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Optimizing Energy Efficiency of Smart Rooms by Monitoring AQL using Hybrid Advanced AI Techniques

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Since the development of smart building technologies is in rise, it is very crucial to optimize the consumption of energy within indoor environments for reducing its operational cost as well as bad effect on environment. Conventional system is constrained to adapt to complex as well as dynamic data which leads to suboptimal energy usage as well as occupant discomfort. AI algorithms have the ability to analyse complex datasets by identifying their patterns in order to generate more accurate predictions. In this paper, an AI-based model is developed to monitor the energy efficiency of smart room appliances using a hybridization of advanced machine learning techniques by considering various factors such as CO2 levels, humidity, temperature, light intensity, PIR sensor data, indoor air quality index, and air quality level. A dataset comprising 1.3 lakh records from 51 rooms is taken into consideration and pre-processed using the K-nearest neighbours imputation technique to handle missing values. Later, the data is visualized graphically across different attributes and classes followed by techniques such as SMOTE-ENN and z-score normalization. Various hybrid classifiers such as Recurrent Neural Networks with Bidirectional Long Short-Term Memory, Bidirectional Gated Recurrent Unit, Deep Neural Networks, and XGBoost, are trained and results from the experimentation phase revealed that, for Data-I, the RNN+Bidirectional LSTM achieved the highest validation accuracy of 99.81% on a loss of 0.0050. Conversely, for Data-II, the RNN+Bidirectional GRU exhibited the best performance, achieving an accuracy of 99.67% with a loss of 0.0221.

Keywords: Energy efficiency, Smart Room, Co2, Humidity, Hybrid approaches, SMOTE-ENN, KNN imputation.

1. Introduction

Energy efficiency mainly refers towards the process where less energy is being used while performing the same task or to achieve the same level of output. This can be done by using various means like usage of appliances which are energy-efficient, optimization of industrial processes, improvising insulation in buildings, as well as using those energy sources which are renewable in nature [1]. It is very important to work on the improvement of energy efficiency as it can help to mitigate climate change by reducing the emission of greenhouse gases. Apart from this, it can also save money which is being used as energy bills for households and finally it can enhance the energy security by reducing dependence on foreign energy sources [2]. In fact, as shown in Figure 1, the global smart home energy management market was worth USD 8.41 billion in 2020 and is predicted to grow 14.7% from 2021 to 2028 [3].

In the current discourse on living a sustainable life, the role of Indoor Air Quality (IAQ) emerges as an important factor that cannot be ignored to improve the energy efficiency. In fact, the relation between the energy efficiency and IAQ has become increasingly apparent because of the intense efforts of societies to minimize the consumption of energy and mitigate its bad impact on environment. In addition to this, various remarkable strides can be achieved in case of efficient use of energy by optimizing indoor air quality [4].

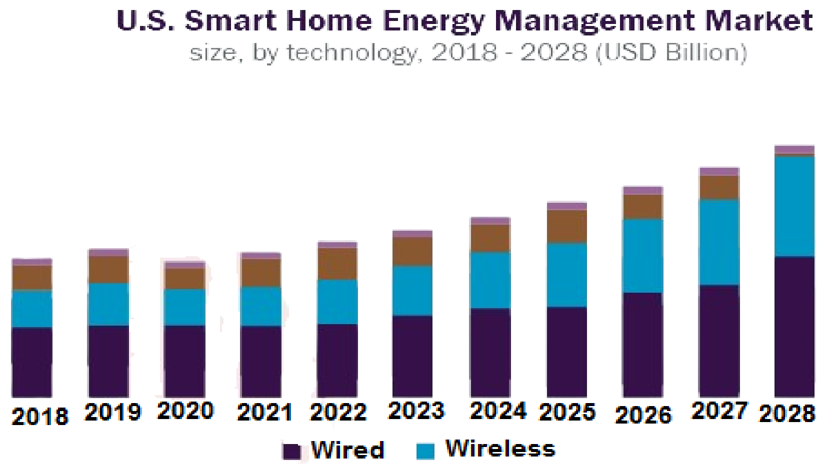


Figure 1: US smart home energy management

There are various traditional techniques which play a crucial role to reduce consumption of energy and minimize its environmental impact within homes. These methods include various methods such as to adopt energy efficient lighting systems and appliances by using simple insulation and weatherization. By using such practices, significant reductions in energy usage can be achieved by the home owners including the associated costs over time [5]. But these conventional energy efficiency techniques also face certain challenges when being applied to residential settings such as investments or the upfront costs for the implementation of energy-efficient upgrades which usually does not fall in the budget of homeowners with limited financial resources and many more [6]. AI-based learning models have the capability to work on these issues and offer customized solutions for optimizing the use of energy to improve building performance, as well as the comfort of an occupant. Unlike traditional methods, AI models can analyse as well as study large amounts of data in real-time for identifying cost-effective energy-saving opportunities to provide personalized recommendations to users. Apart from this, AI systems can also minimize inconvenience to ensure energy savings but without disturbing the comfort or productivity [7].

In fact, there are various researchers who have showed their contribution in the realm of building energy efficiency model for smart rooms using multiple machine and deep learning models such as Ali et al. (2024) [8] predicted the energy performance of urban residential buildings by using ensemble-based machine learning and end-use demand segregation methods. They generated a synthetic dataset of one million buildings and predicted energy performance using 19 vital variables for four residential building archetypes and their study demonstrated a 91% accuracy rate with the ensemble-based machine learning approach which outperformed the traditional method but their model also suffered from data inconsistency. Likewise, Deng et al. (2023) [9] presented AutoBPS and EnergyPlus for simulating building energy use and rooftop PV generation. They found that their method reduced energy demand by 18.5%, with PV installation achieving further savings of 38.6%. Morteza et al. (2023) [10] explored various architectures of deep recurrent neural networks (DRNNs) for medium as well as long-term energy demand predictions. Their proposed DRNN model surpassed support vector machine and gradient boosting regression models by 5.4% and 7.0%, respectively by showcasing its superior performance in energy forecasting accuracy. Pham et al. (2020) [11] proposed a Random Forests (RF) model to predict short-term energy consumption in multiple buildings at hourly resolution. They used five one-year datasets where the RF model demonstrated strong prediction accuracy in various scenarios. Gao et al. (2020) [12] introduced DeepComfort, a deep reinforcement learning framework for thermal comfort control in buildings to predict occupants' comfort levels, followed by a deep deterministic policy gradients-based approach for optimal thermal comfort control. Through simulation, the framework improved thermal comfort prediction by 14.5% and reduces HVAC energy consumption by 4.31%. Somu et al. (2021) [13] introduced CNN-LSTM, a deep learning framework for accurate building energy consumption by using recorded data at predefined intervals. They incorporated means clustering for trend analysis, Convolutional Neural Networks for feature extraction, and Long Short-Term Memory networks for handling temporal dependencies in time series data. Demonstrated with real-time data of IIT-Bombay in India, CNN-LSTM outperformed -means variants of state-of-the-art models in energy demand forecasting.

