Sustainable Smart University: A Short-Term Deep Learning Framework for Energy Consumption Forecast

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***Abstract*—A smart city should ideally be environmentally friendly and sustainable, and energy management is one technique to monitor sustainable use. Similarly, this notion might be applied in an urban form, such as the sort of city in which a university would be located. This research analyzes the possibility for a university to enhance energy management by permitting the adoption of a variety of intelligent technologies that increase the energy sustainability of a city's infrastructure and the effectiveness of its operations. In the first module of the proposed system, we place significant emphasis on the data capabilities necessary to create energy statistics for each of its various buildings. In the second phase of the technique, we employ the collected data to conduct a data analysis of the energy behavior inside micro-cities, from which we derive characteristics. In the third module, we develop baseline regressors to assess the varying degrees of efficacy of the proposed model. Last, we describe a way for developing an energy prediction model using a deep learning regression model to solve the problem of short-term energy consumption forecasting. The performance metric results show that the suggested deep learning model increases performance prediction compared to other traditional regression techniques. The proposed model has superior RMSE, MAE and R squared results compared to alternative regression models.**

***Index Terms*—Deep learning, energy consumption, sustainable urban energy, sustainable smart campus**

I. Introduction

Data on energy management is gathered by smart buildings from a large sensor network. These sensors can predict energy use, alter thermostat settings, and improve the building's safety and resiliency. Controlling and evaluating energy consumption in multiple buildings may be difficult, particularly if power demand is irregular. Only buildings where people live, and work use as much energy. According to projections from the U.S. Department of Energy, by 2020, Americans will use over 20 million megawatt hours (MWh) for residential purposes and over 16 million for commercial purposes, totaling over 29% of all energy consumed [1]. A total of 60% of the energy used in homes is utilized for space cooling, space heating, and electrical equipment [2]. Therefore, forecasting energy usage is a component of building energy management. The projection of energy demand affects both energy-efficient building technology and building operation and maintenance. Building owners can make operational and maintenance decisions based on an estimated energy use. To make financially sound judgments concerning refurbishment and remodeling, such as replacing large building components like hot water, air conditioning (HVAC), power generation, lighting, and refrigeration systems, building owners require reliable energy demand estimations. Building owners benefit from accurate energy demand prediction for energy forecasting, demand reduction, energy audits, efficiency enhancement, and demand response. Precise energy demand estimation is also used in energy policy and planning, building certification, testing, and inspection, and building lifecycle cost management.

According to the Energy Consumption Statistics published in 2020 by the Korea Energy Management Corporation and Korea Energy Agency, academic institutions are using more energy as technology advances. Technology is expected to increase this ratio, which in 2020 accounted for 10.2% of all energy use in educational buildings in Korea. Energy consumption in educational buildings has increased by 16.3% since 2000 [3]. The demand for power in academic laboratories is predicted to increase. Energy use varies depending on the research activity, experiment type, and research facility, although laboratory activity accounts for most of these situations.

Universities and research institutions must manage and analyze energy consumption, decrease energy waste, and optimize energy used to evaluate energy-saving initiatives. An energy prediction framework for smart universities is suggested in this study. Campus data from several components and buildings is combined and brought together on a cloud platform for storage, processing, and communication. The platform also monitors, regulates, and assesses energy usage. Beyond academic study, we consider temporal and environmental elements like temperature and humidity. Many studies have been conducted pertaining to the application of machine learning and deep learning across diverse domains [4–10]. Deep learning may transform unstructured data in a smart campus into information that helps decision-makers in university towns be more energy-conscious. The university city in this research comprises student housing, laboratories, gyms, cafeterias, student offices, and workplaces.

Power grid operators and energy firms may have greater opportunities to improve their energy systems because of smart universities as a small scale for a city's potential to generate information and massive amounts of data using embedded and Internet of Things technology [11]. Additionally, we want to help decision-makers enhance the academic, operational, and commercial performance of university buildings by offering an effective energy management tool.

In this study, we demonstrate how energy data may be used campus-wide for smart energy management in a university

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using deep learning for energy use and prediction. Additionally, we want to show how energy data can help with energy management using the energy management system data from 2019 to 2021, building energy consumption, and meteorological data.

