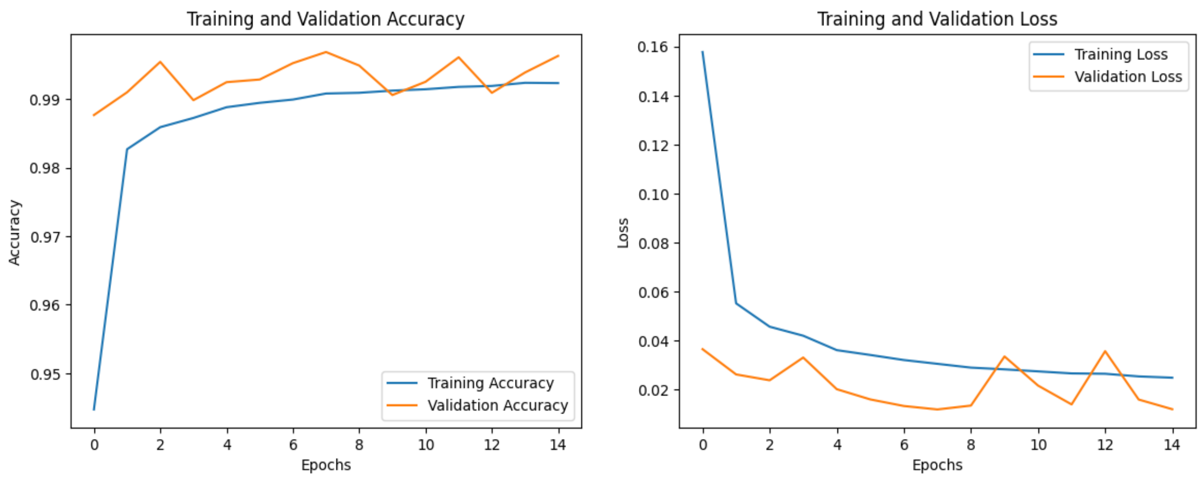


Bidirectional LSTM



LSTM



GRU

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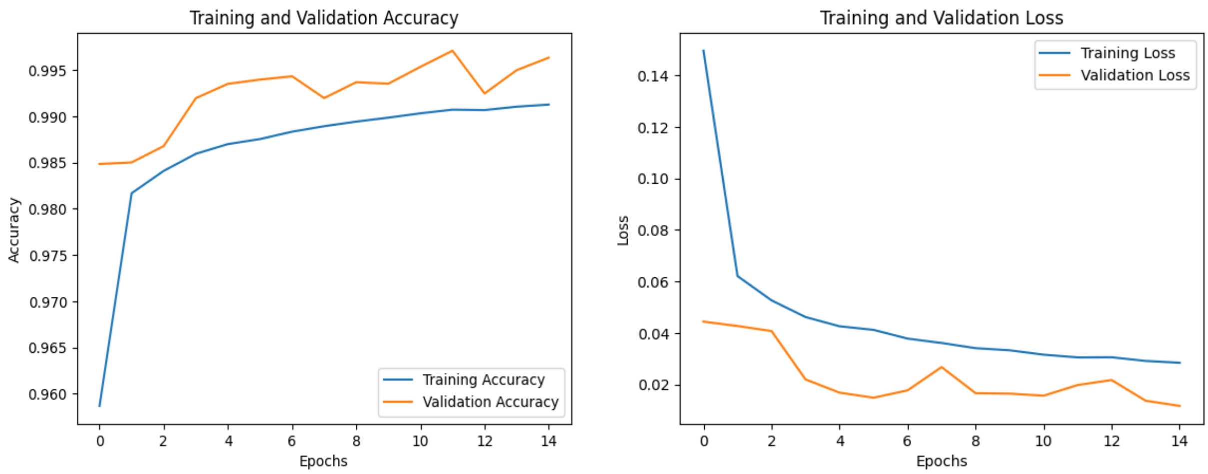
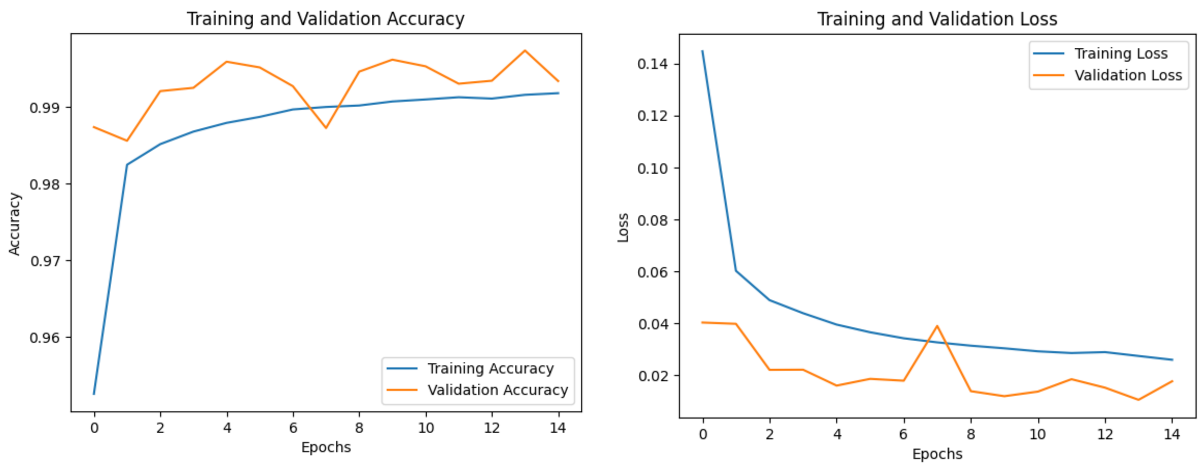