Contribution of the paper

In this paper the aim is to develop an automated system that uses hybrid advanced machine learning techniques to identify as well as classify the air quality level on the basis of multiple parameters including indoor air quality index. The contribution to perform the research is as follows:

- Initially, a dataset consisting of 132007 records with seven attributes, such as CO2 levels, humidity, PIR, temperature, indoor AQI and AQL of 51 rooms were taken into consideration.
- Subsequently, the data was pre-processed to check for irrelevant or missing values followed by graphical visualization to understand the pattern of the dataset.
- For data augmentation and to address class imbalance issue, the SMOTE-ENN technique was employed, and the features of the dataset were standardized through scaling.
- Various hybrid learning techniques were applied and trained with the dataset. The performances of these techniques were later examined using various standard metrics including learning curves and computational time.

2. Methodology

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

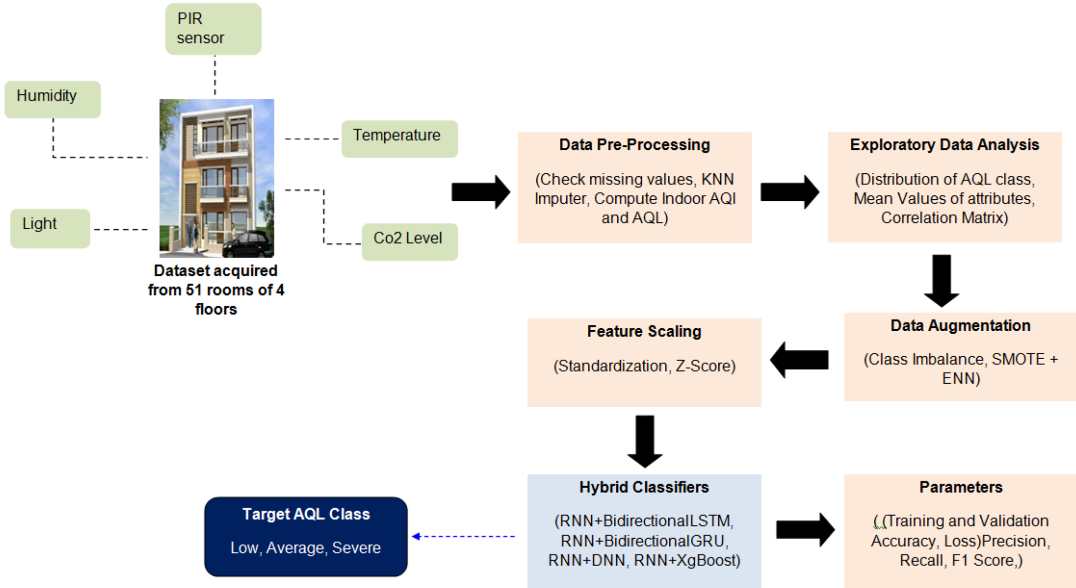


Figure 2: Proposed System Methodology

Dataset: The dataset consists of time series data collected at Sutardja Dai Hall at UC Berkeley from 255 sensors distributed across 51 rooms on their four floors. The data included five types of measurements for each room: CO2, humidity, room temperature, luminosity and motion data from Passive Infrared (PIR) sensors. Apart from this, each entry in the dataset includes a timestamp in Unix Epoch Time (UET) and the corresponding sensor reading [14].

Data Pre-processing: Several steps have been undertaken for pre-processing. Initially, missing or null values are checked for each attribute to ensure integrity and completeness of the data, as shown in Table I. After identifying the missing values, the KNN imputer technique is used to fill them by using information from neighboring points. Subsequently, with a complete dataset, the indoor air quality index (AQI) values for each room are computed and during this process, it is observed that some calculated AQI values are not helpful to meaningful interpretation as well as analysis. Hence, to address this issue, the dataset is refined by excluding records with negative AQI values and two rooms are arbitrarily selected i.e. 415 and 776 for the further execution. Later, based on AQI values, the air quality level (AQL) values are generated as Low (0-50), Average (51-100), and Severe (101-500).

Table I: Attributes with their missing values

Attributes	Data-I (415)	Data-II (776)
Co2	0	1095
Humidity	1113	1
light	1113	1

PIR	55875	59171
Temperature	1114	0

EDA: In this research, the role of EDA is to understand the complex relationships between various environmental factors and energy consumptions for smart room energy efficiency. Figure 3 defines the correlation matrix of the attributes whose values have been recorded from two different rooms i.e. 415 and 776 to identify the relation between them and understand their statistics.

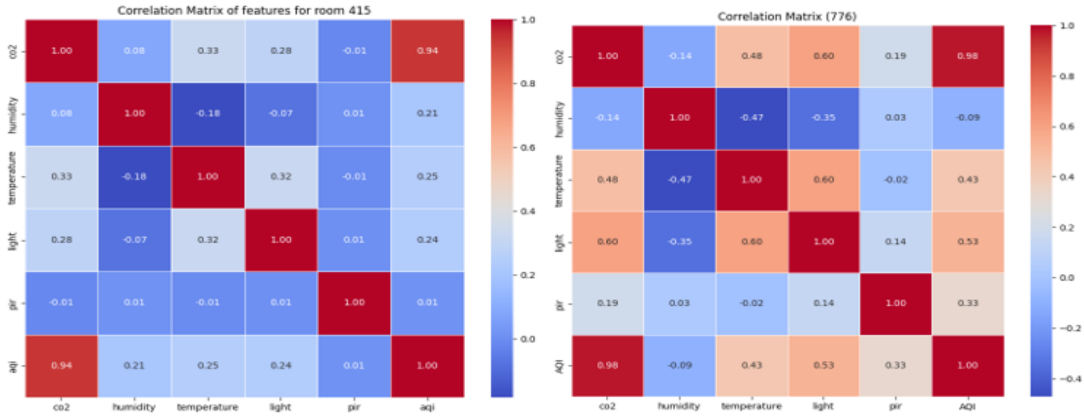


Figure 3: Correlation Matrix

Later, Figure 4 illustrates the distribution pattern of three classes of air quality levels: low, average, and severe. After analysing the data collected from room 415, it can be seen that maximum count is taken up by the LOW with 125143, followed by the AVERAGE class which counts up to 5533 instances, and the SEVERE level with 1330 instances. Conversely, a different pattern can be seen from the data of room 776, where again LOW class takes the highest count of 124252 followed by the least count of SEVERE instances at 182, and an intermediate count of AVERAGE count of 7540.