Although some research [12–14] looks at the relationship between energy consumption and climate change, regression models with a few parameters are used in most studies [15–17] that forecast energy. Analysis of historical data is essential since energy consumption trends differ. Variables include the weather, the seasons, and the work hours of city residents. Even if dynamic patterns are difficult to predict, better municipal energy management and public policy can still be achieved.

Furthermore, by analyzing energy consumption from previous energy studies, residential and non-residential buildings can be further classified. Some studies are covered in residential buildings [18–20]. In the case of Korean building, energy utilization is examined in another research [21–23]. Thus, studies of the non-residential buildings frequently focus on offices, hospitals, and universities [24–27]. This study was influenced by both residential and non-residential building categories. The future of energy consumption must also be determined via analysis. To integrate and compare data, we assess several methods and create a deep learning architecture. Therefore, correct energy delivery is made possible by electrical suppliers and the government by forecasting energy, taking external variables into account, and selecting important variables like specific building consumption. Efficient energy management is of paramount importance for the sustainability and cost-effectiveness of university campuses. In this study, we propose a deep learning architecture that leverages multiple neural networks to forecast energy consumption accurately over a 48-hour period. By utilizing historical energy consumption data from individual buildings, we establish a comprehensive understanding of the university's overall energy usage patterns. External variables, including weather observations, are integrated into the deep learning network to enhance the precision of our energy consumption model.

This research presents a deep learning architecture with several neural networks for 48-hour energy prediction. The foundation is energy consumption. The university's overall energy usage is obtained by identifying the patterns of each building, creating a data structure, and merging those structures. Estimating a university's energy use might lead to better energy regulations and less waste. A deep learning network used in this study applies to the energy consumption model, which also considers external variables, such as weather observations. From the perspective of the smart university, this research aims to comprehend the dynamics of each building to make energy consumption sustainable for the entire city. By examining the energy usage and causes of each structure, we can develop university wide energy-saving strategies. To test our model, we realize the experiments over the campus data, this comparison identifies the accuracy and potential areas for development of our model. We put our model through statistical testing to make sure it meets the requirements for energy consumption forecasting.

After this introductory section, the remainder of this paper is structured as follows: Section II introduces our methodology. Section III explains how to gather, prepare, and analyze data; Section IV contrasts our suggested model with competing regression models; and Section V sums up our conclusions and suggests further research.

II. METHODOLOGY

The framework for predicting university energy consumption is described in this section. The three key elements of the framework for forecast energy consumption are shown in Fig. 1: data collection, preprocessing, and the proposed model recurrent biLSTM. Our proposed deep learning architecture comprises multiple interconnected neural networks. Each network focuses on specific aspects of energy consumption patterns, such as temporal dependencies, weather conditions, and building-specific characteristics. These networks are trained using historical energy consumption data to learn the underlying relationships and capture complex dynamics.

The first two datasets are from South Korea's national university, Incheon National University (INU). In our research, we concentrated on the Global Campus launched in 2009, located in the city of Songdo in Incheon, South Korea. Therefore, we collected detailed energy consumption data from various buildings across the university campus. These data were processed and structured to form a unified dataset, allowing us to capture the diverse energy consumption patterns within the university. Since INU is a young university, much of the equipment in its buildings is also new. INU started gathering information from energy consumption in November 2019. INU Songdo Campus comprises 456,806 m2 of plottage, 216,732 m2 of major buildings, and 35,801 m2 of underground parking. It is at 37.3751° N and 126.6328°E. Most buildings track their energy usage hourly. The “International Exchange Center”, “College of Urban Science”, “College of Business/School of Northeast Asian Studies”, and “College of Social Science/College of Global Law, Politics, and Economics” do not track energy consumption, so this study does not include data from these buildings.

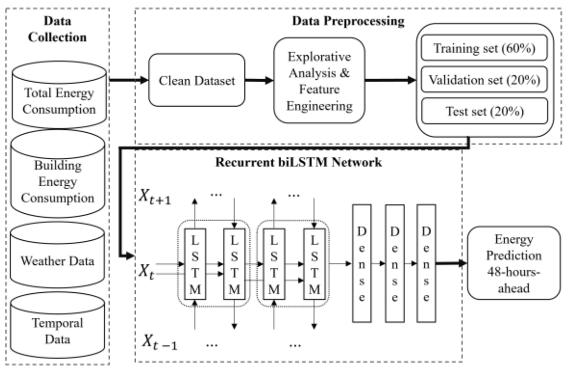

Fig. 1. Energy regression framework for smart universities.

