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Modified CNN Learning Model for Tetouan City Energy Consumption Prediction

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Abstract

Supplying power to regions and households via solar systems is a challenge, since energy production consistently varies owing to changing weather conditions and fluctuating consumer needs. Therefore, mechanisms must be established that accurately predict the user's expected needs and the energy produced. This article proposes a deep learning (DL) approach using a modified convolutional neural network (CNN) to evaluate the load response capability of residential energy customers by extracting typical load patterns. The precise evaluation of customer energy consumption patterns is essential for demand-side load management; nevertheless, it is affected by many variables, including load needs, weather conditions, and available power. A three-zone power usage, weather prediction, and time factor model are provided for the dataset (Tetouan City from 01/01/2017 to 30/12/2017). A modified CNN predicting accuracy is shown by the lowest mean absolute error of 0.1594, mean squared error of 0.04356, and the highest R-squared value of 0.9561. Thus, the suggested technique features a modified deep learning CNN model (Figure. 4) that exhibits considerable efficiency and stability in properly predicting power consumption, applicable in utility demand forecasting, intelligent building energy management (EM), and the integration of renewable energy (RE).

Keywords: Energy Consumption Prediction, Convolutional Neural Network, Deep Learning, Load Forecasting, Dataset.

1 Introduction

The advancement of contemporary science and technology has resulted in a substantial increase in the use of grid-connected sustainable energy sources, including solar electricity (Abdul-Rahaim & Rahi, 2024; Laith et al., 2024, Rahaim et al., 2023 and Gupta & Joshi, 2025). Nonetheless, the variability and unpredictability of renewable energy might result in unstable frequency oscillations (Prakash & Prakash, 2023). It has presented substantial hurdles to the steady functioning of the electricity infrastructure. In recent years, demand-side load power management has emerged as an efficient strategy to alleviate the

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effects of renewable energy and maintain equilibrium between electricity demand, and supply (Hammad et al., 2022). The precise evaluation of customer electricity consumption patterns is the essential foundation (Jaramillo et al., 2024) for demand-side load management; yet, it is affected by many variables, including load requirements, meteorological conditions, and available energy supply. Therefore, performing a thorough assessment of the response capacity for energy users becomes a primary barrier for demand-side load management (Ma et al., 2024). Quantitative and qualitative approaches are often used to categorize forecasting models (Mousa & Rasheed, 2022). Contrasted with quantitative models, which rely on numerical data, qualitative models are based on an individual's unique set of experiences, opinions, and body of knowledge (Nutakki et al., 2024). The two main schools of thought when it comes to making predictions are causal and methods based on past evidence (Raza & Khosravi, 2015). The connection relationship that exists between the utilization of energy and the variables that are input, which include social, economic, and climatic factors, may be investigated using causal approaches. A large number of researchers have proposed energy consumption prediction models, with the majority of these models using AI (artificial intelligence), DL (deep learning) and ML (machine learning) methodologies (Chitra et al., 2022). This methodology in energy efficiency, namely in power demand forecasting, signifies a substantial paradigm change in the energy industry. This shift is driven by the need for more precise, dependable, and efficient energy management systems. It provides unparalleled capabilities in forecasting and regulating power consumption, thereby improving energy efficiency. Since the introduction of AI and ML models, power demand forecasting has advanced significantly. The transition from conventional networks to smart grids and renewable energy integration reflects power system demands and complexity. Early electrical demand forecasting used statistical approaches and simple time-series models. Regression analysis and exponential smoothing worked well for steady consumption patterns but were too rigid and inaccurate for dynamic and complicated power systems. Smart meters and granular usage data changed demand forecasts. The wealth of data allowed for more advanced forecasting methods and machine learning algorithms (Aderibigbe et al., 2023). The growth of forecasting tools mirrors power grid changes. With smart grids, AI and ML are increasingly important. Digitalization and IoT integration in smart grids demand more advanced forecasting models to manage power system reliability and security. Deep learning has made considerable advances in short-term load forecasting, estimating demand from 1 to 24 hours in advance with excellent accuracy. DL models can handle enormous information and discover complicated patterns, making them ideal for smart grid applications.

This work's principal contributions are the invention and implementation of the Deep Energy Predictor Model (DEPM), which integrates many sophisticated methods to markedly improve the power consumption forecasting accuracy, and efficiency. The principal contributions encompass:

- Modified CNN DL model: The main goal of this article is to present a forecast model, namely a modified CNN model for predicting the overall electricity demand on a mid-term hourly resolution.
- Outliers' cancelation Using IQR Method: Outliers may skew analytical and prediction model performance. The Interquartile Range (IQR) approach detected and handled outliers. Outliers, values far outside the interquartile range, are identified by this rigorous statistical method, resulting in more accurate and a cleaner dataset for DL model training.
- Feature Extraction: A crucial stage in dataset preparation for accurate power consumption forecast. It involves feature development, processing, and choosing the best ones from raw data to improve model performance and power use analysis. Generate time series attributes derived from the time series index.

- Data Cleaning: To assure quality and trustworthiness of the dataset, we eliminated duplicates and addressed missing information, so preserving its integrity.
- Data normalization: based on using Z-score normalization (Z-Norm) method to achieve a mean of zero, and a standard deviation (SD) of one standardizes characteristics. changes gradients without modifying network architecture to expedite training and improve model performance.