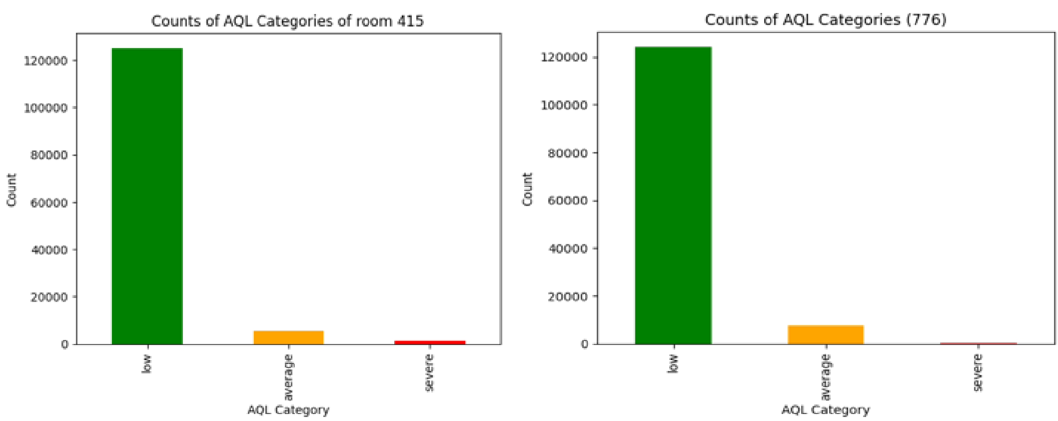


Figure 4: Distribution of AQL classes

In the same way, from Figure 5 and 6, the mean values of attributes like CO2, light, PIR, humidity, and temperature across different air quality levels (low, average, severe) in rooms 415 and 776 are computed to provide the information related to the environmental conditions within each classification. In Figure 5, the average CO2 level in a room classified as having "severe" air quality can indicate potential ventilation issues or high occupancy. Similarly, there is also a graph where the mean value of average and severe air quality levels coincide with zero PIR values, it suggests that either there is minimal human activity in the monitored space or the PIR sensors are not detecting any significant movement.

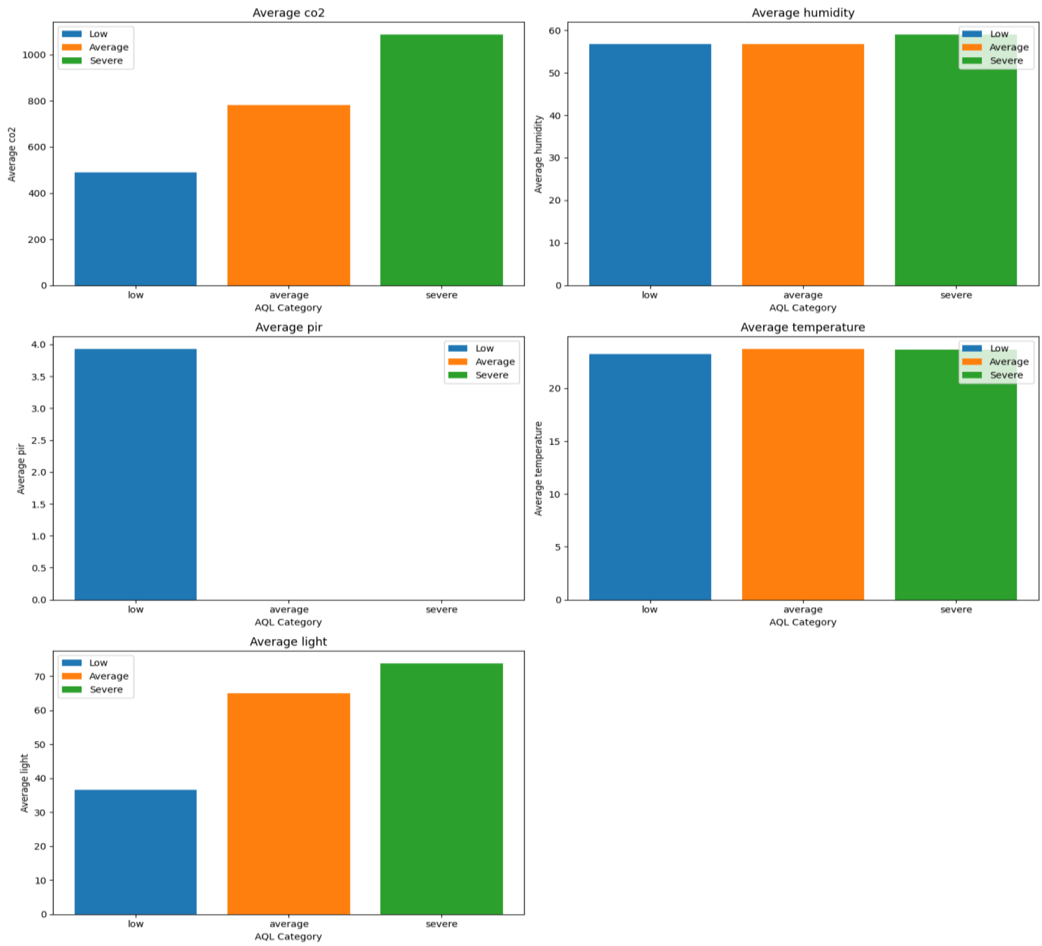


Figure 5: Mean values of attributes taken from Data-I

Likewise, from Figure 6, the minimum mean value of PIR in the low air quality class typically indicates the lowest level of human presence or movement during periods when air quality is categorized as low as compared to the other two classes i.e. average and severe, in the same way a high mean value of light indicate factors such as maximum number of human occupancy, or lighting preferences that contribute to the overall indoor air quality of the room.

In fact, in both the figures, the mean values of humidity across different classes of air quality level (low, average, and severe) are approximately similar within a room which means that the room is equipped with robust environmental control systems, which effectively regulate humidity levels irrespective of variations in air quality. Besides this, it may also suggest that the monitored room is not significantly affected by changes in air quality concerning humidity. In the same way, the similar mean values of temperature across different classes of air quality level indicate effective temperature control mechanisms in place. This consistency suggests that the room maintains a stable temperature regardless of fluctuations in air quality levels.

