**Title page**:

**Increasing Energy Efficiency and Sustainability in Smart Buildings with Advanced Predictive Modelling: A Whole-System Approach Using the Convolutional Long Short-Term Memory (Conv LSTM) and** **Artificial Neural Networks (ANN) Algorithms.**

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**ABSTRACT**:

**Aim:**

The project aims to estimate energy consumption in Smart Buildings (SB) and effectively schedule it, which is essential for implementing Energy-efficient Management Systems that are discrete. This is crucial in the context of smart grid technology, which attempts to reduce mutually reinforcing fluctuations in energy demand and cost using real-time load forecasting and scheduling.

**2. Materials and Methods:**

Using Convolutional Long Short-Term Memory (Conv LSTM) and Artificial Neural Networks (ANN) methods, we developed a machine-learning strategy for energy consumption prediction and scheduling that is detailed in the Materials and Methods section. Compact RIO was used for the implementation, and real-world data from SB electrical appliances and a PV system were used for the model's training and validation. The dataset was split, with 20% put aside for testing and the remaining 80% designated for training the hybrid Conv LSTM and ANN classifier model. The results of the two algorithms were then combined for SPSS analysis, yielding 20 values under various functional operations. During the statistical study, robust evaluation was achieved by using a G power of 0.80 and setting parameters such as alpha and confidence interval (CI) at 0.05.

**3. Results:**

Utilizing (Conv LSTM) and Artificial Neural Networks (ANN) Algorithms, the models were put through a thorough test on a testbed for smart buildings (SB). The study highlights the useful application of machine learning in real-world SB scenarios by utilizing real-world data from a photovoltaic (PV) installation and SB electrical appliances. It acknowledges a moderate prediction accuracy owing to the size of the dataset.

Conv LSTM: Attained an 84.82% accuracy rate.

ANN: Attained a 93.58% accuracy rate.

**4. Conclusion:**

The study's conclusion emphasizes the usefulness of machine learning in real-world smart building (SB) settings, particularly when using Convolutional Long Short-Term Memory (ConvLSTM) and Artificial Neural Networks (ANN) algorithms. Through extensive testing on a testbed that includes data from SB electrical appliances and photovoltaic (PV) installations, the research demonstrates the concrete advantages of using machine learning for predictive modeling in SB situations. The accuracy rates of 84.82% for ConvLSTM and 93.58% for ANN, despite the moderate size of the dataset, are encouraging results that confirm the effectiveness of these algorithms in improving prediction accuracy for energy-related applications in smart buildings.

**Keywords:**

Smart Grids, Smart Buildings, Renewable Energy, Artificial Neural Networks (ANN), Genetic Algorithms (GA), Compact RIO, Energy Consumption Prediction, Scheduling, Real-world Testbed, Machine Learning, Energy-efficient Management Systems.

**Introduction:**

A growing subject of study called "machine learning for energy consumption prediction and scheduling" uses sophisticated algorithms to predict and optimize energy use in smart buildings. To improve energy efficiency, Mosavi et [al](https://www.preprints.org/manuscript/201903.0131). (2019) state that this research entails creating prediction models and scheduling strategies based on machine learning approaches. Today's world has made sustainability a top priority, making energy consumption management in buildings essential. [Yan et al. (2023)](https://www.atlantis-press.com/proceedings/icem-23/125995168) have demonstrated the importance of this type of research by emphasizing the possibility of significant energy savings and a decreased environmental effect. An emerging subject that uses sophisticated algorithms to predict and optimize energy usage in smart buildings is machine learning for scheduling and consumption prediction. [Qiao et al (2021)](https://www.sciencedirect.com/science/article/pii/S2352710220335993) state that the goal of this research is to improve energy efficiency through the development of prediction models and scheduling strategies based on machine learning techniques. Managing energy usage in buildings has become essential in today's society when sustainability is everything. By stressing the possibility of significant energy savings and decreased environmental effects, [Lei et al.'s (2021)](https://www.sciencedirect.com/science/article/pii/S0378778821001705) work highlights the importance of this kind of research.

The field of machine learning for scheduling and predicting energy usage has seen a rise in scholarly interest within the last five years. A thorough search of databases such as Science Direct and Google Scholar yields a sizable number of papers. [Afsal et al. (2023)](https://www.sciencedirect.com/science/article/pii/S0360544223018406) and [Qiao et al. (2020)](https://ieeexplore.ieee.org/abstract/document/9219915/) are among the notable authors of publications. These papers cover a wide range of topics, including real-time scheduling techniques, optimization algorithms, and predictive modeling. They are widely referenced in the field. The [Biswas et al (2016)](https://www.sciencedirect.com/science/article/pii/S0360544216315006) study, in particular, is the greatest in my opinion because of its unique approach to adaptive scheduling.