As a case study, we evaluate the dataset of Tetouan City from 01/01/2017 to 30/12/2017. The following articles remain. Section 2 examines relevant literature. Sections 3 and 4 provide the dataset and CNN overview. The Proposed Methodology begins in Section 5. Section 6 describes dataset processing, whereas Section 7 presents model performance criteria. The deep learning model's results finish in Section 8. The conclusion is in Section 9.

2 Related Works

Energy forecasting is often categorized dividing the time horizon into three- classification: firstly, long term- LT (exceeding one year), secondly midterm- MT (ranging from one month to one year), and finally short term -ST (spanning from one day to one month). Neuronal network (NN) models, extreme learning machines, random forests, and deep learning algorithms are supervised learning methods for forecasting, while k-means clustering, fuzzy clustering, Additionally, various enhanced clustering techniques are unsupervised. Forecasting methods rely on the forecasting horizon, or prediction timeframe. Recurrent neural networks (RNN_S), exponential smoothing, and autoregressive integrated moving average are used for ST- forecasting. State space models, seasonal ARIMA, and machine learning algorithms can anticipate MT. Trend extrapolation, econometric, or causal models are used for LT- forecasting. Also, before selecting consider data availability, quality, underlying assumptions, and issue characteristics. Method combinations and overlaps may exist depending on the forecasting job (Mathumitha et al., 2024). Several scholars have recently focused on improving the efficacy and accuracy of power consumption projections using deep learning architectures, which have shown good performance on unsupervised challenges. A study was given, for example in 2024, Nigar et al. suggested a machine learning (ML)-based method to reliably forecast future energy usage based on previous dataset (PRECON) and environmental factors. Random forest (RF) predicts energy consumption better with 98% R^2 and 0.51 RMSE (root mean square error), while decision tree (DT) is best for personalized energy recommendations with 85% $R^2$and 0.14 RMS (Nigar et al., 2024). whereas in 2024, Ma et al. quantified consumer load response potential using nonnegative matrix factorization and prospect theory (Bhatia & Iyer, 2025). Previous load data is dissected and grouped using nonnegative matrix factorization to discover typical load patterns for different client groups. Consumer reaction potential may also be assessed using dispatchable power capacity, response time, and reliability. This study uses grey correlation analysis and prospect theory to investigate customers' risk and reward perceptions across indicators, taking into consideration their limited rationality and subjective preferences. For power system demands, subjective weights are applied (Ma et al., 2024). Likewise, further research introduced in Kunal et al. modified LSTM technique, wavelet-LSTM, and Hilbert-LSTM are offered for predicting power prices in the ST electricity market for bidding purposes. The prediction outcomes obtained using wavelet-LSTM, and Hilbert-LSTM (1-month dataset spanning 8 years) are as follows: rank correlation of 0.9746 and 0.9749, MSE of 0.2962 and 0.1363, and RMSE of 0.5443 and 0.3692, respectively (Shejul et al., 2024). However, in the article (Tang et al., 2022), K-Medoid clustering revealed realistic load patterns. The suggested system acquires pattern-related feature sets via entropy-based feature selection. The feature selection helped identify key socioeconomic factors affecting load patterns, improved method interpretability, and created a deep learning model to explain the correlation between load pattern distribution and socioeconomic features. It uses pattern-dependent deep neural networks and normalization to increase accuracy. In an article of Swamy et al. authors, the significant improvement in forecasting accuracy due to the incorporation of meteorological data, with optimal results achieved using DL recurrent neural networks (DL- RNNs), traditional autoregressive integrated moving average models (ARIMA), and temporal convolutional networks (TCNs) for predicting residential power consumption (Swamy et al., 2024). Regarding the use of RNNs on the dataset, they may minimize the NMAE error function by fifty percent, since these algorithms retain information by processing data sequentially. Additionally, sequence-to-sequence (Seq2Seq) and RNNs provide generally favorable results; nevertheless, their performance diminishes significantly on datasets with many absenting values. Ultimately, convolutional networks (CNNs) have shown superior performance compared to RNN_S and Seq2Seq algorithms on dataset segments characterized by a significant quantity of missing values and consistent trends (Morcillo-Jimenez et al., 2024). The authors Huang et al. improved long short-term memory neural network (LSTM) for data-forecasting of a local microgrid (MG) in Zhejiang Province, China (Huang et al., 2022). While another authors, favorable outcomes were enhanced with the use of a hybrid parametric multiple linear regression (MLR) and ARIMA time series statistical methodologies in (Momani et al., 2024).

In 2024, Zarghami et al. introduced a new DL model, a spatial temporal hybrid convolutional-transformer (STHCT) network, characterized by distinctive characteristics and enhanced memory capacity. A flexibility index (FI) is presented to assess power system flexibility (PSF) based on forecasted outcomes. The results indicate a minimum prediction error of 2.5% and a maximum error of 10.1% (Zarghami et al., 2024). In another study Chung et al. introduced a parallel CNN – LSTM attention (PCLA) model. The extracted findings indicate a mean absolute error of 57.1%, a mean squared error of 66.2%, and a maximum R-squared value of 94.2% (Chung et al., 2022). Additional research, the convergence speed could be enhanced by an average of 38%, while the relative error could be decreased by 15% with the use of a BP neural network (Bai et al., 2024). Conversely, Ahmad et al. used two powerful architectures an Arterial Neural Network (ANN) alongside Random Forest (RF) on the energy consumption testing dataset, with ANN exhibiting somewhat superior performance compared to RF, yielding R^2 values of 99.73% and 99.66%, respectively (Ahmad et al., 2017). Table 1 provides a synopsis of the literature review that focuses on studies that have investigated energy forecasting. It aims to illustrate the superiority of our methodology over prior techniques regarding simplicity and good outcomes.