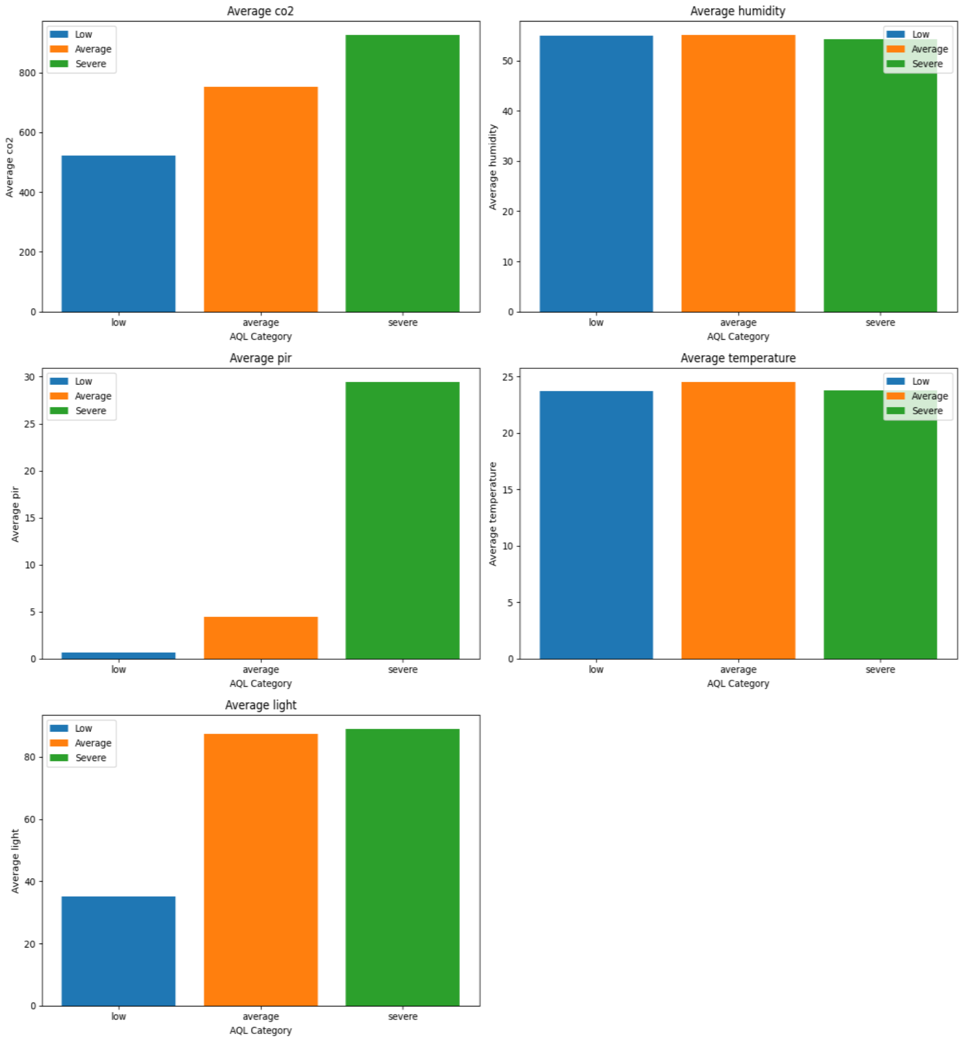


Figure 6: Mean values of attributes taken from Data-II

Data Augmentation: During data analysis, class imbalance issue has been detected for which SMOTE (Synthetic Minority Over-sampling Technique) merged with Edited Nearest Neighbors (ENN) is used to balance it, as presented in Figure 7. SMOTE is a resampling technique that balances the distribution of the class by generating synthetic samples for the minority class and on the other hand, ENN, is an undersampling technique responsible for removing noise from the dataset to improve its quality [15]. It can be represented as

SMOTE+ENN (X,y)= ENN(SMOTE(X_minority),y_minority,k)

Here, X refers to feature matrix of the dataset, y implies target vector of class labels, and k is the number of nearest neighbours used in both SMOTE and ENN.

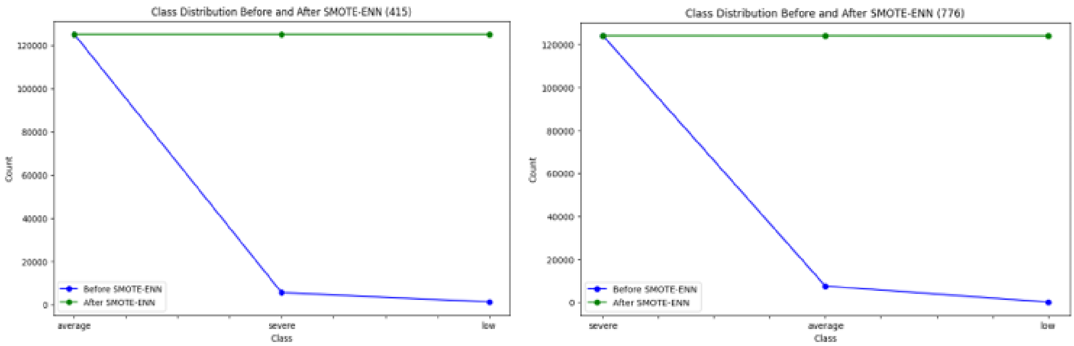


Figure 7: Class balancing after applying SMOTE-ENN

Feature Scaling: In this research, Z-score scaling technique is used that quantifies the deviation of a data point from the mean of a dataset in terms of standard deviations, as shown in Table II and Table III for Data I and Data II respectively. If the value of Z-score is positive, it indicates that the data point is above the mean while as the negative value indicates that data point is below the mean [16].

$z=(x-\mu)/\sigma$

Here, x is the value of input data point, μ is the mean of population, and σ is the standard deviation of population.

Table II: Z-score on Data I

UET	Co2	Humidity	Light	PIR	Temperature	AQI	AQL
325549	1.055964	0.144425	2.379320	-0.023165	0.723173	0.938428	severe
117896	0.143589	0.157201	-0.093807	-0.023165	0.763403	0.129716	average
249640	-1.277454	0.189566	2.190298	-0.023165	0.058066	-1.439350	low

Table III: Z-score on Data II

UET	Co2	Humidity	Light	PIR	Temperature	AQI	AQL
358818	1.110844	-0.257155	0.487516	1.297579	-0.454014	1.167029	severe
210124	-1.228468	1.217274	-1.693483	-0.813769	-0.312602	-1.205204	low
68366	0.746597	-0.247127	-0.176100	-0.813769	-0.771739	0.540879	average

Classifiers: In this paper, Recurrent Neural Networks (RNN) with advanced machine learning techniques are hybridized for assessing their efficacy to handle the complexity of smart building dataset.

Recurrent Neural Networks (RNNs) constitute an important component in the domain to enhance smart building energy efficiency. It comprises of interconnected neurons that maintain a hidden state h_t at each time step t. The update process of the hidden state in an RNN is governed by a nonlinear function f which operates on x_t (current input) and h_{t-1} (previous hidden state). Mathematically, this update is expressed as $h_t = f(x_t, h_{t-1}; \theta)$ where θ represents the parameters of the RNN. The hybrid architecture of RNN and bidirectional LSTM as well as RNN and bidirectional GRU combines the sequential data processing capabilities of RNNs with the enhanced context capturing ability of bidirectional LSTM networks. Here, after RNN process the input time series data sequentially, its output is fed to a bidirectional models which processes the sequence from the start to the end (forward direction), and the other processes it from the end to the start (backward direction). This dual processing captures information from both past and future contexts at each time step [17]. Both GRUs and LSTMs are types of RNN which are designed to capture long-term dependencies and mitigate issues like the vanishing gradient problem but there is a difference in their internal mechanisms and computational efficiency. Mathematically, the forward and backward hidden states of the bidirectional models are denoted as ($\overrightarrow{h_t}$ and $\overleftarrow{h_t}$)respectively and the final output at each time step t is the concatenation of these hidden states:

$$\widetilde{h_t} = [\overrightarrow{h_t}; \overleftarrow{h_t}]$$

Subsequently, the RNN+DNN architecture is used to strengthen both sequential data modeling and deep learning capabilities in order to enhancing predictive performance. Within this hybrid model, the RN model process the time-series data to capture temporal dependencies to generate a sequence of hidden states which are then inputted into a DNN for further processing. DNNs comprise multiple layers of interconnected neurons, with each layer applying a linear transformation followed by a nonlinear activation function to the input data [18]. The output of the DNN is computed using

$$\hat{y} = g(W_n . g(W_{n-1} . \dots g(W_1 . x + b_1) + b_{n-1}) + b_n)$$

where g is the activation function, W_i and b_i are the weights and biases of the i^{th}, and x is the input to the network. At the end, the RNN+XGBoost architecture uses both sequential data modeling and powerful gradient-boosted decision trees where the RNN processes the time-series data to capture temporal dependencies and outputs a sequence of hidden states which is then fed into an XGBoost model as features [18] and the objective function is computed using:

$$\mathcal{L}(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

where l is a differentiable loss function to measure discrepancy between the actual y_i and predicted value $\hat{y}_i$, and Ω is a regularization term that penalizes the complexity of the model.

