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Konutlarda Reel Enerji Tüketimi Kestiriminde Güncel Yapay Zeka Algoritmalarının Uygulanması

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ÖZET

Sanayileşmenin hızlanmasıyla birlikte artan enerji arz talebi artık konutlarda da kullanılan yeni nesil elektronik ekipmanlar nedeniyle her geçen gün artmaktadır. Enerjinin klasik yöntemlerle (doğalgaz, sosil yakıtlar vb.) üretilmesine alternatif olarak geliştirilen be yeşil enerji adı verilen yenilenebilir enerjinin kullanımının yaygınlaşmasıyla beraber bazı sorunlar ortaya çıkmaktadır. Elde edilen elektriğin sisteme entegre bir şekilde verilip takip edilebilmesi için veri izlemesi büyük önem arz etmektedir. Bu amaçla kurulan mikro ve makro ölçekteki akıllı şebekelerin dinamik röle haberleşmesi sayesinde büyük ölçeklerde enerji verileri elde edilmektedir. Nesnelerin interneti (IoT) çağında elde edilen bu verilerin işlenmesi ve analiz edilmesi için derin öğrenmek algoritmaları ve makine öğrenmesi yöntemleri kullanılmaktadır. Bu yöntemlerin sağlamış olduğu doğru analizler sayesinde akıllı şebekeler daha az kayıpla (yüksek verimle) çalışmaktadır. En küçük ölçekli bir kullanıcının enerji tüketim hesabı kestirimi optimize bir enerji yönetimi sağlamaktadır. Elektriğin doğru miktarda (güçte) akışı sağlandıktan sonra ortaya çıkabilecek israfın da önüne geçilebilmektedir. Makine ve derin öğrenme algoritmalarının hızlı ve gelişmiş tepkileri sayesinde hem kullanıcılar hem de üreticiler daha planlı ve sürdürülebilir bir enerji yönetimine sahip olmaktadırlar. Bu çalışmada konutlara ait 4 yıllık elektrik enerji verileri Convolutional Neural Network, Long Short-Term Memory, Random Forest ve K-Nearest Neighbors Regression gibi yöntemlerle analiz edilmiştir. Bu analizler neticesinde tüketilecek enerjinin tahmini yapılmıştır. Çalışmadaki öğrenme algoritmalarının etkinliğini değişen eğitim ve test veri oranlarına göre değerlendirmek için veri seti üç farklı bölme yöntemi kullanılarak bölümlendi: %90 eğitim - %10 test, %80 eğitim - %20 test ve %67 eğitim - %33 test bölümü. Ek olarak, daha ileri değerlendirme için 10 katlı çapraz doğrulama yaklaşımı kullanıldı. Karşılaştırmalı analiz, LSTM modelinin günlük tahminler için en düşük MSE değeri olan 0,0054 ile en iyi performans gösteren model olarak ortaya çıktığını ortaya çıkardı.

Application of Contemporary Artificial Intelligence Algorithms in Real Energy Consumption Estimation in Residences

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ABSTRACT

The acceleration of industrialisation has resulted in a corresponding increase in the demand for energy supplies, driven by the growing use of new generation electronic equipment in residential settings. The advent of renewable energy, or green energy, has prompted a shift away from traditional methods of energy production, such as the use of natural gas and fossil fuels. However, this transition has given rise to a number of challenges. It is of great importance to monitor data in order to integrate the obtained electricity into the system and to monitor it. The acquisition of energy data on a large scale is made possible by the implementation of dynamic relay communication within micro and macro scale smart grids, which have been specifically designed for this purpose. Deep learning algorithms and machine learning methods are employed for the processing and analysis of data obtained in the context of the Internet of Things (IoT). The implementation of these methods enables smart grids to operate with reduced loss and enhanced efficiency. The estimation of energy consumption at the smallest scale facilitates the implementation of optimised energy management strategies. By ensuring the flow of electricity in the optimal amount (power), the potential for waste can be mitigated. The rapid and sophisticated responses of machine and deep learning algorithms facilitate more structured and sustainable energy management for both users and producers. In this study, four years' worth of electrical energy data from residential sources was analysed using techniques such as Convolutional Neural Network, Long Short-Term Memory, Random Forest and K-Nearest Neighbours Regression. The resulting analyses enabled the estimation of energy consumption. To assess the efficacy of learning algorithms in the study across varying training and test data ratios, the dataset was partitioned using three distinct division methods: hold-out (90% training - 10% testing), hold-out (80% training - 20% testing), and a 67% training - 33% testing split. Additionally, a 10-fold cross-validation approach was employed for further evaluation. Comparative analysis revealed that the LSTM model emerged as the top-performing model, boasting the lowest MSE value of 0.0054 for daily forecasts.

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INTRODUCTION

In the current landscape, residential and commercial buildings account for approximately 30% to 40% of total energy demand [1,2], with projections indicating a further rise in this proportion. This escalation in energy demand underscores the growing significance of renewable energy production. The effective integration of renewable energy into the grid requires the development of efficient energy transfer mechanisms, which has led to a significant increase in research activity focused on smart electricity grids and the ability to meet societal demands.

Smart grids, characterized by enhanced communication channels between producers and consumers [3,4], enable real-time monitoring, prediction, scheduling, and adaptive production based on local energy consumption patterns. These networks promise substantial environmental and economic benefits, including optimized electricity transmission with minimized energy losses due to shorter transmission lines, expedited outage resolution, heightened security against sabotage, seamless integration of renewable energy sources, and reduced costs associated with fault detection and repair [5].

The incorporation of artificial intelligence (AI) in electrical network management facilitates efficient planning and real-time control of dynamically evolving power supplies. Consequently, recent research efforts have increasingly delved into this domain [6], with a notable emphasis on leveraging deep learning and machine learning techniques for energy consumption estimation. Such endeavors hold the promise of enabling future electricity networks to forecast energy consumption accurately, allowing users to implement energy-saving measures at the building level. Traditionally, energy consumption forecasting encompasses three temporal categories: short-term forecasts (ranging from one day to one week), medium-term forecasts (spanning from one week to one year), and long-term forecasts (extending beyond one year).

Energy estimation of buildings is a difficult problem because it depends on many different factors (climatic conditions, devices used by the consumer, frequency of use, etc.) [7]. Therefore, taking everything into account when estimating energy will produce more efficient results. Estimating energy consumption; It will make it easier to calculate the amount of energy that needs to be produced and the amount of energy that needs to be stored. In addition, it will enable quick decisions in energy management as it will allow predicting where, when and how much cost will be required. In this way, time-saving methods will be implemented more easily. Future programming will be healthier and more reliable.