Table 1: A synthesis of prior research articles concentrating on energy methodologies

Ref.	Method/s	Data required	Findings
Ma et al., 2024	Nonnegative matrix factorization (NMF), and prospect theory	The Irish Social Science Data	Simulations show that the proposed method incorporates customer subjective preferences for multiple indicators, increasing load response potential. Ensures more accurate changeable load power estimate.
Nigar et al., 2024	RF and DT	Pakistan Residential Electricity Consumption Dataset (PRECON)	RF outcomes: 98% R^2 value and 0.51 RMSE, and DT outcomes: 85% R^2 and 0.14 RMSE.
Shejul et al., 2024	wavelet-LSTM, and Hilbert-LSTM	The dataset used is collected from the IEX electricity market (one month dataset of eight years).	wavelet-LSTM and Hilbert-LSTM rank correlation 0.9746, 0.9749, MSE 0.2962, 0.1363, and RMSE 0.5443, 0.3692, respectively.
Swamy et al., 2024	Temporal convolutional network (TCN)	https://fordatis.fraunhofer.de/handle/fordatis/215.	$RMSE_{min}$ 0.296, $MAPE_{min}$89.445, and MAE_{min}0.191.

Morcillo-Jimenez et al., 2024	Seq2Seq, LSTM, MLP, and CNN	The ICPE office building located in Bucharest	MLP models do not outperform others. Reduced NMAE error function by half using RNNs. using Seq2Seq like RNN, they got decent results.
Bai et al., 2024	BP neural network.	The data are available from the corresponding author.	MAE 0.10314, MSE 0.012479, and MAE 10.8894%.
Momani et al., 2024	MLR, and ARIMA	National Electric Power Company (NEPCO) (https://nepco.com.jo).	ARIMA provided lower error indices with the values of RMSE 3.57%, MSE 0.13%, and MAE 54.36.
Zarghami et al., 2024	CT-Transformer	The data are available from the corresponding author.	With a 2.5% solar production prediction error, the CT-Transformer outperforms the convolution network, which had 10.1%. MAPE 0.011, MAE 0.058, and, RMSE 0.069
Tang et al., 2022	K-Medoid	2019 smart meter data and Pecan Street socioeconomic data	MSE 0.017, and average error reduction of 46.5%.
Chung et al., 2022	PCLA	District heater (DH) data for the heat load forecasting model were gathered from a power plant in Chungcheongnam-do, Korea.	MAE, MSE, and R^2 are 0.571, 0.662, and 0.942, respectively.
Huang et al., 2022	LSTM	YUQING ZHENG	MAPE 0.0332 and RMSE / W 1016.68
Ahmad et al., 2017	ANN, and RF.	The data are available from the corresponding author.	ANN performed better than RF, R^2 is 0.9973 and 0.9966, respectively.
Proposed system	Modified CNN	Tetouan City from 01/01/2017 to 30/12/2017.	MAE, MSE, and R^2 are 0.1594, 0.04356, and 0.9561, respectively.