Performance Metrics

In the context of smart city classification based on air quality index (AQI), several key metrics are typically used to evaluate the performance of classification models. Accuracy, the proportion of correctly classified instances, provides an overall measure of model performance [19].

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative}}$$

Loss, often measured using metrics like cross-entropy, quantifies the difference between predicted and actual values, serving as a gauge of model convergence and optimization.

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

Precision, a measure of the proportion of correctly predicted positive cases among all predicted positive cases, is crucial for assessing the model's ability to avoid false positives in identifying areas with poor air quality while as Recall, computes the ability of the model to capture all actual positive cases that are correctly identified.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

F1 score balances the performance of model on the basis of their precision and recall. It is mostly useful when there is no balance between positive and negative instances.

$$\text{F1 score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Recall} + \text{Precision}}$$

3. Results

The section presents the results of the models which have been trained by the data collected from both the rooms in different subsections.

Analysis of models for the Data I of Room 415

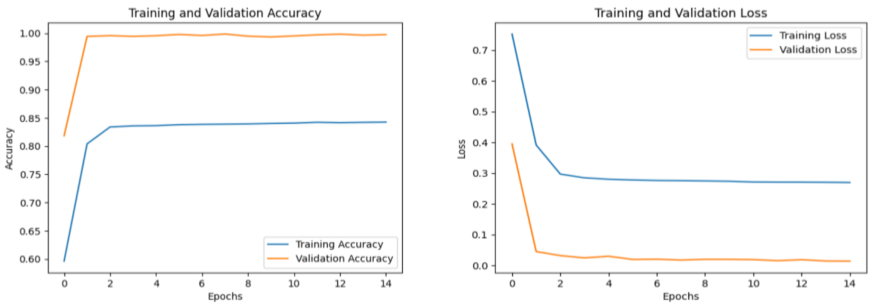
Table IV presents a comparative analysis of different models based on their performance metrics, specifically accuracy and loss, on both training and validation datasets.

Table IV: Analysis of models (Room 415)

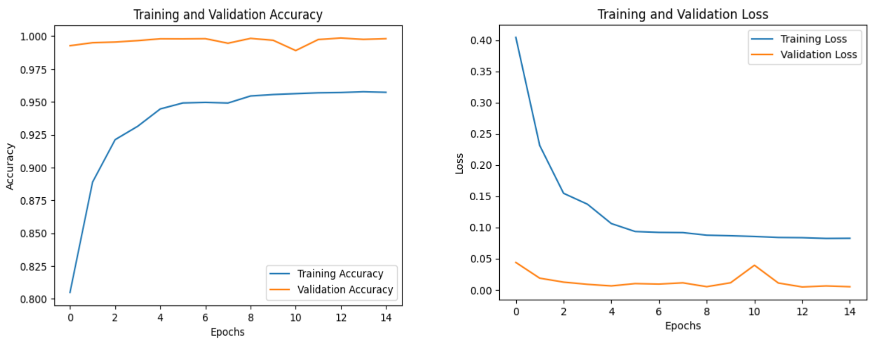
Models	Training		Validation	
	Accuracy	Loss	Accuracy	Loss
RNN+Bidirectional GRU	84.25	0.2696	99.75	0.0139
RNN+Bidirectional LSTM	95.73	0.0826	99.81	0.0050
RNN + DNN	39.29	1.3675	33.17	0.9535
RNN + XgBoost	87.20	21.89	99.76	0.0118

Employing a bidirectional GRU, demonstrates an accuracy of 84.25% on the training set and 99.75% on the validation set, with respective losses of 0.2696 and 0.0139. Likewise, using a bidirectional LSTM, further improvement in performance has been observed with an accuracy (95.73%) on the training and 99.81% on the validation with lower loss values. On combining a simple RNN with a DNN, exhibits relatively poor performance. With an 39.29% as training accuracy and 33.17% as validation accuracy along with high values of loss i.e. 1.3675 and 0.9535 respectively, this model fails to capture the underlying patterns in the data. RNN+XGBoost, demonstrates competitive training and validation accuracies of 87.20% and 99.76% respectively. However, the loss values, particularly the training loss of 21.89, suggest potential overfitting of RNN+XgBoost.

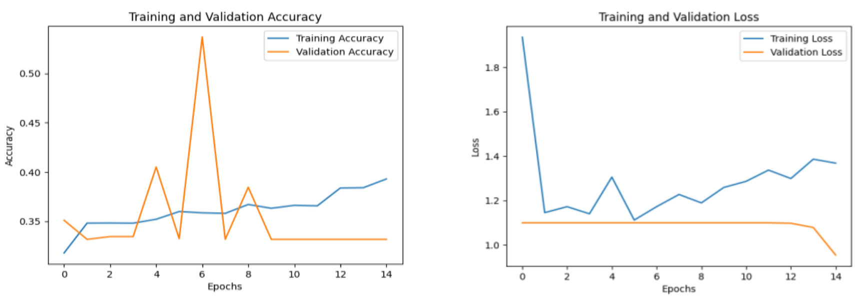
In addition to this, the models have been also examined on the basis of their learning curves and it has been found that they show a serious cause of underfitting except RNN+DNN which shows overfitting (Figure 8).



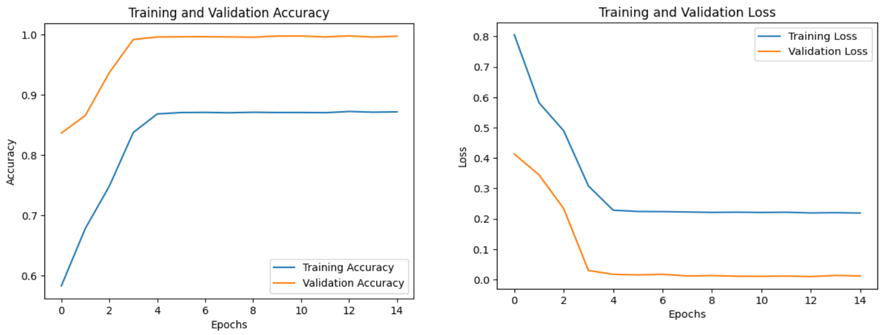
a) RNN+Bidirectional GRU



b) RNN+Bidirectional LSTM



c) RNN + DNN



d) RNN + XgBoost

Figure 8: Assessing the classifiers on the basis of their validation accuracy and loss

Table V provides insights into the classification performance of models on the basis of precision, recall, and F1-score.