Stacked LSTM



Stacked GRU

Figure 8: Learning curves for models trained on Data-II to highlight differences in performance between training and validation dataset

Table 7 presents a comprehensive evaluation of various deep learning models using precision, recall and F1 score metrics for energy efficient home appliances Data-II.

Table 7: Analysis of models for the energy efficient home appliances Data-II

Models	Precision	Recall	F1score
MLP	0.9957	0.9957	0.9957
RNN	0.9943	0.9943	0.9942
Bidirectional GRU	0.9940	0.9940	0.9939
Bidirectional LSTM	0.9945	0.9945	0.9945
LSTM	0.9920	0.9973	0.9946
GRU	0.9963	0.9963	0.9962
Stacked LSTM	0.9959	0.9964	0.9961
Stacked GRU	0.9961	0.9966	0.9949

Analysis of model performance reveals several interesting patterns:

The GRU and Stacked GRU models demonstrated superior performance in minimizing false positives, achieving the highest precision values of 0.9963 and 0.9961 respectively. The Stacked LSTM and MLP models followed closely with precision scores of 0.9959 and 0.9957 respectively.
In terms of recall, the LSTM model achieved the highest value of 0.9973 demonstrating exceptional ability in identifying true positives. Despite its lower precision of 0.9920 it maintained a strong F1 score of 0.9946. The Stacked GRU, Stacked LSTM and GRU models also showed strong recall performance with values of 0.9966, 0.9964 and 0.9963 respectively coupled with F1 scores of 0.9949, 0.9961 and 0.9962.
The MLP model demonstrated robust performance with a balanced F1 score of 0.9957. However, the Bidirectional GRU and Bidirectional LSTM models showed relatively lower performance, with precision and recall values of 0.9940 and 0.9945 respectively suggesting less consistent performance compared to other models.
To further analyze the models' performance across different classes a 3x3 confusion matrix has been created (Figure 9) providing detailed insights into the models' prediction patterns and their effectiveness in classifying different categories.