3 Dataset Overview

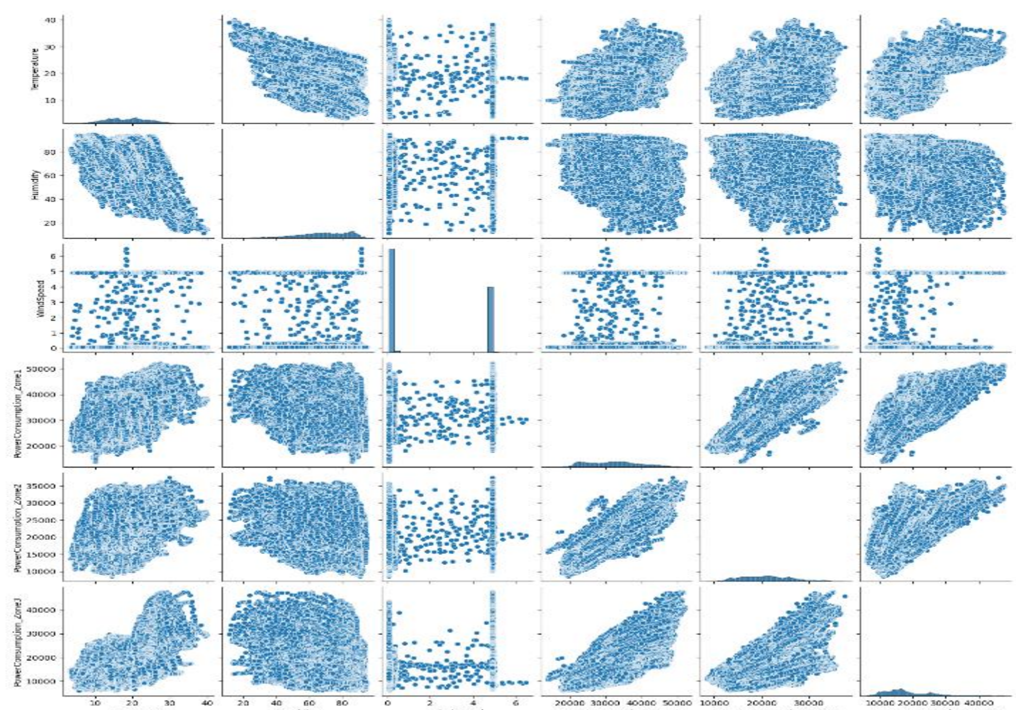


Figure 1: Data virtualization

Tetouan City data for energy consumption predication were used. The dataset has 52,416 instances of energy usage recorded at 10-minute intervals. Each observation is characterized by nine feature columns which are: Date, and Time (ten-minute interval), Weather factors (Temperature, Humidity, Wind Speed, General Diffuse Flows, Diffuse Flows), and Power Consumption of three zones. It contains data on the electricity consumption of consumers from 01/01/2017 to 30/12/2017. Figure 1 shown the relationship between interrelationships among quantitative variables.

4 Convolutional Neural Network (CNN) Overview

CNN_S are a category of ANNs that demonstrate remarkable efficacy in processing and analyzing grid-structured data. CNN_S are inspired by the structure and function of the visual cortex in the brain, applying a convolutional layer to the input data in order to extract localized characteristics. The convolutional layer (CL), pooling layer (PL), and fully connected layer (FCL) make up a CNN (as shows in Figure 2). A CNN relies on its basic convolutional layers, which use filters to extract localized characteristics from the input data.

This process culminates in a feature map that highlights the input data areas relevant to the current task. To increase the network's computational efficiency and decrease the spatial dimensions of feature maps, PL_S are often included after CL_S. With the features gleaned from the convolutional and pooling layers, the fully connected layers round out the prediction process. These levels, which are similar to those in a traditional- NN, take in data from the training set and utilize it to make predictions about the task at hand (Benti et al., 2023).

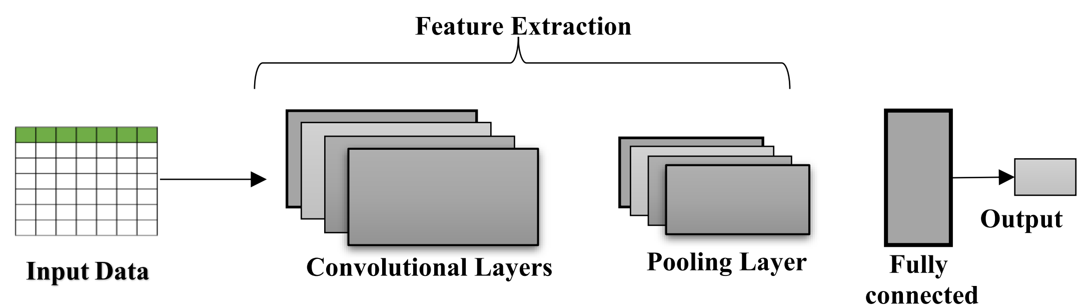


Figure 2: Convolutional neural network (abdul-hamza et al., 2023)

5 The Proposed Methodology

The article goal introduces a modified deep-learning CNN model for predicting energy usage, applicable in future green energy systems for managing generated energy in relation to user demand, as shows in Figure 3.

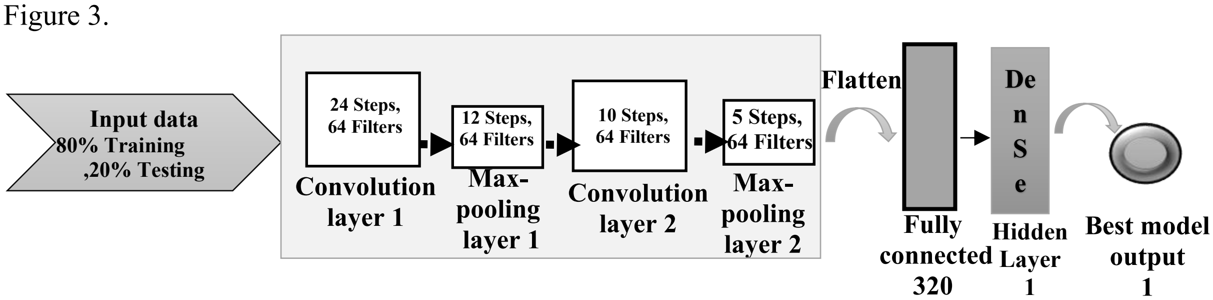


Figure 3: The proposed CNN model

This suggested model relies solely on a CNN framework, introducing a novel concept that yields optimal predictive outcomes. Figure 4 illustrates that we conducted data preparation, which including outlier removal, missing value imputation, remove duplicator, normalization (based z- score normalization), and feature selection. Subsequently, we proceeded to segment the data by zone to use the modified CNN learning method and derive the optimal predictive model for each zone. Our objective is to predict the energy requirements of three zones in Tetouan City for the forthcoming 10 minutes. In order to build our prediction model, the initial dataset has to be sequentially split into a training, and testing set. Owing to the energy usage over three zones, we divided the dataset into three segments and established training and validation subsets within each. The time series exhibits constant behavior over the years, and to attain extremely accurate predictions, our study suggests that we can effectively partition the data into zones. Utilized a modified convolutional neural network for each zone. The prediction model constructed using CNN comprises two successive stages: a CL followed by a PL. Consequently, we divide the dataset into training and validation subsets. The training samples comprised 80% of the observations from each zone, while the remaining 20% were allocated for validation.