Table V: Examination of classifiers for different parameters (Room 415)

Models	Precision	Recall	F1score
RNN+Bidirectional GRU	0.9974	0.9974	0.9972
RNN+Bidirectional LSTM	0.9977	0.9980	0.9954
RNN + DNN	0.9998	0.9998	0.9998
RNN + XgBoost	0.9996	0.9997	0.9998

BidirectionalGRU indicate robust performance by demonstrating high precision and recall values both at 0.9974 and an F1-score of 0.9972. BidirectionalLSTM, also displays excellent precision as 0.9977 and recall as 0.9980, which contribute to an F1-score of 0.9954. RNN+DNN, presents highly accurate and reliable classification outcomes by computing balanced precision, recall, and F1-score values, all at 0.9998. RNN+XGBoost, demonstrates similarly balance performance with precision and recall both at 0.9996 and an F1-score of 0.9998.

Furthermore, a confusion matrix of models has been generated to comprehend the true and predicted values of each class, in Figure 9.

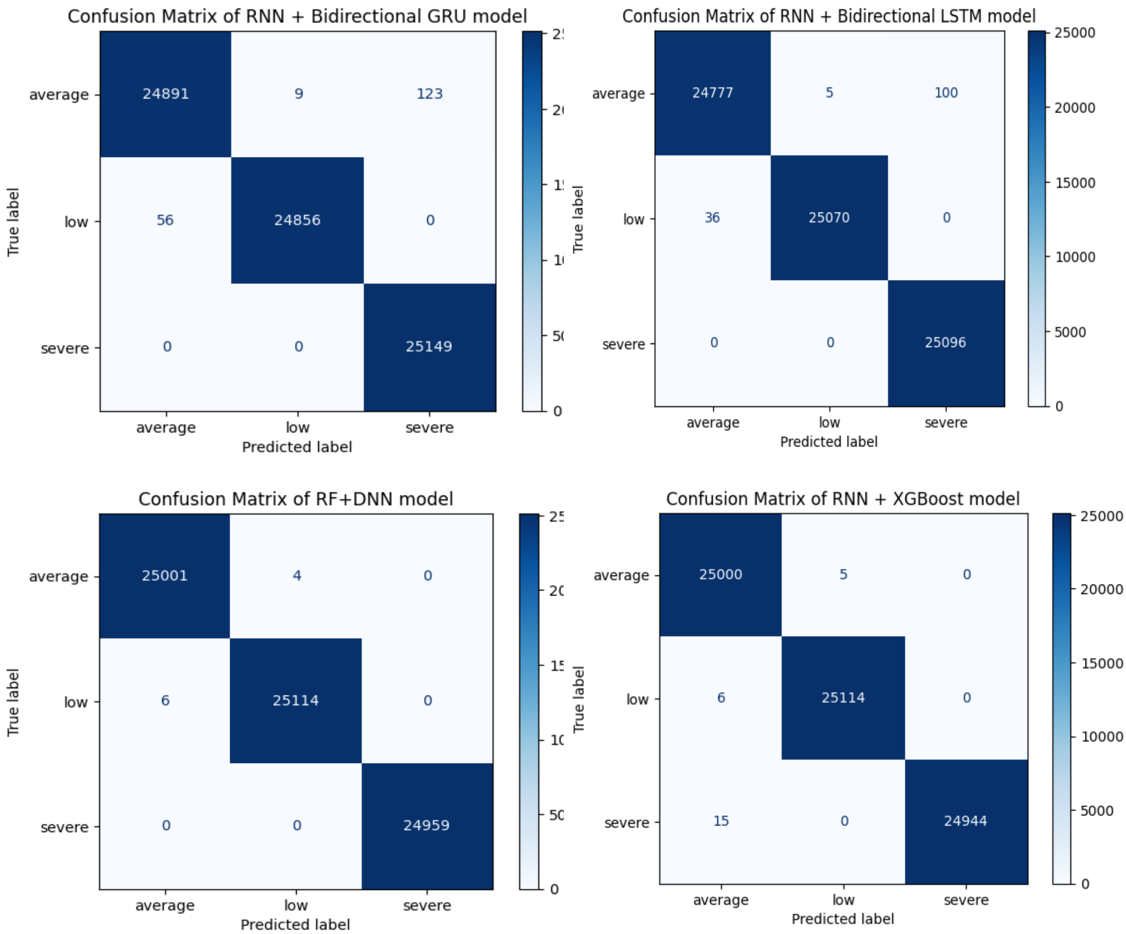


Figure 9: Confusion matrix of models for Data-I

Table VI presents the execution of models for different classes of smart room datatset in the form of "Low," "Average," and "Severe".

Table VI: Execution of models for different classes of room 415

Models	Class	Precision	Recall	F1score
RNN+Bidirectional GRU	Low	0.9996	0.9977	0.9986
	Average	0.9977	0.9947	0.9961
	Severe	0.9951	1.00	0.9975
RNN+Bidirectional LSTM	Low	0.9998	0.9985	0.9914
	Average	0.9985	0.9957	0.9970
	Severe	0.9960	1.00	0.9979
RNN + DNN	Low	0.9998	0.9997	0.9997
	Average	0.9997	0.9998	0.9997

	Severe	1.00	1.00	1.00
RNN+ XgBoost	Low	0.9998	1.00	0.999
	Average	0.9991	0.9998	0.999
	Severe	1.00	0.9993	0.9996

RNN + DNN and RNN + XGBoost models achieve almost perfect scores across all metrics and highlight their impact to accurately identifying patterns in case of Low class. In the "Average" class, albeit of having lower scores than Low class, the performance of all models remains strong. Finally, in the "Severe" class, RNN + DNN model achieves perfect scores across all metrics, which indicates its ability to handle even the most challenging datasets effectively. Similarly, the RNN + XGBoost model demonstrates excellent precision and F1-score, albeit with a slightly lower recall, suggesting some difficulty in correctly identifying all instances within this class. The bidirectional models also perform well by computing good scores of these metrics to showcase their capacity in handling such data scenarios.

Analysis of models for the data-II of Room 776

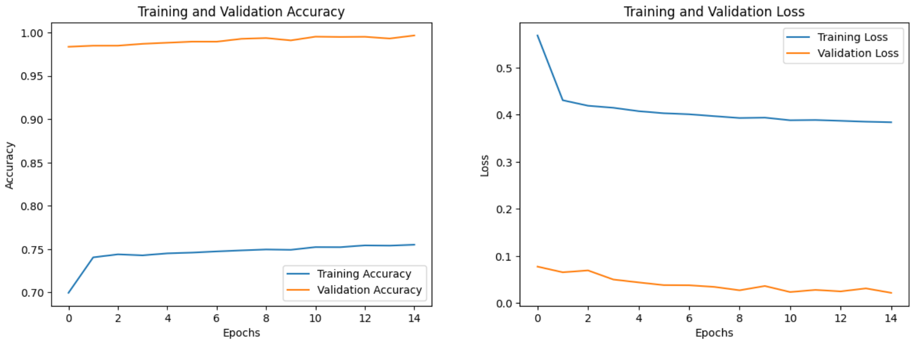
Table VII presents the performance metrics for four different models on both the training and validation datasets.