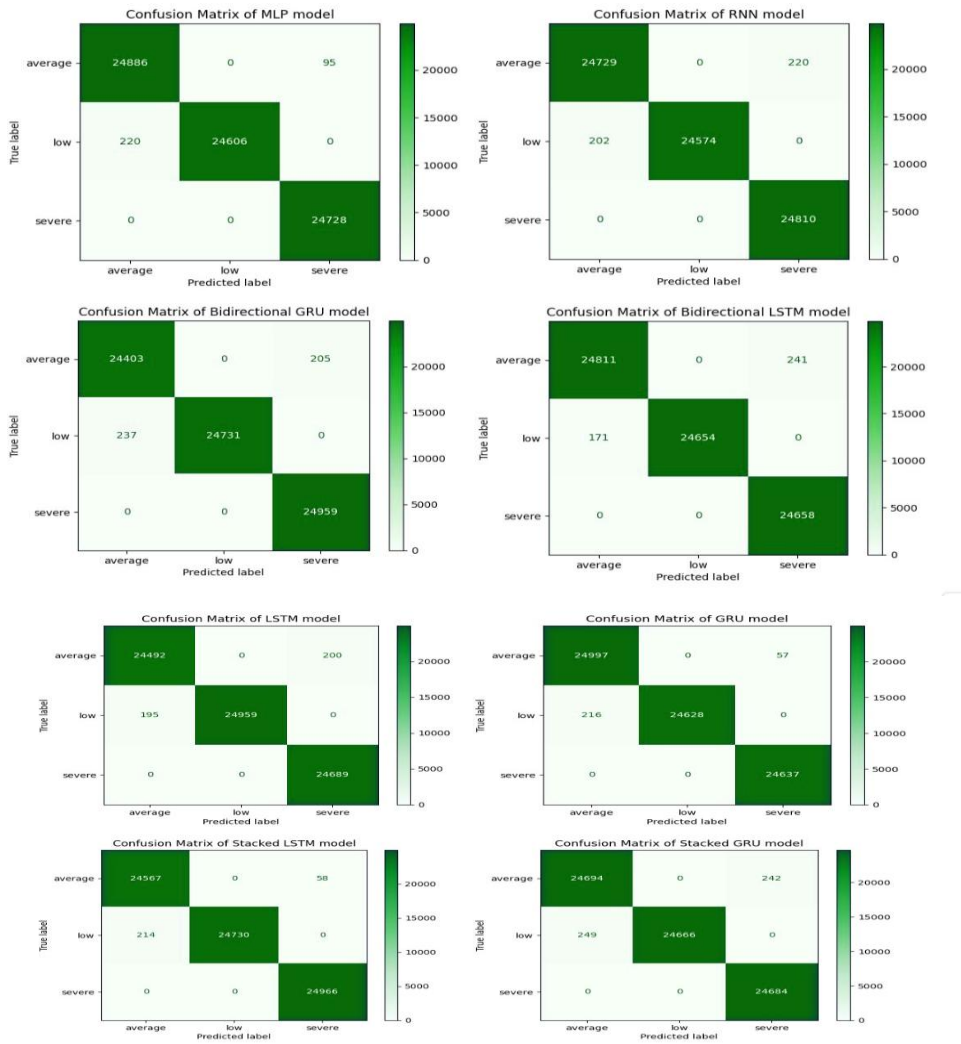


Figure 9: Confusion matrix showing model predictions versus actual values for Data-II across air quality levels: Low, Average and Severe
Table 8 presents a detailed class-wise analysis of model performance across three air quality categories (Low, Average and Severe) using precision, recall and F1-score metrics.

Table 8: Evaluation of model performance in distinguishing air quality levels (Low, Average, Severe) in Data-II

Models	Class	Precision	Recall	F1score
MLP	Low	1.00	0.9911	0.9955
	Average	0.9912	0.9961	0.9936
	Severe	0.9961	1.00	0.9980
RNN	Low	1.00	0.9918	0.9958
	Average	0.9918	0.9911	0.9914
	Severe	0.9912	1.00	0.9955
Bidirectional GRU	Low	1.00	0.9905	0.9952
	Average	0.9903	0.9916	0.9909
	Severe	0.9918	1.00	0.9958
Bidirectional LSTM	Low	1.00	0.9931	0.9966
	Average	0.9932	0.9904	0.9918
	Severe	0.9903	1.00	0.9951
LSTM	Low	0.9922	1.00	0.9961
	Average	0.9921	0.9919	0.9919
	Severe	0.9919	1.00	0.9959
GRU	Low	1.00	0.9913	0.9956
	Average	0.9914	0.9977	0.9945
	Severe	0.9976	1.00	0.9987
Stacked LSTM	Low	1.00	0.9914	0.9957
	Average	0.9913	0.9979	0.9945
	Severe	0.9964	1.00	0.9982
Stacked GRU	Low	1.00	0.9900	0.9949
	Average	0.9898	0.9999	0.9948
	Severe	0.9902	1.00	0.9950

Analysis of model performance across different classes reveals several interesting patterns:

Low Air Quality Class:

Most models demonstrated perfect precision (100%) in classifying low air quality instances with the exception of LSTM which achieved perfect recall instead. However, several models showed lower recall values: MLP (0.9911), RNN (0.9918), Bidirectional GRU (0.9905), GRU (0.9913), Stacked LSTM (0.9914) and Stacked GRU (0.9900), indicating challenges in identifying true positive instances. The

Bidirectional LSTM showed slightly better performance with a recall of 0.9931 and an F1 score of 0.9966.