The Korea Meteorological Administration (KMA) reported climate variables related to the city of Songdo, such as air pressure, temperature, dew point, precipitation, wind speed, and sky conditions. By acquiring temporal data from the point at which it was captured, the time series of the model was kept up to date.

The data sources combined contains one dependent variable: total energy consumption, the following independent variables: nine meteorological elements, four temporal variables, and the energy consumption of 17 academic buildings, including two dormitories, one sport center, and one gymnasium, for the time between November 30, 2019, and January 19, 2021. 9976 records in 32 columns were gathered over the course of 14 months.

To enhance algorithm performance, Section III outlines data preparation, an exploratory study, data modification, and data transformation. In order to evaluate model performance and hyperparameter tuning, the input data is divided into three sets: a training set with 60% of the total data, a validation set with 20%, and a test set with 20%. To use deep neural networks, the data preparation module must first offer numerical values within a specific range [28]. In contrast to ordinal categorical variables, which are represented numerically, nominal categorical variables are converted into several binary variables.

About the proposed recurrent biLSTM network, the model comprises 2 bidirectional LSTM, or biLSTM. The biLSTM is made up of two LSTMs. One of the LSTMs processes the input in a forward manner, while the other processes it in a backwards way [28, 29]. BiLSTMs are an excellent way to expand the quantity of information that is available to the network, which improves the context that is available to the algorithm (for example, being aware of the energy that will be consumed immediately and the energy that has been consumed, all seen as a time series).

In the third module, the ideal hyperparameters for the suggested network are selected. First, a grid search strategy is used in both the training and validation modules. The proposed deep learning model is proven by comparisons with other regression models. In this study, 6 algorithms were used, which are divided into 4 categories. The single regression methods investigated in this work are linear regression and k-nearest neighbors regressor (k-NN). CatBoost was selected as the ensemble regression method, Gaussian Process as Bayesian method approach. Finally, artificial neural networks (NN) and our proposed biLSTM are the algorithms used as part of the deep learning category.

Selected models are thoroughly examined at the end using and unseeing data. By estimating energy use 48 hours in advance, the recommended biLSTM regression model performed best on different metrics over the test set.

III. Data Analysis

This section preprocesses and analyzes the energy dataset from INU. The dataset starts recording data from 10:00 a.m. on November 30th, 2019, to January 17th, 2021, making a total of 9975 records. All variables use data with an hourly input. Energy consumption and time-dependent aspects are discussed in subsection A. Independent factors, variable energy usage in buildings, and meteorological information are covered in the following B and C subsections.

A. *Energy Consumption*

Energy meters on INU campus keep track of usage hourly. Fig. 2 shows the time series of energy consumption in INU, which in turn is divided into the three datasets (training, validation, and test) which will be discussed more in detail in the results section. The trend component enhances the monitoring of energy consumption by displaying low-frequency variations. From Fig. 2 can be observed that from December 2019 indicates an increase in energy use. The trend component for December 2019 indicates a decrease in energy use until the beginning of June 2020. This was due to the outbreak of COVID-19, which began in the year 2020 and, since then, the use of energy has been decreasing. In addition, due to this situation, many undergraduate students stopped going to the University, starting to take classes online. Moreover, it was not the case for the professors, administrative area and students of masters and doctorates.

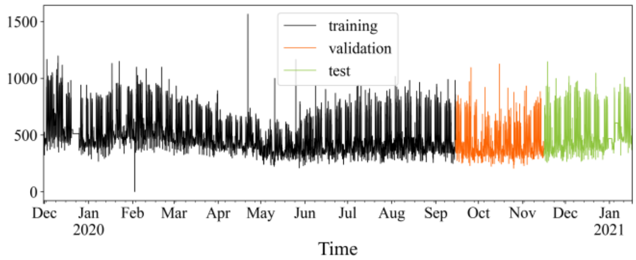

Fig. 2. Energy consumption of INU from November 2019 to February 2021.