In the 2016 study led by Elena Mocanu and her colleagues, the focus was on estimating energy consumption in buildings using deep learning methodologies. Specifically, newly developed stochastic models, namely CRBM (Conditional Restricted Boltzmann Machine) and FCRBM (Fully Conditional Restricted Boltzmann Machine), were employed for this purpose. The researchers utilized the "Individual Household Electric Power Consumption Data Set" obtained by Hebrail and Berard, which is publicly available in the UCI Machine Learning Repository [8]. This dataset comprises individual residential customer data recorded at 1-minute intervals over a span of four years.

The study encompassed the application of predictions under seven distinct scenarios, each employing various machine learning techniques. Specifically, Artificial Neural Networks (ANN), Support Vector Machines (SVM), Recurrent Neural Networks (RNN), CRBM, and FCRBM methods were employed across these scenarios. The scenarios investigated are delineated as in Table 1:

Table 1
Different scenarios for deep learning (DL) application

Scenario	Energy Consumption	Solution Duration for DL
1	15 minutes	1 minute
2	1 hour	1 minute
3	1 day	1 minute
4	1 day	15 minutes
5	1 week	15 minutes
6	1 week	1 hour
7	1 year	1 week

In summary, the Fully Conditional Restricted Boltzmann Machine (FCRBM) demonstrated superior performance compared to state-of-the-art prediction methods such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Recurrent Neural Networks (RNN), and the Conditional Restricted Boltzmann Machine (CRBM). As the prediction horizon expands, both FCRBM and CRBM exhibit heightened efficacy, with error rates approximately half that of the ANN method. These methodologies yield comparable results and demonstrate potential for real-time applications in home and building automation systems. Notably, rather than estimating total active power directly, a more efficient approach involves estimating and aggregating sub-measurements to arrive at total active power.

In a separate study by Tae-Young Kim et al., minute, hourly, daily, and weekly predictions were conducted using Linear Regression, Long Short-Term Memory (LSTM), and Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) algorithms [9]. The "Individual Household Electric Power Consumption Data Set" by Hebrail and Berard served as the dataset [10]. Results indicate that the CNN-LSTM algorithm outperformed other algorithms, achieving mean squared error (MSE) values of 0.3738 per minute, 0.3549 per hour, 0.1037 per day, and 0.0952 per week.

In the research conducted by Xiaoou Monica Zhang and colleagues, the Support Vector Regression (SVM) modeling approach served as the predictive algorithm. This methodology was applied to conduct hourly and daily predictions for 15 distinct households' electricity usage data spanning the years 2014 to 2016 [11]. Feature selection and data visualization techniques were employed through exploratory data analysis. The ensuing analyses revealed the feasibility and reliability of predicting residential energy consumption by leveraging weather conditions, calendar parameters, and time-of-use pricing. Notably, the SVM model exhibited satisfactory accuracy in both daily and hourly forecasts for specific residential applications.

Yasemin Kocadayi and her team endeavored to estimate the annual energy consumption of the TR81 region (comprising Zonguldak, Karabuk, and Bartin) utilizing artificial neural networks (ANNs). Input data for the ANN model included building surface areas, population figures, as well as import and export data [12]. The model's performance was evaluated based on metrics such as mean square error, mean absolute error, and correlation coefficient. Through the ANN model, energy consumption projections for the TR81 region spanning 2016 to 2020 were obtained. The findings underscored the ANN model's proficiency in accurately predicting electrical energy consumption within the region, demonstrating a high level of precision.

Derya Yılmaz and her team investigated project risks with a specific focus on heating and electricity demands in buildings. They introduced an innovative model for predicting performance gaps using machine learning classification techniques. The study gathered data on performance gaps and project risks through a web-based survey conducted across 77 buildings. Four machine learning algorithms—Naive Bayes, k-NN, SVM and RF—were evaluated to determine the most effective model.

The results revealed that Naive Bayes demonstrated superior accuracy in predicting the direction of heating performance gaps (72.50%), negative heating performance gaps (71.81%), positive electricity performance gaps (77.08%), and negative electricity performance gaps (83.85%). Furthermore, both k-NN and SVM exhibited higher accuracy in predicting the direction of electricity performance gaps (79.00%) and positive heating performance gaps (76.04%) [13].

A study performed by Flavian Emmanuel_Sapnken et al. utilizes a dataset from 7,559 buildings and employs nine Machine Learning (ML) models to estimate their energy consumption. Results indicate that the deep neural network (DNN) emerges as the most effective ML model, achieving MAE, MSD, and RMSE of 0.93, 1.12, and 1.06, respectively, in less than 7 seconds, despite the large dataset size. Its R^2 value is also the highest at 0.96, indicating that the DNN approach can explain 96% of the energy consumption in buildings, with only 4% remaining unexplained, likely due to limitations in independent variables. Moreover, this outcome remains consistent across building clusters and various climate zones. Their model proposes a model that professionals can utilize during the design phase of construction projects. This model enables consideration of all critical aspects for designing energy-efficient buildings. It serves as a decision-making tool to control and optimize projects, allowing for anticipation of energy consumption even before construction begins [14].

P. Balakumar et. al. suggest implementing a Demand Side Management (DSM) program within a smart grid to decrease the utility grid's Peak to Average Ratio (PAR) and lower end-users' electricity tariffs. It advocates for the use of renewable energy combined with an Energy Storage System (ESS) in the DSM controller to improve both economic and environmental aspects for end-users. To develop the DSM program, the article proposes a framework based on Recurrent Neural Network (RNN), specifically Long Short-Term Memory (LSTM), for forecasting Science Block (SCB) energy consumption every minute and 5 minutes for Energy Production Control (EPC) and Renewable Energy Generation (REG). The performance of this deep learning model is evaluated using metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared. The suggested LSTM framework demonstrates superior performance compared to other listed rival techniques in short-term Energy Production Control (EPC) for Science Block (SEIB) and Renewable Energy Generation (REG). For both short-term REG and EPC forecasting, the LSTM model achieves an accuracy with an R^2 value nearly close to one. With their proposed deep learning-based real-time DSM controller, the electricity tariff of SEIB is reduced by 4.4% on January 1st, 2022, and by 14.86% on January 2nd, 2022. Similarly, the utility grid's Peak to Average Ratio (PAR) is minimized to 5.10% and 11.79%, respectively [15].

This study examined the estimation of energy consumption in a house where smart systems are used, comparing it with DL and ML methods. The findings may vary depending on the type of house, for example if it is a smart building or in an urban area. Therefore, in this study, commercial enterprises were excluded, as their consumption could not be evaluated. Within the scope of this study it is not to estimate the demand factor or consumption, but rather to identify the most efficient method using existing consumption data.