Table VII: Analysis of models (Room 776)

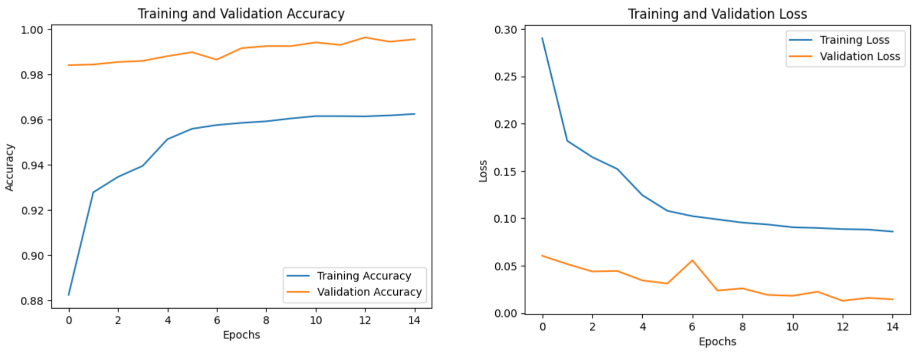
Models	Training		Validation	
	Accuracy	Loss	Accuracy	Loss
RNN+Bidirectional GRU	75.43	0.3844	99.67	0.0221
RNN+Bidirectional LSTM	96.62	0.0864	99.56	0.0144
RNN + DNN	42.92	1.2139	47.61	0.8524
RNN + XgBoost	95.92	0.0797	99.17	0.0289

RNN+Bidirectional GRU model performs well on the dataset by obtaining an accuracy of 75.43% on the training set and a higher accuracy of 99.67% on the validation set with the losses of 0.3844 and 0.0221 respectively. Moving to the RNN+Bidirectional LSTM model, it achieves higher accuracy on the training set, at 96.62%, but computed lower validation accuracy, at 99.56% with the respected associated losses as 0.0864 and 0.0144. Likewise, the RNN+XGBoost model also demonstrates strong performance by achieving a training accuracy of 95.92% on 0.0797 as training loss and validation accuracy of 99.17% on 0.0289 as validation loss. But on the other hand, the RNN+DNN model shows its struggle to learn from training data as it shows poor performance by computing only 42.92% as training accuracy and 47.61% as validation accuracy with highly notable losses of 1.2139 for training and 0.8524 for validation.

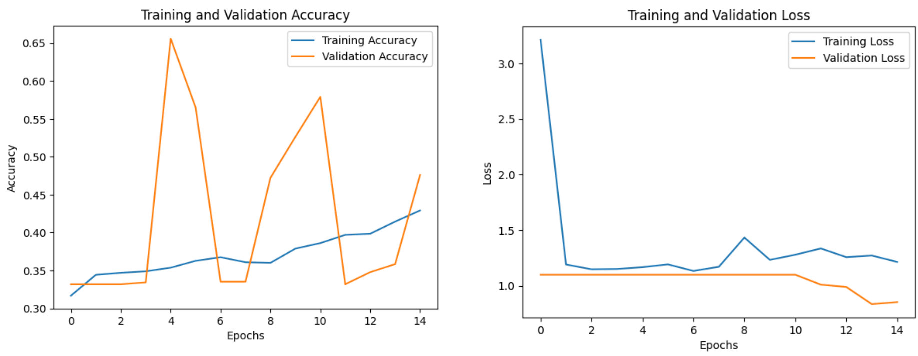
Furthermore, the models have been also evaluated based on their learning curves, revealing a significant issue of underfitting (Figure 10).



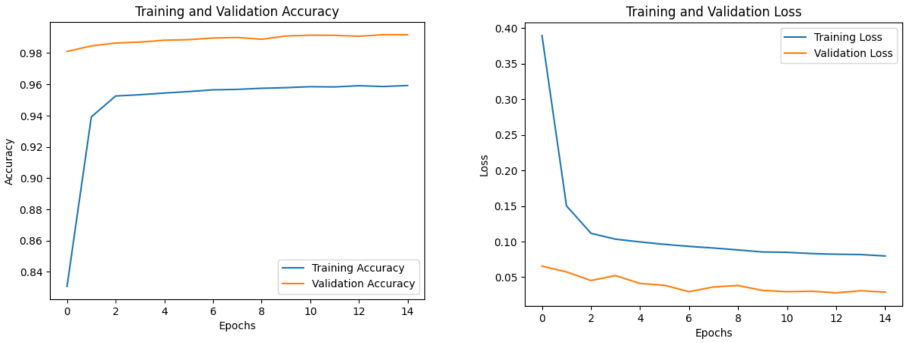
a) RNN+Bidirectional GRU



b) RNN+Bidirectional LSTM



c) RNN + DNN



d) RNN + XgBoost

Figure 10: Graphical assessment of classifiers

In addition to this, Table VIII presents precision, recall, and F1-score metrics for four different models: RNN+Bidirectional GRU, RNN+Bidirectional LSTM, RNN+DNN, and RNN+XgBoost.

Table VIII: Examination of classifiers for different parameters (Room 776)

Models	Precision	Recall	F1score
RNN+Bidirectional GRU	0.9979	0.9967	0.9973
RNN+Bidirectional LSTM	0.9956	0.9956	0.9955
RNN+DNN	0.9989	0.9989	0.9989
RNN+XgBoost	0.9971	0.9996	0.9983

RNN+DNN model demonstrates outstanding performance by obtaining the highest precision, recall, and F1-score among all models, with values of 0.9989 for each metric followed by RNN+BidirectionalGRU model effectively minimizes the false positives and captures the high proportion of true positives by achieving the high precision, recall, and F1-score, with values of 0.9979, 0.9967, and 0.9973 respectively. RNN+XgBoost model also achieves high precision and F1-score, with values of 0.9971 and 0.9983 respectively, while exhibiting the highest recall of 0.9996 among all models while as RNN+Bidirectional LSTM model obtains the least value of precision, recall, and F1-score values of 0.9956, 0.9956, and 0.9955 respectively.

In addition to this, the confusion matrix of the models has been also generated to understand the actual as well as predicted value of each class (Figure 11).