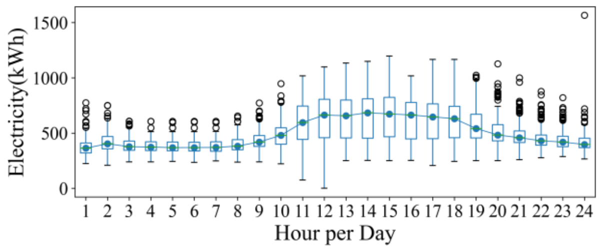

Fig. 3. Energy consumption distribution of INU per hour by day.

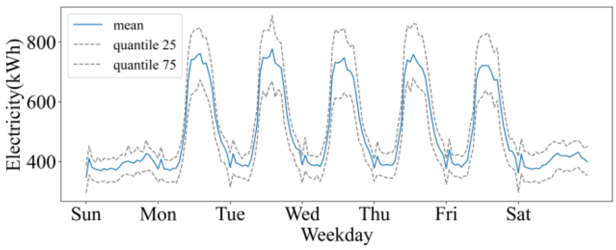

Fig. 4. Mean of the energy consumption distribution of INU per weekday.

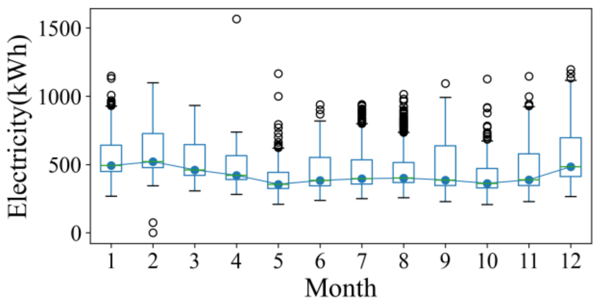

Fig. 5. Energy consumption distributions of INU per month.

Fig. 3 presents the energy consumption distribution each 24 hours per day. In addition, the behavior pattern of administrative staff, students and teachers can be observed. Therefore, working hours need additional energy, as expected. Energy consumption increases from 8 am and begins its decrease between 10 and 11 pm. Additionally, an outlier performed at 24 hours can be observed, which could be due to some experiment that consumed a high amount of energy. That was presumably an experiment at Building 4 in the department of computers and information. Fig. 4 shows the distribution of the average by day of the week. As expected, we see a normal work schedule from Monday to Friday with a minimum of energy consumption on the weekend. Fig. 5 presents a boxplot of the monthly energy consumption. Because in South Korea the weather seasons are very clear, this is also observed in using energy consumed at the University. When heating is used, energy use in 2020 increases from the end of January to beginning of March and decreases from March to May. Air conditioning contributes to a slight rise in summer between June to September of energy usage and a decrease in fall season. Winter energy demand has increased because of heating.

B. Energy in Building Structures

Energy metering sensors in certain buildings track energy consumption hourly. They are examined in this section. Seventeen buildings were analyzed, getting the individual energy consumption shown in Table I. Within our analysis we could observe variable 04.Information_Computing is the outlier from Fig. 3 and 5. The variables 07.Information_Technology, 08.College_Engineering, and 10.GuestHouse show several outliers between September and December 2020. The 06.Library building, which was closed for COVID-19 prevention from mid-February to mid-February June 2020, used less energy. The university offices, faculty offices, the central laboratory department, the arts and physical education department, and the student center use power continuously. The department of natural sciences and student residences used less energy because of more online courses.

TABLE I: BUILDINGS ANALYZED FROM INU

Variable name
01.University_Headquarters
02.Faculty_Hall
04.Information_Computing
05.Natural_Science
06.Library
07.Information_Technology
08.College_Engineering
09.Joint_Experiment
10.GuestHouse
11.Welfare_Hall
12.Convention
15.College_Humanities
16.Art_Sports
17.Student_Hall
18-1.Dormitory
20.Sport_Center
21.Gym

C. Weather Variables

To capture important weather data that weather forecasting might lack, this study uses weather observation data for energy consumption prediction. The choice of weather observation and forecast is dependent on how they differ. Weather observations are reported by KMA every hour, while predictions are reported every three hours. The eight measured climatic variables obtained from the city of Songdo are shown in Table II. Additionally, we transform the variable Wind_Speed and Wind_Direction into their respective cosine and sine forms as shown in equations (1) and (2).