MATERIALS AND METHODS

With the advent of technological advancements, researchers are fervently engaged in enhancing efficiency across various domains [16-18]. Among these endeavors, numerous studies are dedicated to advancing the energy sector. Notably, smart grids represent a pivotal facet of these efforts, offering streamlined energy distribution, management capabilities, and integration of renewable energy sources into production processes [19-21]. Across such endeavors, the efficacy of predictive methodologies has seen significant enhancement through the development of novel algorithms [22,23].

The principal objective of this study is twofold: firstly, to glean insights into future energy consumption patterns through the estimation of energy usage employing deep learning and machine learning techniques; and secondly, to devise a model that not only aids in curbing energy consumption but also facilitates prudent household expenditure planning.

Data Set

The dataset utilized in this study originates from the Individual Household Electric Power Consumption dataset retrieved from the UCI Machine Learning Repository database. This dataset comprises records of electrical power consumption, measured in kilowatt-hours, recorded every minute within a household located in France, spanning from December 2006 to November 2010 (47 months). The dataset, a time series, encompasses a total of 2,075,259 measurements, capturing various time-dependent power-related variables. Notably, the dataset primarily focuses on the total active power measurement values, denoted as "Global_active_power," representing kilowatts consumed by households, amidst seven distinct variables [10].

To facilitate compatibility with machine learning and deep learning algorithms, the dataset necessitated preprocessing and conversion into a suitable format. Notably, the household electrical power consumption dataset exhibited some missing values within the measurements, such as observed on April 28, 2007. Addressing this issue, missing values were imputed by replacing them with the average power consumption values recorded during corresponding minutes across other years. Subsequently, the processed dataset was saved as a new entity, ready for analysis.

In the final stage of data preprocessing, the observations recorded every minute were transformed into daily electrical power consumption quantities measured in kilowatt-hours (kWh). This conversion was implemented to facilitate the estimation of daily energy consumption, thereby condensing minute-by-minute observations into daily totals. Consequently, the dataset encompasses a total of 1442 daily observation values. The actual daily electrical power consumptions following the data preprocessing phase are visually depicted in Figure 1, illustrating the variations in kWh consumption over time. Furthermore, the characteristics of the active power data subsequent to the conversion of the dataset into daily values are detailed in Table 2, providing insights into the statistical properties and distributional aspects of the transformed dataset.

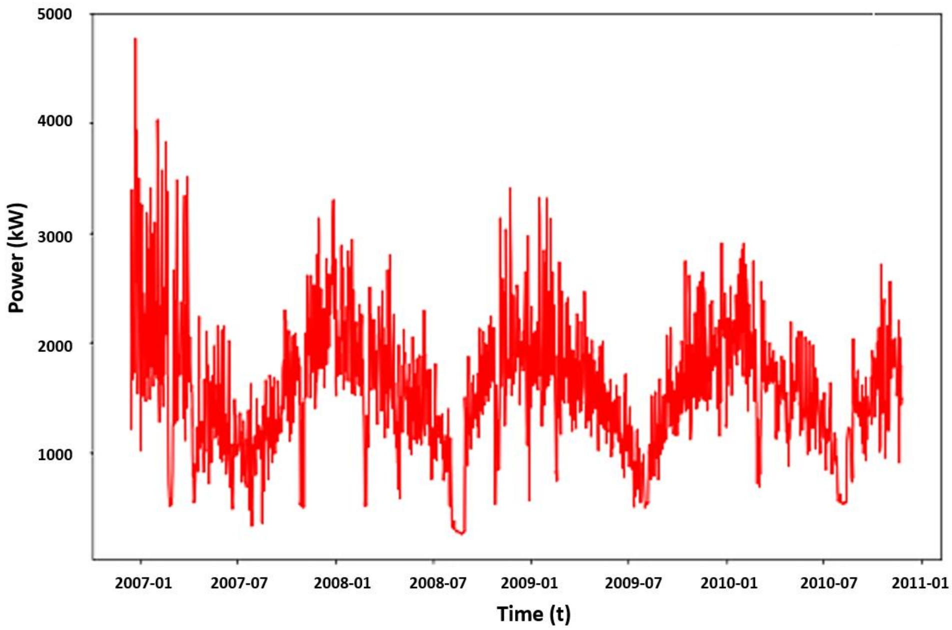

Figure 1
Actual daily electrical power consumption graph after data preview phase

Table 2
Properties of the data set

Data Set Length	1442
Average	1567.839069
Std	597.306856
Minimum	250.298000
25%	1176.195000
50%	1543.253000
75%	1894.467500
Maximum	4773.386000

When conducting time series analysis, the first step involves assessing whether the series exhibits stationarity. Stationarity is characterized by consistent mean and variance of observations over time, indicating that the series does not undergo significant changes across time periods. A stationary time series typically lacks discernible trends or seasonality, making it more amenable to modeling. Statistical modeling techniques often presuppose stationarity for effective application.

In contrast, non-stationary time series display temporal variations such as trends, seasonal effects, or other structural dependencies on the time index. In such cases, summary statistics like mean and variance may fluctuate over time, complicating the modeling process by introducing shifts in the underlying data dynamics. Traditional time series analysis and forecasting methodologies aim to stabilize non-stationary data by identifying and mitigating trends and seasonal effects.

Several approaches exist to assess stationarity in a time series dataset. These include:

Graphical Examination: Time series plots can be visually inspected for evident trends or seasonal patterns.

Summary Statistics: Statistical metrics computed over different seasons or random segments of the data can be compared to identify any pronounced differences, which may indicate non-stationarity.

Statistical tests serve as a valuable tool for assessing whether time series data meet the criteria for stationarity. While these tests rely on certain data assumptions, they offer a swift means of confirming stationarity or non-stationarity. In this study, the Augmented Dickey-Fuller (ADF) test was employed to scrutinize the stationarity of the time series [24]. The ADF test belongs to a class of statistical tests known as unit root tests and is among the most widely utilized methods in this domain. This test leverages an autoregressive model and employs an information criterion to optimize across various lag values.

The null hypothesis (H0) posited by the ADF test suggests that the time series contains a unit root and is thus non-stationary. Conversely, the alternative hypothesis (H1) refutes the null hypothesis, indicating that the time series lacks a unit root and is stationary. The outcome of the ADF test is typically interpreted through the computed p-value. A p-value below a specified threshold (e.g., 5% or 1%) signifies rejection of the null hypothesis, signaling stationarity. Conversely, a p-value surpassing the threshold indicates failure to reject the null hypothesis, implying non-stationarity.

In the context of the Augmented Dickey-Fuller (ADF) test:

- When the p-value is greater than 0.05, the null hypothesis (H0) is not rejected. This indicates that the data contains a unit root and is non-stationary.
- Conversely, when the p-value is less than or equal to 0.05, the null hypothesis (H0) is rejected.

This suggests that the data lacks a unit root and is stationary.