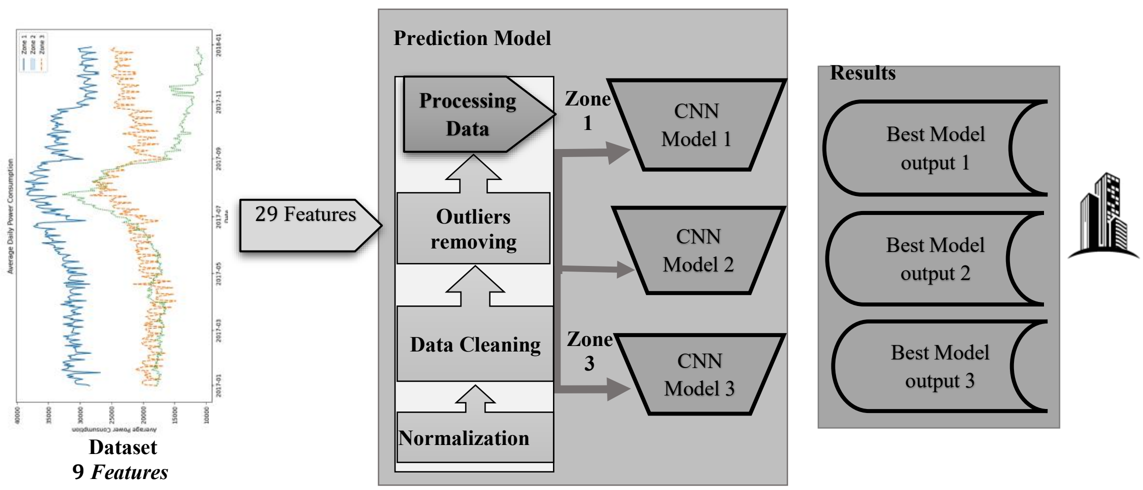
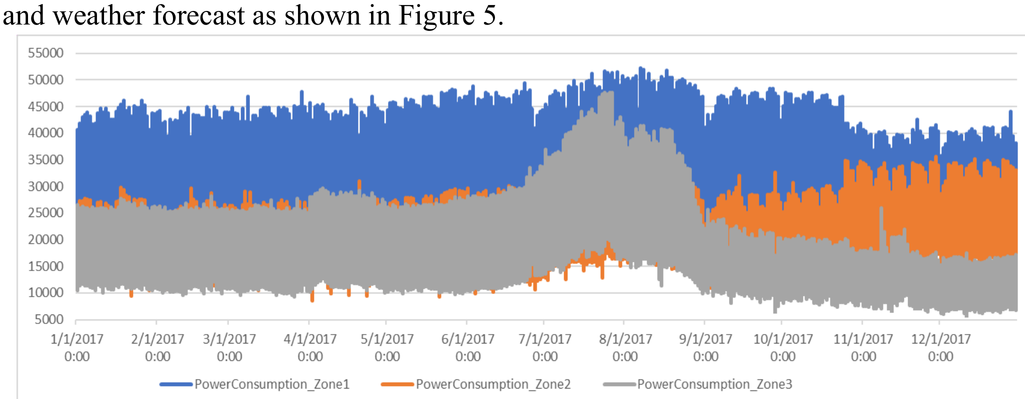


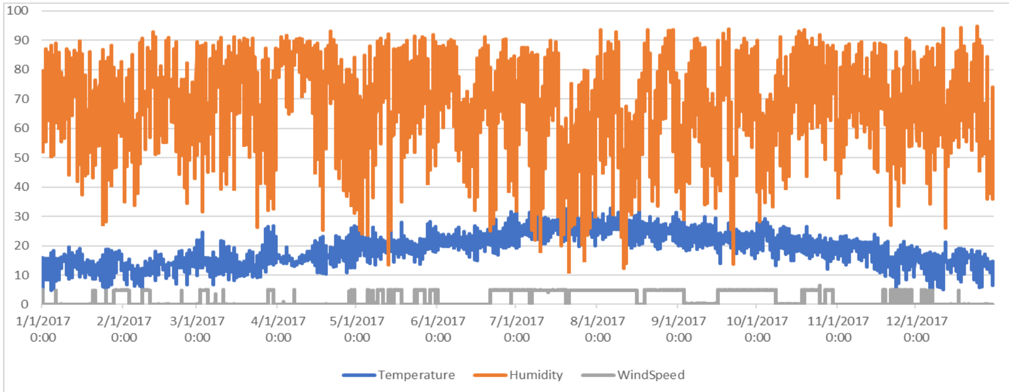
Figure 4: Proposed methodology

6 Dataset Processing

The dataset for the energy load forecasting model consists of time factor, energy consumption of three zones, and weather forecast as shown in Figure 5.