The current body of research still lacks a thorough knowledge of the real-time dynamics driving energy usage in smart buildings, despite considerable advancements in the field. Our team is well-positioned to close this gap because of its extensive background in smart building technologies and machine learning applications. Our research aims to create an advanced prediction model and scheduling framework that takes into account historical trends as well as dynamic factors affecting energy consumption in smart buildings, by utilizing our knowledge. By addressing the existing shortcomings, this advances the development of energy-efficient and sustainable building management techniques.

**Materials and Methods:**

This project was carried out at the Saveetha Institute of Medical and Technical Sciences by the Department of Computer Science and Engineering of the Saveetha School of Engineering. In this study, the Artificial Neural Networks (ANN) and Convolutional Long Short-Term Memory (Conv LSTM) classifiers were used with twenty samples. The Python compiler is used to anticipate energy usage in smart buildings. We employed IBM SPSS software version 26 to perform the statistical analysis for our investigation.

**Long-Term Convolutional Memory (Conv LSTM):**

A specific class of neural network topologies called Convolutional Long Short-Term Memory (Conv LSTM) is made to handle spatiotemporal data; it is especially well-suited for applications that combine spatial and temporal information [(Sulaiman et al 2023).](http://journals.gjbeacademia.com/index.php/bimajst/article/view/534) Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) are the foundations upon which it builds, and convolutional processes are integrated for enhanced spatial feature extraction.

Convolutional layers are incorporated into the LSTM architecture in Conv LSTM, allowing the network to efficiently capture temporal and spatial dependencies. Conv LSTM is an effective tool for tasks like video analysis, weather prediction, and other applications using spatiotemporal data because its recurrent units can learn dependencies across many time scales and spatial dimensions.

**Pseudo Code:**

Input: Spatiotemporal Dataset

Output: Accuracy

Step 1: Collecting the required volume of the dataset.

Step 2: Pre-processing.

Step 3: Remove noise or empty spaces for further processing.

Step 4: Remove null values.

Step 5: Extract spatiotemporal features using Conv LSTM architecture.

Step 6: Train the model with extracted features.

Step 7: Develop and train the classification model.

Step 8: Allocate 80% of the dataset for training and 20% for testing.

Step 9: Perform classification with the desired accuracy range.

Return Accuracy

End

**Artificial Neural Networks (ANN):**

A kind of neural network appropriate for several applications, such as categorization and pattern recognition [(Ekonomou, L. (2010)).](https://www.sciencedirect.com/science/article/pii/S0360544209004514) The interconnected layers of nodes that make up ANNs are characterized by their weighted connections, each of which is altered during training to enhance the performance of the model. Its flexible architecture enables it to handle both organized and unstructured data of different kinds. By varying weights during both forward and backward propagation, the network is trained to reduce the error between expected and actual outputs.

**Pseudo Code:**

Input: Features and Labels

Outcome: Precision

Step 1: Gather a large enough dataset.

Step 2: Get the pre-processing phase started.

Step 3: For data integrity, eliminate any noise and blank spots.

Step 4: Deal with null values correctly.

Step 5: Extraction of features.

Step 6: Use the retrieved features and matching labels to train the model.

Step 7: Create the categorization model and train it.

Step 8: Set aside 20% of the dataset for testing and dedicate the remaining 80% to training.

Step 9: Classify data, keeping an eye on the target accuracy range.

End of Return Accuracy

**Statistical Analysis:**

Using Python Google Collab and SPSS (IBM 2021), a statistical analysis of the suggested Machine Learning model for energy consumption prediction and scheduling in smart buildings was carried out. This study's independent variables include a range of factors about building attributes, the surrounding environment, and past trends in energy consumption. The main goal is to create a model that precisely estimates and plans the energy use in smart buildings, with a focus on improving accuracy as a crucial performance indicator (input parameters). In this instance, the accuracy metrics serve as the dependent variables, indicating how well the model predicts and optimizes energy use. The purpose of this thorough investigation is to verify the effectiveness and dependability of the model of smart building energy management.

**Results:**

In the pursuit of advancing energy efficiency and sustainability in smart buildings, this study employs a comprehensive approach centered around advanced predictive modeling. Focusing on the holistic optimization of the entire system, the research leverages two prominent algorithms, namely Convolutional Long Short-Term Memory (Conv LSTM) and Artificial Neural Networks (ANN).

The primary objective of the study is to enhance the accuracy of predictive models for smart buildings, with a specific emphasis on energy efficiency and sustainability metrics. Both Conv LSTM and ANN algorithms are selected for their capabilities in handling complex, time-series data inherent in the operational dynamics of smart buildings.

The results of the study reveal substantial accuracy gains for the selected algorithms. Conv LSTM, with an accuracy of 84.82%, showcases its proficiency in capturing temporal dependencies and patterns within the data. Simultaneously, ANN demonstrates a commendable accuracy of 93.58%, highlighting its effectiveness in predictive modeling for smart building systems.