The results of the Augmented Dickey-Fuller (ADF) test are presented in Table 3. The computed ADF test statistics yielded a value of -3.697385. In the context of the ADF test, a more negative statistic increases the likelihood of rejecting the null hypothesis. Notably, the calculated ADF value fell below the critical value corresponding to a significance level of 1%. This discrepancy implies that the null hypothesis will indeed be rejected with a significance level of less than 1%. Moreover, the computed p-value was found to be less than or equal to 0.05. This observation leads to the rejection of the null hypothesis, indicating that the time series exhibits stationarity or lacks a time-dependent structure. In summary, both the ADF test statistic and the p-value converge to suggest the rejection of the null hypothesis, thus affirming the stationarity of the time series data.

Table 3
ADF test results

ADF Statistics	-3.697385
p-value	0.004150
Critical Values	
1%	-3.4357
5%	-2.8645
10%	-2.5686

Application of MLA

In machine and deep learning algorithms, it is worth noting that the percentages of training and testing data can vary for different applications [25,26]. In studies involving large data sets, it is often the case that set division is done at different percentages in order to get the most accurate results [27-29]. Therefore, in our study, we tested data division percentages at different rates in order to gain a better understanding of the impact of this on the results.

To assess the efficacy of learning algorithms in the study across varying training and test data ratios, the dataset was partitioned using three distinct division methods: hold-out (90% training - 10% testing), hold-out (80% training - 20% testing), and a 67% training - 33% testing split. Additionally, a 10-fold cross-validation approach was employed for further evaluation. The implementation of the proposed models was executed utilizing Keras version 2.2.4 with Tensorflow backend, leveraging the Python 3.6 programming language. The machine learning and deep learning algorithms employed in our investigation are extensively documented in scholarly literature. These methodologies find application across various disciplines and are notably prevalent in estimating household energy consumption, which constitutes the focal point of our research [30,31].The selected machine learning algorithms for time series prediction tasks included RF, KNN and LR. By employing a range of diverse partitioning strategies and meticulous algorithmic selections, the study sought to conduct a comprehensive evaluation of the efficacy and resilience of the learning models in accurately forecasting time series data.

Random Forest Algorithm

The Random Forest algorithm is comprised of multiple decision trees operating as an ensemble. In this approach, each individual tree generates a set of predictions, and the class with the highest number of votes among the trees is selected as the final prediction of the model [32].

$$\mathrm{RFfii} = \frac{\sum_{j \in all\ tress} * normfiij}{\mathrm{T}} \tag{1}$$

Rffii = Importance of feature calculated from all trees in RF algorithm

$normfiij$ = Normalized coefficient for i in tree j

T= Total number of decision trees

The "n_estimators" parameter, which indicates how many decision trees will be drawn in the RF algorithm, is taken as 10.

K-Nearest Neighbours Regression

The k-NNR algorithm is often employed in applications prioritizing interpretability of output, computational efficiency, and predictive accuracy. When utilizing the k-NNR algorithm, the Euclidean distance metric (as represented in equation 2) is frequently employed as the distance measure. This metric is applicable to real-valued vectors and quantifies the straight-line distance between the query point and another observed point, as depicted by the following formula [33].

$$\sqrt{\sum_{i=1}^{k}(x_i - y_i)^2} \tag{2}$$

The Manhattan distance, denoted by Equation 3, is an alternative distance measure commonly used in various applications. This metric calculates the absolute difference between two points (x_i ve y_i). Due to its visualization resembling movement along city blocks, it is also known as taxi distance or city block distance. This distance measure is often depicted using a grid, illustrating the path one must traverse via city streets to travel from one address to another.

$$\sum_{i=1}^{k} |x_i - y_i| \tag{3}$$

$$\left(\sum_{i=1}^{k}(x_i - y_i)^q\right)^{1/q} \tag{4}$$

The Minkowski distance, as expressed in Equation 4, serves as a versatile distance metric that encompasses both Euclidean and Manhattan distance measurements. The parameter *p* within the formula facilitates the creation of additional distance metrics. Specifically, when *p* equals two, the formula reduces to represent the Euclidean distance, while when *p* equals one, it represents the Manhattan distance. In the context of the k-Nearest Neighbors Regression (k-NNR) algorithm, the *n_neighbors* parameter, indicating the value of *k*, is set to 3.

Linear Regression

Linear Regression stands as one of the fundamental models in machine learning, employed to discern the relationship between one or more predictor variables and outcome variables. This technique is widely utilized for predictive analysis and modeling purposes, known by various names such as simple linear regression, multiple regression, multivariate regression, ordinary least squares regression, and simply regression.

The formulation of linear regression is represented by the equation:

$$y = ax + b$$

where: y denotes the dependent variable, x represents the independent variable(s), b signifies the slope of the line, and a denotes the intersection point of the line with the y-axis.

The objective of this model is to establish a linear relationship that optimally describes the association between the independent and dependent variables by fitting a straight line to the data points.

Application of Deep Learning Algorithms

Traditionally, linear methods have been favored in time series forecasting due to their well-established principles and effectiveness in handling simple forecasting tasks. However, deep learning methods offer a compelling alternative by enabling the automatic learning of complex mappings from inputs to outputs, accommodating multiple inputs and outputs simultaneously. CNNs are a specialized type of neural network architecture tailored for processing image data. They are highly effective for tasks like image recognition, classification, and object detection. Leveraging their capacity to autonomously extract intricate features from raw input data, CNNs can be effectively applied to time series forecasting problems. On the other hand, Recurrent Neural Networks (RNNs), such as the Long Short-Term Memory (LSTM) network, possess the capability to directly learn across multiple parallel sequences of input data. This characteristic makes them particularly well-suited for time series forecasting tasks. Given the effectiveness demonstrated by CNNs and LSTM methods in addressing time series forecasting challenges, these methodologies were selected for inclusion in the study.

Convolutional Neural Networks

The foundational principles of the Convolutional Neural Network (CNN) algorithm were initially introduced by Kunihiko Fukushima in 1980 [34]. Since its inception, continuous development has led to its current state, where the CNN algorithm has emerged as one of the most prevalent techniques within the realm of deep learning. Notably, CNNs are primarily utilized for the analysis of visual images and are also referred to as invariant space artificial neural networks [35]. Their applications span diverse domains including image and video recognition, recommendation systems, image classification, medical image analysis, natural language processing, and data prediction.

In the proposed CNN model, a series of layers were employed, each serving specific functions within the architecture. These layers include a 1D convolution layer, a dropout layer, a 1D maximum pooling layer, a flatten layer, a fully connected layer (hidden layer), and a final fully connected layer for output. Figure 2 illustrates the arrangement of these layers along with their respective parameter values.