(a)



(b)

Figure 5: Time series relationship for: (a) zones power consumption, and weather factors

There is a clear patterns of energy consumption depending on the different days of the week, and months. To reflect this characteristic in CNN model training, features extracted from date information were used. Feature selection was conducted with a dataset of 29 characteristics. The output list enumerates the names of 29 features: humidity temperature, velocity of wind, general diffused flows, diffused flows, power consumption (zones 1, 2, and 3), hour, minute, day of the week, quarter, month, day, year, season, day of the year, day of the month, and week of the year. It is the weekend, the beginning of the month, the end of the month, the commencement of the quarter, the conclusion of the quarter, a working day, business hours, peak hour, minute of the day, and minute of the week. We generate a heat-map to illustrate the correlations in Figure 6, using a red gradient to represent increasing degrees of positive-correlation and blue for negative-correlation.

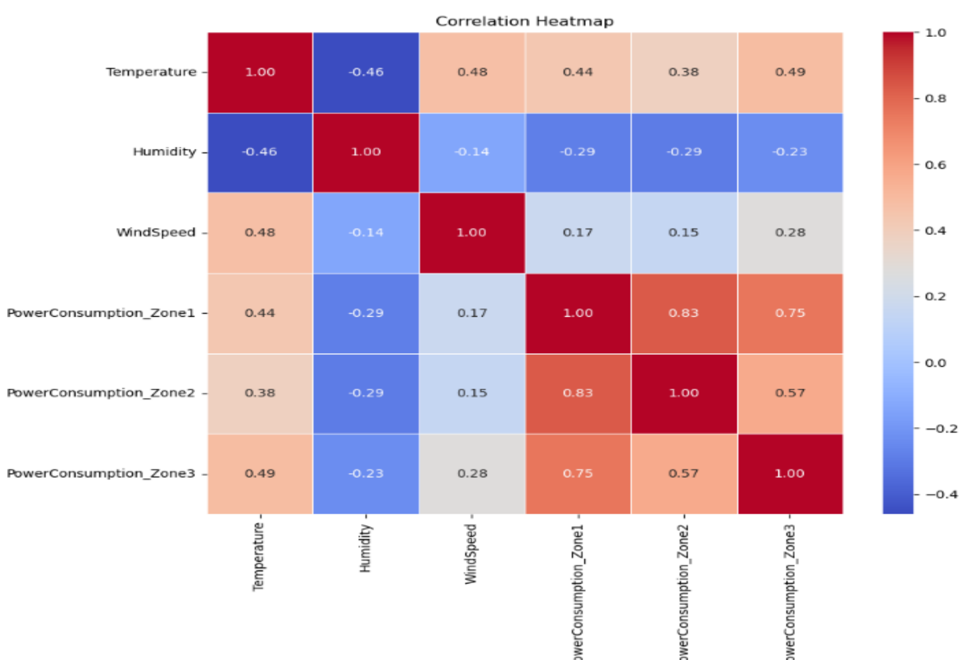
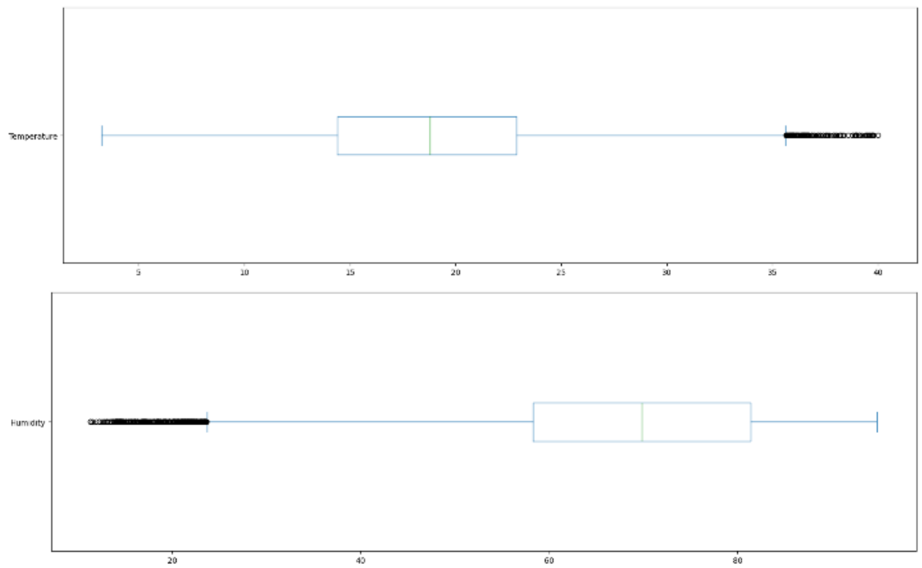