$$Wx = Wind\_Speed * \cos((Wind\_Direction(deg) * \pi)/180). \quad (1)$$

$$Wy = Wind\_Speed * \sin((Wind\_Direction(deg) * \pi)/ 180). \quad (2)$$

TABLE II: WEATHER VARIABLES FROM SONGDO, YEONSU-GU, INCHEON, SOUTH KOREA

Variable name
Dew_Point
Humidity
Precipitation
Pressure
Sky Condition
Temperature
Wind_Speed
Wind_Direction(deg)
Wx
Wy

IV. RESULTS

We begin with an explanation of how the experiments are conducted, followed by a discussion of the dataset and the dates that correspond to each partition. Second, we present performance metrics used to evaluate the models. Third, we present the hyper-parameters with which each approach performs best. Each model was then put to the test. Finally, we compare our forecasting model to those of our competitors.

To evaluate the performance of our model, we conducted extensive testing and analysis on the university campus dataset. The results showed that our deep learning architecture achieved a high level of accuracy in predicting energy consumption over a 48-hour horizon. By examining the discrepancies between predicted and actual energy consumption, we identified potential areas for model refinement and further improvement. As stated previously, data collection covers fourteen months, from November 30th, 2019, to January 17th, 2021. Each algorithm was optimized using the training and validation sets. The training set will operate between November 30th, 2019, at 10:00 and September 14th, 2020, at 21:00. The validation set changes hyperparameters using data between September 14th, 2020, 21:00 and November 15th, 2020, 23:00. Fig. 2 depicts the test set, which compares and evaluates model performance from November 15th, 2020, 23:00 to January 17th, 2021, 00:00.

The resulting models were evaluated using the performance metrics of Root Mean Squared Error (RMSE) shown in (3), mean absolute error (MAE) demonstrated in (4), and R squared (R^2) described in (5) to determine the experiment effectiveness. The RMSE assesses the deviation between the predicted and actual energy consumption and penalizes significant errors accordingly. MAE measures the absolute average difference between expected and actual energy consumption. R squared measures the correlation with energy consumption and prediction.

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 / N}. \tag{3}$$

$$\mathrm{MAE} = \sum_{i=1}^{N}|y_i - \hat{y}_i| / N. \tag{4}$$

$$R^2 = \sum_{i=1}^{N}(\hat{y}_i - \bar{y})^2 \,/\, \sum_{i=1}^{N}(y_i - \bar{y})^2. \tag{5}$$

where y_i is the measured energy, $\hat{y}_i$ is the predicted energy, $\bar{y}$ is the mean measured energy consumed in INU, and N is the total number of observations.

The optimal hyperparameters for each model were determined using a grid search. The proposed biLSTM model was evaluated in multiple experiments. Scikit-learn and TensorFlow 2.6 with Python 3.8 were used for all experiments with an Intel Core i9-9900KF CPU and 16 GB of DDR4 RAM, and the hyper-parameter optimization procedure was configured to be identical for all data inputs.

The hyperparameter candidates in this research are listed and the range of values evaluated for each algorithm's hyperparameters is shown in Table III. Examined were two single regressions, one boosting ensemble, one Bayesian regression, and two deep learning algorithms. Linear Regression, k-NN, CatBoost, Neural Network, Gaussian Process, and biLSTM are among the algorithms considered. The optimal number of neighbors for k-NN is twenty. The optimal hyperparameters for CatBoost include a depth of 3, 50 iterations, and a learning rate of 0.01. The optimal number of layers for a Neural Network is one, the optimal number of neurons is 200, and the optimal learning rate is 0.01. The optimal kernel for the Gaussian Process is Matern. The optimal number of layers for biLSTM is 3, the optimal number of neurons is 96, the optimal number of LSTM neurons is 512, the optimal dropout rate is 0.2, and RMSprop is the optimal optimizer. These findings suggest that the selection of hyperparameters can have a substantial effect on the efficacy of regression models, and that modifying the hyperparameters can lead to improved results.