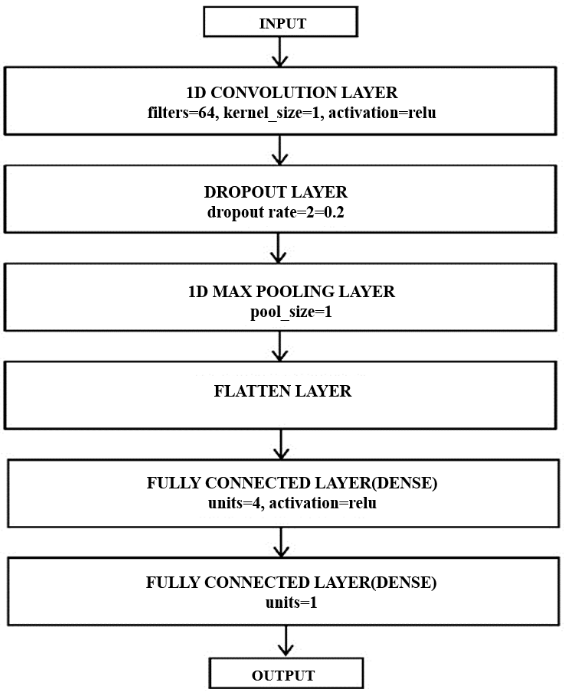

Figure 2
The layers of CNN model

Long-Short Term Memory

LSTM networks are a type of Recurrent Neural Network (RNN) architecture designed to effectively handle sequential data and address the vanishing gradient problem typically found in traditional RNNs. LSTMs are widely used in deep learning for tasks involving time-series data, natural language processing, and other sequence prediction problems [36]. The motivation behind the development of the LSTM algorithm stems from the inherent long-term memory recall challenges observed in traditional RNN algorithms. In contrast to the single layer in RNN models, LSTM models incorporate four distinct layers, each representing feedback connections. These layers encompass various gates, including the input gate, forget gate, and output gate [37].

LSTM algorithms are particularly well-suited for tasks involving classification, processing, and prediction based on time series data. In the proposed Bidirectional LSTM (BLSTM) model, an LSTM layer and a fully connected layer are employed for the output. Figure 3 provides a visual representation of the model's layers, along with their respective parameter values.

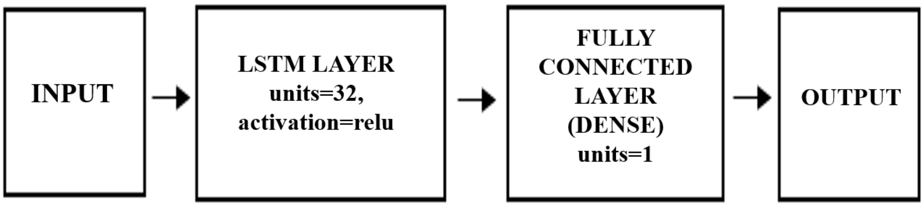

Figure 3
The layers of LSTM Model.

Evaluation Criterias

Root Mean Squared Error

RMSE serves as a metric to quantify the error rate between two datasets, specifically comparing predicted values to observed values. As depicted in Equation 5, RMSE calculates the square root of the average of the squared differences between predicted and observed values. A smaller RMSE value indicates a closer correspondence between the predicted and observed values, reflecting higher accuracy in the predictive model.

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(f_i - o_i)^2} \qquad (5)$$

f = expected values, o = observed values, n = number of samples

Mean Squared Error

MSE quantifies the proximity of a regression line to a set of data points. It serves as a risk function, representing the expected value of the square of the error loss. Calculated by averaging the squared errors from the data regarding a function, MSE is expressed as the mean of these squared errors. Unlike RMSE, which involves taking the square root of the average squared errors, the formula for MSE (equation 6) does not include the root operation, thereby providing a measure of the average squared discrepancy between predicted and observed values [38].

$$\frac{1}{n}\sum_{i=1}^{n}(f_i - o_i)^2 \qquad (6)$$

The implemented code encompasses the following steps:

1. Perform the data reading operation: Read the dataset containing the relevant information for the analysis.

2. Prepare for cross-validation: Define the parameters and setup necessary for conducting cross-validation.
3. Normalize the data: Scale the input features to ensure uniformity and facilitate the modeling process.
4. Separate the data into training and testing: Partition the dataset into training and testing subsets for model evaluation.
5. Model building: Construct the machine learning or deep learning model using the training data.
6. Make predictions: Utilize the trained model to predict outcomes for the testing data.
7. Obtain cross-validation results: Evaluate the model's performance using cross-validation techniques to assess its generalization ability.
8. Calculate MSE, RMSE, and Accuracy Rates: Compute performance metrics such as MSE, RMSE and Accuracy Rates to quantify the model's predictive accuracy and effectiveness.

These steps collectively form a structured approach to data analysis and model building, ensuring thoroughness and reliability in the analytical process.

RESULTS

In this article, various algorithms were applied with optimized parameter values using different data splitting methods (90% training - 10% test, 80% training - 20% test, and 67% training - 33% test) and cross-validation techniques. Performance analysis results were then presented. Specifically, evaluations of the algorithms applied to the dataset, where training and test data were different splitting rate test method, were conducted based on performance criteria, focusing on daily and weekly data. The findings of these evaluations are summarized in Table 4.

According to the results presented in Table 4, the LSTM model yielded the lowest MSE value of 0.0055. Comparatively, the CNN algorithm achieved an MSE of 0.0056, the RF algorithm attained 0.0066, the k-NNR algorithm resulted in 0.0073 MSE, and the LR algorithm produced an MSE of 0.0058.

Table 4
The comparison of algorithms based on different splitting data rate

Data Splitting	Algorithm	Daily			Weekly		
		MSE	RMSE	Accuracy rate	MSE	RMSE	Accuracy rate
90% training 10% testing	CNN	0.0056	0.0750	0.9944	0.01	0.10	0.9899
	LSTM	0.0054	0.0748	0.9946	0.01	0.1022	0.9896
	RF	0.0066	0.0816	0.9933	0.015	0.122	0.9849
	k-NNR	0.0073	0.0856	0.9927	0.0085	0.0919	0.9915
	LR	0.0058	0.0765	0.9941	0.0090	0.0949	0.9909
80% training 20% testing	CNN	0.0057	0.0760	0.9943	0.0068	0.0828	0.9931
	LSTM	0.0056	0.0753	0.9944	0.0075	0.0866	0.9925
	RF	0.0072	0.0851	0.9927	0.0098	0.0988	0.9902
	k-NNR	0.0084	0.0921	0.9915	0.0067	0.0825	0.9932
	LR	0.0055	0.0745	0.9945	0.0073	0.084	0.9927
67% training 33% testing	CNN	0.0061	0.0785	0.9939	0.0084	0.0919	0.9916
	LSTM	0.0059	0.0774	0.9941	0.0089	0.0944	0.9910
	RF	0.0075	0.0868	0.9924	0.010	0.10	0.9891
	k-NNR	0.0094	0.0973	0.9905	0.012	0.1122	0.9874
	LR	0.0062	0.0786	0.9938	0.0088	0.094	0.9911

According to the results in Table 4, it was seen that the Linear Regression model was the model that gave the smallest MSE value with a value of 0.0055. When MSE values of other methods are examined; The CNN algorithm showed performance with 0.0057, LSTM algorithm 0.0056, RF algorithm 0.0072 and k-NNR algorithm 0.0084 MSE values, respectively.