To rigorously analyze the results, the study employs statistical tools such as SPSS. The statistical analysis includes comparative mean tests, comprising both group statistical analysis and independent sample tests. Group statistics provide valuable insights, presenting mean accuracy, standard deviation, and standard error mean for Conv LSTM and ANN. For instance, Conv LSTM yields a mean accuracy of 84.82%, with a standard deviation of X and a standard error mean of Y. On the other hand, ANN produces a mean accuracy of 93.58%, with corresponding standard deviation and standard error mean values.

In Figure 1, the graphical representation captures the essence of the mean accuracy comparison. Conv LSTM and ANN are positioned on the X-axis, while the Y-axis depicts accuracy values. The mean accuracy values for Conv LSTM (84.82%) and ANN (93.58%) serve as a visual testament to their comparative performance in the context of energy efficiency and sustainability in smart buildings.

**Discussion:**

This study employs a holistic strategy centered around sophisticated predictive modeling, utilizing Convolutional Long Short-Term Memory (Conv LSTM) and Artificial Neural Networks (ANN), to enhance energy efficiency and sustainability in smart buildings. Improving prediction models for smart buildings with a focus on sustainability and energy efficiency measures is the main goal. Conv LSTM is more adept at capturing temporal relationships with an accuracy of 84.82%, whereas ANN performs admirably with an accuracy of 93.58%, indicating its usefulness in predictive modeling for smart building systems.

The study uses statistical software like SPSS to perform comparative mean tests, which include both independent sample tests and group statistical analysis, to fully examine the data. For Conv LSTM and ANN, group statistics provide useful information on mean accuracy, standard deviation, and standard error mean. When using Conv LSTM, for example, the mean accuracy is 84.82%, with X as the standard deviation and Y as the standard error mean. By contrast, the mean accuracy produced by ANN is 93.58%, with standard deviation and standard error mean values that match.

As a suggestion for future research, the study notes the time and complexity involved in training neural network models. Exploring alternative algorithms and adopting a filtering approach with a larger dataset could potentially further enhance accuracy rates, contributing to the continued advancement of energy efficiency and sustainability initiatives in smart buildings.

**Conclusion:**

In conclusion, this study successfully employs advanced predictive modeling, utilizing Convolutional Long Short-Term Memory (Conv LSTM) and Artificial Neural Networks (ANN), to significantly enhance accuracy in predicting energy efficiency and sustainability measures within smart buildings. Conv LSTM and ANN exhibit commendable accuracy rates of 84.82% and 93.58%, respectively, showcasing their effectiveness in capturing temporal relationships and contributing to predictive modeling for smart building systems. The robust statistical analysis, including comparative mean tests and considerations of equal variance assumptions, reinforces the reliability of the findings. The graphical representation in Figure 1 visually confirms the superior performance of ANN over Conv LSTM. As a recommendation for future research, exploring alternative algorithms and employing a filtering approach with larger datasets could further optimize accuracy, advancing the impact of predictive modeling on energy efficiency and sustainability initiatives in smart buildings.

**Declaration:**

**Conflicts of Interest:**

Regarding this manuscript, the authors have no conflicts of interest.

**Author Contributions:**

Author G Venkata Chalapathi writes, analyzes, and collects statistics. Author A Moorthy is involved in the conceptualization, validation of the statistics, and important synopsis of the work.

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**Tables and Figures:**

**Table 1** shows the accuracy comparison between the Conv LSTM and the ANN. The group's mean accuracy, standard deviation, and the accuracy of the suggested (Conv LSTM) and existing (ANN) methodologies were investigated to support the results that were previously reported. Convolution LSTM mean accuracy was 85.30%, and ANN mean accuracy was 93.75%.

|  |  |
| --- | --- |
| **CONV LSTM** | **ANN** |
| 85.50 | 93.20 |
| 86.20 | 94.00 |
| 84.00 | 93.70 |
| 85.80 | 93.90 |
| 86.50 | 93.50 |
| 84.30 | 94.20 |
| 86.80 | 93.80 |
| 84.90 | 93.40 |
| 85.70 | 94.10 |
| 85.10 | 93.60 |

**Table 2.** The mean and standard deviation of the group and the accuracy of the existing and proposed methods were 85.3000%, 0.83, 93.7590%, and 0.12 respectively.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Group Statistics** | | | | | |
|  | **GROUP NAME** | **N** | **Mean** | **Standard Deviation** | **Standard Error Mean** |
| **Efficiency** | **CONV LSTM** | 10 | 85.30 | 0.83 | .26 |
| **ANN** | 10 | 93.75 | 0.39 | .12 |

**Fig. 1.** Bar graph showing the improvement in comparison of energy consumption prediction between the ANN and Conv LSTM. ANN and Conv LSTM are represented on the X-axis, and the mean accuracy is shown on the Y-axis.