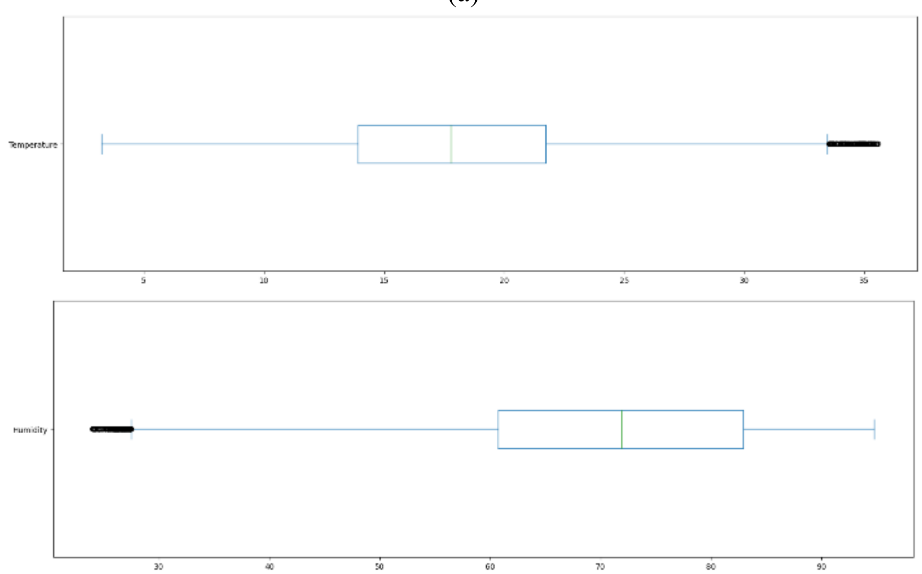
Figure 6: Heat-map correlation between features

Before training, outlier removal for the dataset (main 9- data feature) was performed depended on the lower limit and upper limit based on Interquartile Range (IQR) method (Mramba et al., 2024). Figure

7 illustrates the elimination of temperature and humidity outliers as an example. To guarantee the quality and trustworthiness of the dataset, we eliminated duplicates and addressed missing information, so preserving its integrity. Also, based on using Z-score normalization (Z-Norm) method to achieve a mean of zero and a standard deviation of one standardizes characteristics. changes gradients without modifying network architecture to expedite training and improve model performance (Kim et al., 2025; Nayak & Rout, 2024).



(a)



(b)

Figure 7: The elimination of temperature, and humidity outliers, (a) before, and (b) after, respectively

7 Model Performance Criteria

According to the evaluation criteria utilized in the majority of similar articles in peer-reviewed literature, such as (Momani et al., 2024; Chung et al., 2022). In a regression model, the R-squared (R^2) value indicates how well do the predictor factors explain the variation in the result variable, the equation is as follows (Momani et al., 2024; Chung et al., 2022):

$$R^2 = 1 - \frac{\sum_i (m_i - \widehat{m}_i)^2}{\sum_i (m_i - \overline{m}_i)^2} \quad (1)$$

Where m_i : is the actual value, $\overline{m}_i$: is the average value, and $\widehat{m}_i$: is the estimated value. Elevated R^2 values indicate superior model fit. Furthermore, the MAE- mean absolute error and MSE- mean squared error were used as metrics to evaluate the correctness of the proposed model, as shown in Eqs. (2) and (3), respectively (Chung et al., 2022; Abdullah et al., 2025).

$$MAE = \frac{1}{s}\sum_{i=1}^{s} \lceil m_i - \widehat{m}_i \rceil \quad (2)$$

$$MSE = \frac{1}{s}\sum_{i=1}^{s} (m_i - \widehat{m}_i)^2 \quad (3)$$

where s is the quantity of observations.

8 Results and Discussion

The suggested prediction model utilises modified CNNs for anticipating electricity usage. This model analyses past power use trends, meteorological data, and other pertinent aspects to forecast future energy demand. We executed and operated the model in Python. The first phase in the operational framework of the proposed modified CNN model involves using extensive data that is very pertinent to the specific issue at hand. Our research relied on the Tetouan City dataset from January 1, 2017, to December 30, 2017, which provides data on electricity usage across three zones and weather stations that give present and forecasted conditions influencing demand. To guarantee the dataset is sufficiently varied for the design to generalize well to previously unencountered information across several dissimilar scenarios, we computed additional characteristics to augment the primary dataset features. New features include Load derived Variables (quarter, season, week of the year, weekend, working day, business hours, quarter end, and quarter start) and time (hours, minutes, day of the week, months, day, year, weekend, month start, month end, minute of the day, day of the year, day of the month, and minute of the week). The aggregate number of characteristics is 29.

The dataset is then preprocessed with various approaches. This step entails the elimination of outliers utilising the Interquartile Range (IQR) method, as illustrated in Figure. 7, along with Data Cleaning to ensure the dataset's quality and reliability. We removed duplicates and rectified missing information to maintain its integrity, and Data normalization utilizing the Z-score normalization (Z-Norm) method standardizes features to achieve a standard deviation of one, and a mean of zero. thereby enhancing the model's convergence during training. This approach modifies gradients without altering the network architecture, thereby accelerating training and enhancing model performance.