The LSTM model demonstrated the lowest MSE value, registering at 0.0059. In comparison, the CNN algorithm exhibited an MSE of 0.0060, the RF algorithm yielded 0.0075, the k-NNR algorithm resulted in 0.0094 MSE, and the LR algorithm achieved an MSE of 0.0062.

Additionally, Table 5 outlines the accuracy rates obtained from transactions conducted with Cross-Validation. These results provide further insights into the performance of the algorithms under evaluation.

Table 5
Comparison of Algorithms According to Transactions Performed with Cross-validation.

Algorithm	Daily	Weekly				
	MSE	RMSE	Accuracy rate	MSE	RMSE	Accuracy rate
RF	0.006011	0.07752	0.993998	0.013841	0.11764	0.986162
k-NNR	0.03121	0.17665	0.96884	0.11812	0.34374	0.88198

According to the comparisons made, the loss rate graph of the LSTM model, which is the best performing model applied to the data set for which training and test data were created with the 90% training-10% test splitting method, is shown in Figure 4.

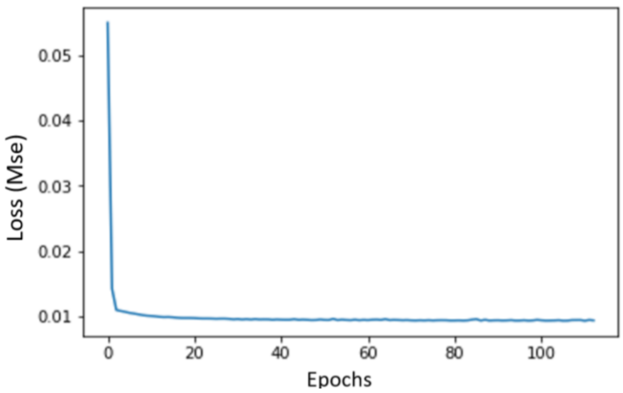

Figure 4
LSTM model loss rate graph (90% training-10% testing)

The figure depicting the comparison between predictions generated by the LSTM model and actual observations from the dataset, where training and test data were partitioned using the 90% training-10% test splitting approach, is presented in Figure 5.

Figure 6 illustrates the graph comparing the actual values and predicted values of the k-NNR algorithm, utilizing the highly effective 80% training-20% test splitting method for estimating weekly consumption values.

DISCUSSION AND CONCLUSIONS

Given the surge in smart grid technologies and the widespread adoption of electricity generation methods, the measurement of energy usage and the formulation of savings plans have gained paramount significance. The literature abounds with numerous studies aimed at estimating consumption through various methodologies. This is owing to the profound potential of modeling and forecasting future electricity consumption, which can lead to substantial energy conservation efforts.

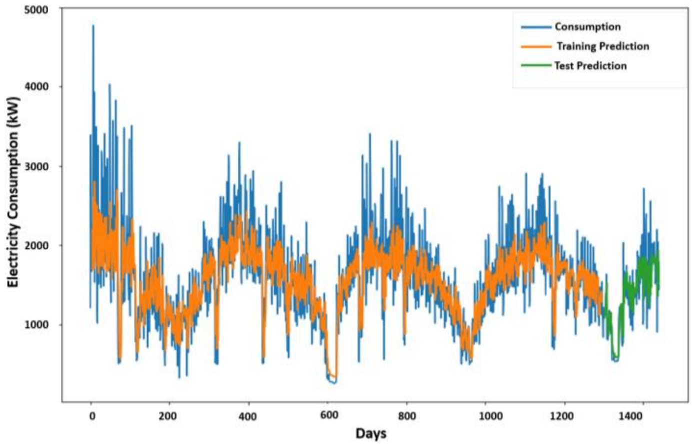

Figure 5
Comparison of real data and LSTM prediction (Daily) values

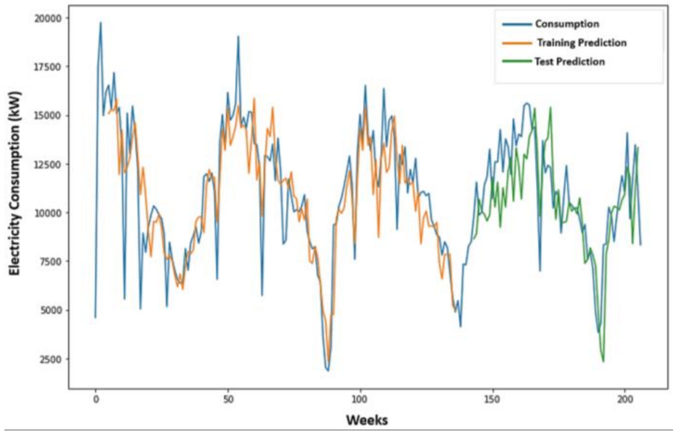

Figure 6
Comparison of real data and k-NNR predicted (weekly) values

The main goal of our work is to establish an infrastructure capable of forecasting future energy consumption by leveraging DL and ML techniques for estimating energy usage. Moreover, the envisaged model is poised to contribute significantly to curbing energy consumption and facilitating the planning of household expenditures. Furthermore, insights will be gleaned into the requisite production levels. The methodologies selected for our study are extensively employed in scholarly literature. Specifically, the LSTM method has demonstrated a noteworthy increase in accuracy percentage compared to existing literature in our research [39,40]. This achievement is readily apparent upon comparison with the literature, where other utilized methods have also exhibited substantial success [41]. The research yielded favorable outcomes in estimating electrical power consumption through the application of CNN, LSTM, RF, k-NNR, and Linear Regression methods. Comparative analysis revealed that the LSTM model emerged as the top-performing model, boasting the lowest MSE value of 0.0054 for daily forecasts. Conversely, for weekly predictions, the k-NNR algorithm exhibited superior performance with an MSE value of 0.0067. Notably, the study indicated a higher success rate in estimating daily energy consumption compared to weekly energy consumption.