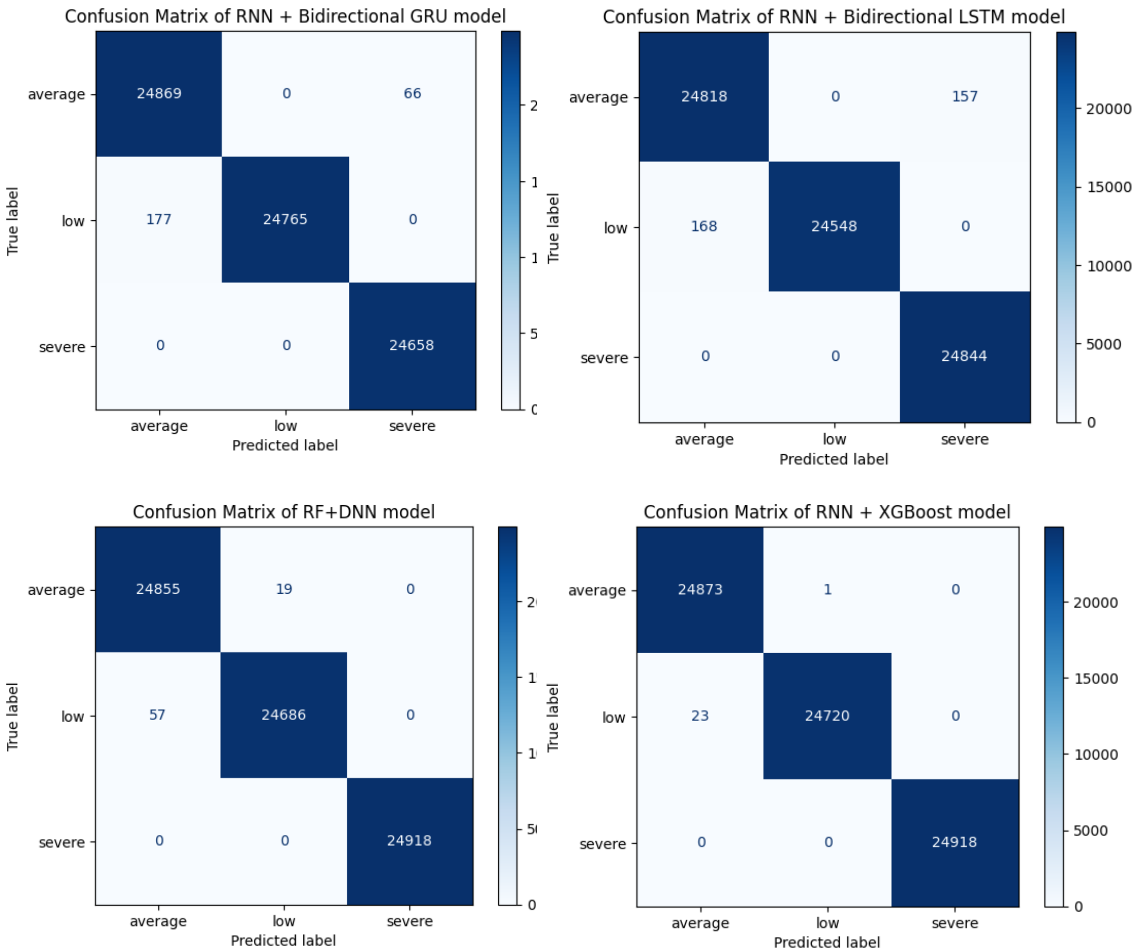


Figure 11: Confusion matrix of models for Data-II

Table IX offers the analysis of models across different classes of dataset as "Low," "Average," and "Severe," based on precision, recall, and F1-score metrics.

Table IX: Execution of models for different classes of room 776

Models	Class	Precision	Recall	F1score
RNN+Bidirectional GRU	Low	1.00	0.9929	0.9964
	Average	0.9969	0.9973	0.9970
	Severe	0.9973	1.00	0.9986
RNN+ Bidirectional LSTM	Low	1.00	0.9932	0.9965
	Average	0.9932	0.9937	0.9934
	Severe	0.9937	1.00	0.9968
RNN + DNN	Low	0.9992	0.9976	0.9983
	Average	0.9977	0.9992	0.9984

	Severe	1.00	1.00	1.00
RNN + XgBoost	Low	0.9999	0.9990	0.9994
	Average	0.9914	0.9999	0.9956
	Severe	1.00	1.00	1.00

In the "Low" class, all models compute high precision scores which indicate a low false positive rate except RNN + DNN and RNN + XGBoost models. However, slight variations can be seen in recall and F1-score across models, with the RNN + DNN and RNN + XGBoost models showing highest recall values as compared to the RNN + Bidirectional models. Moving to the "Average" class, a consistent performance is being observed across most models, with drifting around 99% range of these metrics and here RNN + DNN model shows its ability to effectively capture a high proportion of true positives. However, the RNN + XGBoost depict a slightly higher false positive rate because of low precision. In the "Severe" class, RNN+XgBoost stand out where as all models demonstrate correctly identifying of instances with minimal false positives and negatives.

Table X presents the overall computational time taken by the models to process the Data I and Data II. Despite of their efficiency in handling long term dependencies, RNN+GRU took the longest training time of 4 hours followed by RNN+Bidirectional Long Short-Term Memory networks which took 3 hours and 45 minutes. RNN+DNN proved to be efficient by having training time of 2 hours and 30 minutes along with RNN+XgBoost which completed training in 2 hours and 15 minutes. This reduction in time is due to the ability of the models to handle the structured data and reduce the overall complexity as well as training duration compared to bidirectional architectures.

Table X: Computational time of models

Models	Time frame
RNN+Bidirectional GRU	4 hrs
RNN+Bidirectional LSTM	3 hrs 45 min
RNN+DNN	2 hr 30 min
RNN+XgBoost	2 hrs 15 min

4. Conclusion

The paper emphasizes the role of using advanced machine learning techniques for enhancing energy efficiency in indoor environments. Through the development as well as implementation of hybrid approaches, Recurrent Neural Networks with Bidirectional LSTM and GRU computed high validation accuracies as well as the results also demonstrate the effectiveness of the proposed hybrid classifiers in accurately classifying air quality levels based on multiple parameters. However, few limitations encountered during our research such as the issue of underfitting and the poor performance of RNN+DNN in terms of accuracy and loss which can be improved by using optimization techniques in order to generate robust as well as generalizable results. Moving forward, there are several avenues for future research which includes more advanced AI techniques as well as the optimizers, diversity of dataset, and integration of technologies such as IoT devices and sensor networks to investigate the energy efficiency of a room more properly and its cost effectiveness.

Statements and Declarations

Competing Interests

On behalf of all authors, the corresponding author states that there is no competing interest / conflict of interest.

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Author Contribution

First author Jasbir Singh Saini mainly contributed for the conceptualisation of the research work, analysis of results, data curation and writing original draft of manuscript. Second author, Sunny Arora contributed in conceptualisation of research, selection of tools to be applied for this work and supervision. Third author Sushil Kamboj contributed for writing the manuscript, analysis of results, and supervision.

Data Availability Statements

Dataset comprising 1.3 lakh records related to smart building systems are taken from https://www.kaggle.com.

Research involving Human and/or Animals

Not applicable

Informed Consent

Not applicable

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