TABLE III: HYPERPARAMETER EVALUATION RESULTS FOR REGRESSION MODELS

Algorithm	Hyperparameter
Linear Regression	-
k-NN	n_neighbors = {2, 3, 4, 5, 10, **<u>20</u>**, 40, 80}
CatBoost	depth = {**<u>3</u>**, 6, 8, 10}, iterations = {30, **<u>50</u>**, 100}, learning_rate = {0.0001, 0.001, **<u>0.01</u>**, 0.1}
Neural Network	num_layers = {**<u>1</u>**, 2, 5, 7, 9}, num_neurons = {5, 10, 15, 20, 40, 80, 100, **<u>200</u>**}, learning_rate = {0.0001, 0.001, 0.01, **<u>0.1</u>**}
Gaussian Process	kernel = {'RationalQuadratic', **<u>'Matern'</u>**, 'RBF', 'DotProduct'}
BiLSTM	num_layers = {2, **<u>3,</u>** 5, 7, 9}, num_neurons = {**<u>96</u>**, 256, 512}, lstm_num_neurons = {256, **<u>512</u>**, 1024}, dropout_rate = {**<u>0.2</u>**, 0.3}, optimizer ={**<u>'RMSprop'</u>**}

* The optimal outcomes are emphasized using underlining and bold formatting.

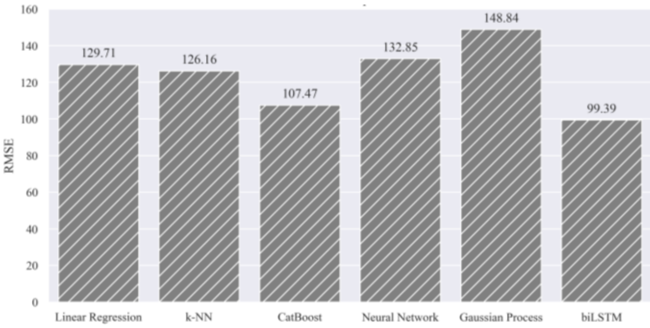

Fig. 6. Comparing predicted and observed energy consumption performance on test dataset using RMSE performance metric.

Fig. 6 shows the RMSE values of the evaluated algorithms utilized for the prediction of energy consumption 48 hours-ahead. Based on the data presented in Fig. 6, it can be inferred that the biLSTM model exhibits the highest level of performance, as evidenced by its RMSE value of 99.39. This suggests that the biLSTM algorithm is the most precise method for forecasting energy usage up to 48 hours in advance. The CatBoost algorithm has demonstrated the second highest level of performance, achieving an RMSE value of 107.47. The k-NN algorithm exhibits a favorable performance, as evidenced by its RMSE value of 126.16. On the contrary, it can be observed that the Linear Regression model, Neural Network, and Gaussian Process models exhibit elevated RMSE values in comparison to the remaining algorithms. This suggests that their predictive capabilities are comparatively inferior in forecasting energy consumption 48 hours in advance.

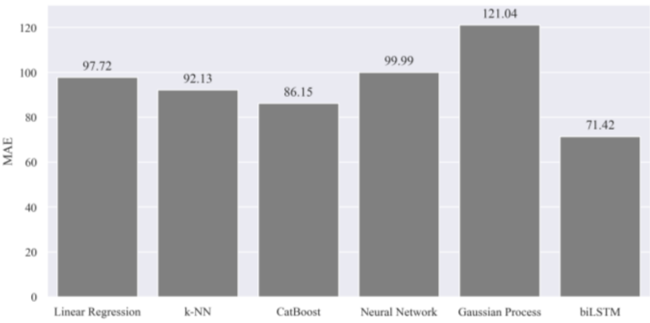

Fig. 7. Comparing predicted and observed energy consumption performance on test dataset using MAE performance metric.

Based on the findings presented in Fig. 7, it is evident that the biLSTM model exhibits superior performance in predicting energy consumption 48 hours-ahead, as evidenced by its minimal MAE of 71.419. This suggests that the biLSTM model is the most precise algorithm for this dataset. This discovery corroborates the values obtained Fig. 6, wherein the biLSTM architecture is likewise recognized as the top performer, as determined by RMSE metrics. The CatBoost algorithm demonstrated the second highest level of performance, exhibiting an MAE of 86.153. Subsequently, the k-NN algorithm followed with an MAE of 92.126. On the other hand, it is possible to note that the Linear Regression model, Neural Network, and Gaussian Process models demonstrate higher MAE values, indicating a greater degree of error in comparison to the remaining algorithms.