Furthermore, when subjected to Cross-Validation, the Linear Regression algorithm demonstrated perfect accuracy with an accuracy rate of 1.0, signifying an exact match with the dataset. The developed model is poised to estimate electrical power consumption with remarkable precision, closely approximating actual observation values. Consequently, the LSTM model, which demonstrated superior performance in estimating electrical power consumption, was deemed the most suitable choice. Moreover, the developed LSTM model showcased enhanced efficacy in smart grid management or evaluation compared to other applied methods. Through the predictions generated by this approach, savings plans can be formulated effortlessly and with heightened reliability.

When evaluating the performances of LSTM models across different division methods, notably, a superior success rate was attained with the LSTM model applied to the dataset partitioned with the 90% training-10% test splitting method, surpassing other splitting techniques. Similarly, for CNN models, enhanced performance was evident when employing the 90% training-10% test splitting method compared to alternative methods. In the case of RF models, optimal success rates were achieved when utilizing the 90% training-10% test splitting method. Likewise, for k-NNR models, superior performance was observed with the 90% training-10% test splitting method. Conversely, when analyzing the performances of Linear Regression models across division methods, intriguingly, a higher success rate was attained with the Linear Regression model applied to the dataset partitioned with the 80% training-20% test splitting method, diverging from the trends observed with other algorithms. It is noteworthy that Linear Regression did not exhibit a proportional increase in efficiency with the extension of the training series, distinguishing it from other algorithms.

Upon examining the impact of training and test data splitting methods on the performance of the proposed models, a discernible trend emerges: as the size of the training set increases across the utilized splitting methods, the prediction performance of the models demonstrates a consistent improvement. This observation underscores the pivotal role of a larger training set in enhancing model training and subsequently yielding more accurate and reliable predictions. This finding underscores the importance of expanding the dataset for future studies, as it facilitates the development of more robust models and ensures greater consistency in predictions. Moreover, future endeavors may explore the potential of enhancing predictions through the utilization of different deep learning models, leveraging increased dataset sizes to further refine and optimize model performance.

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Ethical Statement

This article is derived from the master’s thesis entitled “Comparison of deep learning and machine learning methods for estimating energy consumption in houses” that was completed under the supervision of Prof. Dr. Aysel ERSOY (Master’s Thesis, Istanbul University-Cerrahpaşa, Istanbul, Türkiye, 2020). The data and insights presented herein are based on the findings of the aforementioned thesis, with permission from the author. This work aims to build upon and expand the research conducted in the original thesis, contributing to the ongoing discourse in the field.

Author Contributions

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REFERENCES

[1] S. Fathi, R. Srinivasan, A. Fenner, S. Fathi, Machine learning applications in urban building energy performance forecasting: A systematic review, *Renewable and Sustainable Energy Reviews*. 133 (2020), 110287. doi:10.1016/J.RSER.2020.110287

[2] S. Yang, M.P. Wan, W. Chen, B.F. Ng, S. Dubey, Model predictive control with adaptive machine-learning-based model for building energy efficiency and comfort optimization, *Applied Energy*. 271 (2020), 115147. doi:10.1016/J.APENERGY.2020.115147

[3] N.T. Mbungu, R.M. Naidoo, R.C. Bansal, M.W. Siti, D.H. Tungadio, An overview of renewable energy resources and grid integration for commercial building applications, *Journal of Energy Storage*. 29 (2020), 101385. doi:10.1016/J.EST.2020.101385

[4] A. Rejeb, K. Rejeb, S. Simske, H. Treiblmaier, S. Zailani, The big picture on the internet of things and the smart city: a review of what we know and what we need to know, *Internet of Things (Netherlands)*. 19 (2022), 100565. doi:10.1016/J.IOT.2022.100565

[5] A.H. Al-Badi, R. Ahshan, N. Hosseinzadeh, R. Ghorbani, E. Hossain, Survey of smart grid concepts and technological demonstrations worldwide emphasizing on the Oman perspective, *Applied System Innovation*. 3 (2020) 1–27. doi:10.3390/ASI3010005

[6] M. Hacıbeyoglu, M. Çelik, Ö. Erdaş Çiçek, Energy Efficiency Estimation in Buildings with K Nearest Neighbor Algorithm, *Necmettin Erbakan University Journal of Science and Engineering*. 5(2) (2023), 65–74. doi:10.47112/neufmbd.2023.10

[7] Y. Liu, H. Chen, L. Zhang, X. Wu, X. jia Wang, Energy consumption prediction and diagnosis of public buildings based on support vector machine learning: A case study in China, *Journal of Cleaner Production*. 272 (2020), 122542. doi:10.1016/J.JCLEPRO.2020.122542

[8] E. Mocanu, P.H. Nguyen, M. Gibescu, W.L. Kling, Deep learning for estimating building energy consumption, *Sustainable Energy, Grids and Networks*. 6 (2016), 91–99. doi:10.1016/J.SEGAN.2016.02.005

[9] T.Y. Kim, S.B. Cho, Predicting residential energy consumption using CNN-LSTM neural networks, *Energy*. 182 (2019), 72–81. doi:10.1016/J.ENERGY.2019.05.230

[10] H. Georges and B. Alice. Individual household electric power consumption, *UCI Machine Learning Repository*. 2012. https://doi.org/10.24432/C58K54.

[11] X.M. Zhang, K. Grolinger, M.A.M. Capretz, L. Seewald, Forecasting Residential Energy Consumption: Single Household Perspective, içinde: *Proceedings - 17th IEEE International Conference on Machine Learning and Applications, ICMLA 2018*, 2018: ss. 110–117. doi:10.1109/ICMLA.2018.00024

[12] Y. Kocadayi, O. Erkaymaz, R. Uzun, Estimation of Tr81 area yearly electric energy consumption by artificial neural networks, *Bilge International Journal of Science and Technology Research*. 1 (2017), 59–64.

[13] D. Yılmaz, A.M. Tanyer, I.D. Toker, A data-driven energy performance gap prediction model using machine learning, *Renewable and Sustainable Energy Reviews*. 181 (2023), 113318. doi:10.1016/J.RSER.2023.113318

[14] F.E. Sapnken, M.M. Hamed, B. Soldo, J. Gaston Tamba, Modeling energy-efficient building loads using machine-learning algorithms for the design phase, *Energy and Buildings*. 283 (2023), 112807. doi:10.1016/J.ENBUILD.2023.112807

[15] P. Balakumar, T. Vinopraba, K. Chandrasekaran, Deep learning based real time Demand Side Management controller for smart building integrated with renewable energy and Energy Storage System, *Journal of Energy Storage*. 58 (2023), 106412. doi:10.1016/J.EST.2022.106412

[16] B. Peker, F. A. Çuha, ve H. A. Peker, Analytical solution of Newton's law of cooling equation via kashuri fundo transform, *Necmettin Erbakan University Journal of Science and Engineering*.