Predictions are then extracted from this processed dataset using the updated CNN model. In reality, the batch size used during CNN training depends on several factors, such as dataset size (train-test splits), computational capabilities, etc. When deciding how quickly or slowly to complete the model development phase as opposed to deploying it for a production use case, batch plays a crucial role. Although it comes at the expense of higher computing overhead each iteration, reducing batch sizes is linked to quicker convergence and maybe improved generalization. A drawback of higher batch sizes is that they may lead to quicker training progress convergence at the expense of fewer updates, which may result in worse generalization when dealing with more complicated models or smaller datasets. To get the best DNN performance for certain applications and computing conditions, batch size parameters must be empirically tested and optimized. To achieve a suitable balance between efficiency and model quality, adjustments should take into consideration the interaction of size of batch, learning-dynamic, and the data intrinsic complexity. It separated the observations from each zone into training samples, which made up 80% of the total, and validation samples, which made up 20%. During the testing phase, the findings indicated that the losses across 100 epochs consistently decreased, beginning at 0.4051 and concluding at 0.0331, as seen in Figure. 8. This provides a favorable assessment of the performance and efficacy of the suggested CNN model.

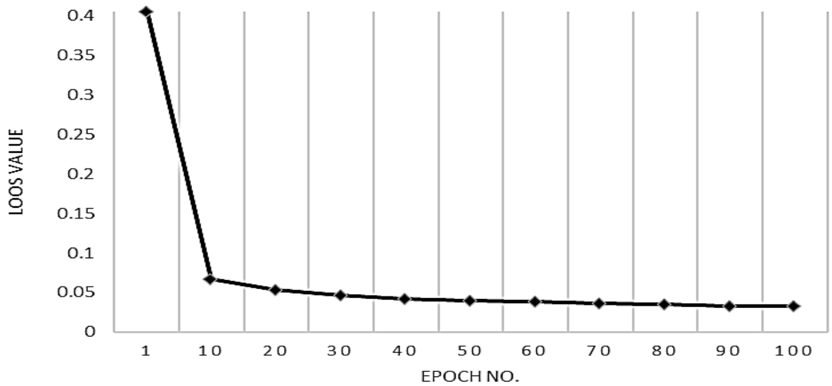


Figure 8: Minimal Loss Values in Relation to the Number of Epochs

The proposed methodology (Figure 4) demonstrates significant efficiency and stability in accurately forecasting power use, with applications in intelligent building power management, utility demand prediction, and renewable energy incorporation. The previously established average prediction accuracy demonstrates that the proposed performance exceeds that of the non-hybrid models by 95.61%, while also achieving results comparable to hybrid methods, indicating great consistency in recognizing true positives without losing specificity. Figure 9 illustrates the actual power compared to the expected power for the year 2017. The findings demonstrate a robust association between the actual outcomes and the predictive model predictions, with MAE and MSE values of 0.1594 and 0.04356, respectively.

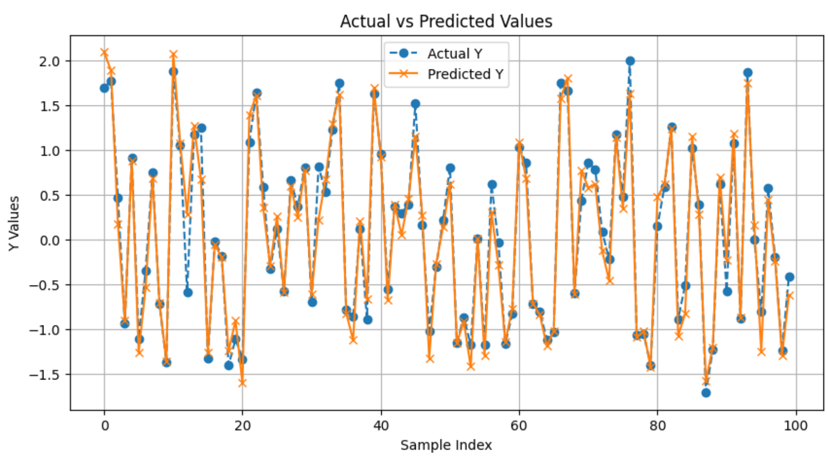


Figure 9: Actual versus predicted results

9 Conclusion and Future Works

for assessing future energy demand, Forecasting, estimate, and prediction are essential. Efficient energy distribution planning depends on precise estimates to equilibrate demand and supply. Forecasting inaccuracies may substantially affect operational expenses, network security, and quality of service. The suggested technique features a modified deep learning CNN model (Figure. 4) that exhibits considerable efficiency and stability in properly predicting power consumption, applicable in utility demand forecasting, intelligent buildings energy management (EM), and the integration of renewable energy sources (RES_S). It attained robust outcomes in this analysis, demonstrating an accuracy of 95.61%, with MAE- Mean Absolute Error and MSE- Mean Squared Error values of 0.1594 and 0.04356, respectively. This strong performance highlights CNN's capability to precisely estimate power use, making it particularly suitable for power management applications where accuracy is critical.

Future study must focus on expanding the application of the suggested CNN to more datasets and including real-time data. Further exploration with other DL architectures may improve the model's performance in broader contexts.

Data Availability

The authors affirm that the majority of research data in this work is open and accessible without limitations. This link ends much of the data:
https://www.kaggle.com/datasets/fedesoriano/electric-power-consumption.

Conflicts of Interest

The authors claim no conflicts of interest.

Author Contributions

This article was written by Zahraa Taleb included concepts, methodology, software, verification, formal analysis, research, data curation, and authoring of the first draft. The second and third authors managed, reviewed, edited, and supervised this paper.

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