The analysis of R squared values shown in Fig. 8 shows that the biLSTM algorithm exhibits superior performance, as evidenced by its R squared value of 0.695. This finding corroborates the values of RMSE and MAE, in which the biLSTM architecture was determined to be the optimal performer. According to the results, the CatBoost algorithm showed the second highest level of performance, exhibiting an R squared value of 0.620. Subsequently, the k-NN algorithm displayed an R squared value of 0.476.

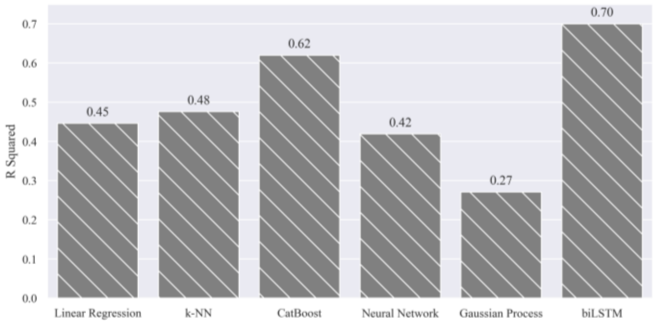

Fig. 8. Comparing predicted and observed energy consumption performance on test dataset using R squared performance metric.

To summarize, the outcomes delineated in Fig. 8 are consistent with the preceding two performance metrics, which ascertained biLSTM and CatBoost as the top performers based on the RMSE and MAE metrics. The findings presented in Fig. 8 validate that biLSTM is the most effective algorithm for the energy consumption prediction of INU in forecasting energy usage 48 hours in advance, with CatBoost and k-NN following in second and third place, respectively.

V. Conclusions

Integrating artificial intelligence in the prediction of energy consumption has the potential to augment energy efficiency in smart universities. This is a critical element in the attainment of a sustainable urban environment. Through precise energy consumption forecasting, colleges and universities can make necessary adjustments to their energy usage, mitigating consumption and minimizing their ecological impact. The deep learning framework proposed in this study for short-term energy consumption forecasting can be considered as an important resource towards attaining a sustainable urban environment within the boundaries of smart universities. Through integrating this framework with initiatives aimed at improving energy efficiency, reducing waste generation, and advocating for environmentally conscious transportation, academic institutions can make substantial strides in fostering a more sustainable future for their respective communities. The concept of energy efficiency pertains to the optimal utilization of energy in various urban infrastructures, including buildings and transportation systems.

Our research presents a sophisticated deep learning architecture for accurate 48-hour energy prediction in smart university campuses. By analyzing the energy consumption patterns of individual buildings and incorporating external variables, we contribute to enhancing energy efficiency and sustainability. The statistical testing conducted on our model confirms its suitability for energy consumption forecasting, providing valuable insights for energy management decision-making in smart universities and beyond.

The results show that the proposed biLSTM algorithm shows exceptional efficacy in predicting energy consumption within a lead time of 48 hours. It can be inferred that the biLSTM algorithm outperforms other methods. The biLSTM algorithm can be considered as the most suitable for this task getting the performance metrics of RMSE = 99.39, MAE = 71.42 and R squared of 70%. Hence, understanding the energy consumption dynamics of each building within a smart university environment enables the development of effective energy-saving strategies at the campus level. Our research contributes to this goal by providing accurate energy consumption forecasts and insights into the underlying causes of energy usage patterns.

Therefore, there are several limitations in our study, such as the analysis of regressions using time series algorithms, analysis of data from other universities, data of other years where COVID-19 did not exist. It is necessary to do more experiments and test other types of deep learning structures like transformers or seq2seq, so we would like to do more studies in the future. Also, future work should focus on incorporating real-time data streams, refining the model's architecture, and expanding the research to other smart city contexts.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

BC conducted the research, methodology, experiments, and wrote the paper; KK conducted conceptualization, methodology, validation, and supervision; all authors had approved the final version.

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