6(1) (2024), 10–20. doi:10.47112/neufmbd.2024.29

[17] B. Akgayev, S. Akbayrak, M. Yılmaz, M. S. Büker, ve V. Unsur, Assessing the feasibility of photovoltaic systems in Türkiye: Technical and economic analysis of on-grid, off-grid, and utility-scale PV installations, *Necmettin Erbakan University Journal of Science and Engineering*. 6(1) (2024), 69–92. doi: 10.47112/neufmbd.2024.33

[18] N. Kulaksız, M. Hançer, Flight tests for aircraft in simulink-flightgear environments and comparison of aerodynamic effects on stability/frame axes, *Asrel Aerospace Research Letters*. 1 (2022), 69–83. doi:10.56753/ASREL.2022.2.1

[19] J.C. Kim, S.M. Cho, H.S. Shin, Advanced power distribution system configuration for smart grid, *IEEE Transactions on Smart Grid*. 4 (2013), 353–358. doi:10.1109/TSG.2012.2233771

[20] O. Majeed Butt, M. Zulqarnain, T. Majeed Butt, Recent advancement in smart grid technology: Future prospects in the electrical power network, *Ain Shams Engineering Journal*. 12 (2021), 687–695. doi:10.1016/J.ASEJ.2020.05.004

[21] C. Crozier, T. Morstyn, M. McCulloch, The opportunity for smart charging to mitigate the impact of electric vehicles on transmission and distribution systems, *Applied Energy*. 268 (2020), 114973. doi:10.1016/J.APENERGY.2020.114973

[22] M. Karakoyun, A. Özkış, Development of binary moth-flame optimization algorithms using transfer functions and their performance comparison, *Necmettin Erbakan University Journal of Science and Engineering*. 3(2) (2021), 1-10.

[23] T. Ahmad, R. Madonski, D. Zhang, C. Huang, A. Mujeeb, Data-driven probabilistic machine learning in sustainable smart energy/smart energy systems: Key developments, challenges, and future research opportunities in the context of smart grid paradigm, *Renewable and Sustainable Energy Reviews*. 160 (2022), 112128. doi:10.1016/J.RSER.2022.112128

[24] R.I.D. Harris, Testing for unit roots using the augmented Dickey-Fuller test: Some issues relating to the size, power and the lag structure of the test, *Economics Letters*. 38 (1992), 381–386. doi:10.1016/0165-1765(92)90022-Q

[25] Y.H. Bhosale, K.S. Patnaik, Bio-medical imaging (X-ray, CT, ultrasound, ECG), genome sequences applications of deep neural network and machine learning in diagnosis, detection, classification, and segmentation of COVID-19: a Meta-analysis & systematic review, *Multimedia Tools and Applications.* 82 (2023), 39157–39210. doi:10.1007/S11042-023-15029-1

[26] M.M. Islam, F. Karray, R. Alhajj, J. Zeng, A Review on deep learning techniques for the diagnosis of novel coronavirus (COVID-19), *IEEE Access*. 9 (2021), 30551–30572. doi:10.1109/ACCESS.2021.3058537

[27] P. Manikandan, U. Durga, C. Ponnuraja, An integrative machine learning framework for classifying SEER breast cancer, *Scientific Reports.* 13 (2023), 1–12. doi:10.1038/s41598-023-32029-1

[28] R. Anand, S.V. Lakshmi, D. Pandey, B.K. Pandey, An enhanced ResNet-50 deep learning model for arrhythmia detection using electrocardiogram biomedical indicators, *Evolving Systems*. 15 (2024), 83–97. doi:10.1007/S12530-023-09559-0/TABLES/7

[29] A. Uddin, M. Islam, A. Talukder, A.A. Hossain, A. Akhter, S. Aryal, M. Muntaha, Machine learning based diabetes Detection Model for false negative reduction, *Biomedical Materials & Devices*. 2 (2023), 427–443. doi:10.1007/s44174-023-00104-w

[30] R. Olu-Ajayi, H. Alaka, I. Sulaimon, F. Sunmola, S. Ajayi, Building energy consumption prediction for residential buildings using deep learning and other machine learning techniques, *Journal of Building Engineering*. 45 (2022), 103406. doi:10.1016/J.JOBE.2021.103406

[31] H. Ma, L. Xu, Z. Javaheri, N. Moghadamnejad, M. Abedi, Reducing the consumption of household systems using hybrid deep learning techniques, *Sustainable Computing: Informatics and Systems*. 38 (2023), 100874. doi:10.1016/J.SUSCOM.2023.100874

[32] M. Schonlau, R.Y. Zou, The random forest algorithm for statistical learning, *Stata Journal*. 20 (2020), 3–29. doi:10.1177/1536867X20909688

[33] O. Kramer, K-Nearest Neighbors. In: Dimensionality Reduction with Unsupervised Nearest Neighbors. *Intelligent Systems Reference Library*, vol 51. (2013). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-38652-7_2

[34] K. Fukushima, Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position, *Biological Cybernetics*. 36 (1980), 193–202. doi:10.1007/BF00344251/METRICS

[35] X. Wang, Y. Zhao, F. Pourpanah, Recent advances in deep learning, *International Journal of Machine Learning and Cybernetics*. 11 (2020), 747–750. doi:10.1007/S13042-020-01096-5/METRICS

[36] A. Sherstinsky, Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network, *Physica D: Nonlinear Phenomena*. 404 (2020), 132306. doi:10.1016/J.PHYSD.2019.132306

[37] R.C. Staudemeyer, E.R. Morris, Understanding LSTM -- a tutorial into long short-term memory recurrent neural networks, *Neural and Evolutionary Computing*. (2019). https://arxiv.org/abs/1909.09586v1

[38] E. Yavuz, Comparison Of Deep Learning And Machine Learning Methods For Estimating Energy Consumption In Houses, M.Sc. Thesis, *Istanbul University-Cerrahpaşa Institute of Graduate Studies Department of Electrical and Electronic Engineering*, Istanbul, 2020.

[39] J.Q. Wang, Y. Du, J. Wang, LSTM based long-term energy consumption prediction with periodicity, *Energy*. 197 (2020), 117197. doi:10.1016/J.ENERGY.2020.117197

[40] S. Alaloul, B.A. Tayeh, M.A. Musarat, D. Durand, J. Aguilar, M.D. R-Moreno, An analysis of the energy consumption forecasting problem in smart buildings using LSTM, *Sustainability*. 14 (2022), 13358. doi:10.3390/SU142013358

[41] R. Olu-Ajayi, H. Alaka, I. Sulaimon, F. Sunmola, S. Ajayi, Building energy consumption prediction for residential buildings using deep learning and other machine learning techniques, *Journal of Building Engineering*. 45 (2022), 103406. doi:10.1016/J.JOBE.2021.103406