Average Air Quality Class:

Most models maintained high performance metrics (above 0.99) except for Stacked GRU. The Bidirectional GRU, RNN, LSTM and Bidirectional LSTM showed slightly lower F1 scores (0.9909, 0.9914, 0.9919 and 0.9918 respectively) due to variations in precision or recall. The Stacked GRU demonstrated high sensitivity with a recall of 0.9999, though with a lower precision of 0.9898, resulting in an F1 score of 0.9948. Several models showed lower recall values: RNN (0.9911), Bidirectional GRU (0.9916), Bidirectional LSTM (0.9904) and LSTM (0.9919) indicating challenges in correctly classifying positive instances.

Severe Air Quality Class:

All models achieved perfect recall (1.00) demonstrating excellent ability to identify severe air quality instances. The GRU and Stacked LSTM models showed superior performance with F1 scores of 0.9987 and 0.9982 respectively. The MLP and RNN models achieved slightly lower F1 scores (0.9980 and 0.9955). The Stacked GRU and Bidirectional LSTM showed the lowest precision scores (0.9902 and 0.9903 respectively) suggesting areas for improvement in their prediction capabilities.

Table 9 presents a comprehensive analysis of computational efficiency across different deep learning models for both Data I and Data II.

Table 9: Overall execution time of applied learning models for Data-I and Data-II to underscore the impact of model complexity on computational efficiency

Models	**Time frame**
LSTM	1 hour 25 min
GRU	1 hour 40 min
Stacked LSTM	1 hour 40 min
Stacked GRU	2 hour
MLP	1 hour
RNN	1 hour 30 min
Bidirectional GRU	2 hour
Bidirectional LSTM	2 hour 5 min

Analysis of Computational Efficiency:

The MLP model demonstrated superior computational efficiency with the shortest training time of 1 hour attributed to its simpler architecture. In contrast, the more complex architectures required significantly longer training times: Stacked LSTM (1 hour 40 minutes), Stacked GRU (2 hours), Bidirectional LSTM (2 hours 5 minutes) and Bidirectional GRU (2 hours). The RNN, LSTM and GRU models showed moderate training times of 1 hour 30 minutes, 1 hour 25 minutes and 1 hour 40 minutes respectively.

Practical Applications and Implications:

The superior performance of Bidirectional GRU and Stacked LSTM models in terms of accuracy and loss makes them particularly suitable for real-time energy optimization systems in smart homes. These models can effectively manage dynamic adjustments in heating, ventilation and lighting systems based on indoor air quality parameters such as CO_2 levels and temperature, optimizing energy efficiency while maintaining occupant comfort.

The insights gained from learning curves particularly the observed fluctuations in training and validation accuracy provide valuable guidance for hyper parameter tuning in real-world deployments. The SMOTE-ENN technique for class balancing proves particularly effective in homes with uneven energy consumption patterns such as those with seasonal variations in appliance usage.

The execution time analysis presented in Table 9 offers crucial insights for scenarios where computational efficiency is paramount such as real-time energy management systems requiring rapid model updates and predictions. These practical applications demonstrate the potential of deep learning models in creating effective energy-saving solutions for residential buildings contributing to both sustainability and efficiency goals.

4. CONCLUSION

This research demonstrates significant progress in leveraging deep learning techniques for enhancing energy efficiency in home appliances. Through comprehensive analysis of environmental parameters including CO2 levels, humidity and temperature, these models have shown promising results in optimizing energy consumption and promoting sustainable practices.

The Bidirectional GRU and Stacked LSTM models emerged as superior performers among all tested classifiers achieving remarkable accuracy and low loss values for data collected from rooms 415 and 776. These results underscore the transformative potential of AI-driven approaches in revolutionizing energy management systems for smart homes. The models' ability to optimize real-time decision-making in smart appliances presents significant opportunities for reducing energy costs and minimizing environmental impact.

The findings highlight the broader implications for integrating AI-driven approaches into energy policies and sustainability strategies potentially leading to more effective reductions in residential energy consumption and contributing to climate change mitigation efforts.

Authors' Contributions:

The research paper represents a collaborative effort with distinct contributions from each author:
J.S.S.[1], S.A.[2] and S.K.[3] were primarily responsible for the original draft preparation and formal analysis of the research findings. The methodology development was a joint effort between J.S.S.[1]and S.A.[2]. The analysis results were thoroughly reviewed by all three authors (J.S.S.[1], S.A.[2] and S.K.[3]) to ensure accuracy and validity of the findings.

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