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Stacked Ensemble Machine Learning Model of Energy Consumption Prediction

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Abstract
The need for energy has significantly increased in recent decades as a result of rapid urbanization, excessive energy consumption and population growth. This leads to environmental problems such as climate change, water and air pollution. Predicting energy consumption can reduce these problems and helps energy management and efficacity. In this paper, we investigate the performance of several machine learning methods, such as linear regression, K-Nearest neighbor, support vector regressor, random forest, gradient boosting, and stacking to predict energy consumption in Tetouan city, in Morocco. To evaluate the performance of these models, evaluation metrics such as MAE, RMSE, and R2 were used. Stacking method provided outstanding performance and the best result with R^2 of 98.13%, 98.11% and 99.05% in zone 1, 2, 3, respectively.

Keywords: *Machine Learning, Ensemble Model, Energy Consumption, Prediction*

Yığılmış Topluluk Makine Öğrenmesi Modeli ile Enerji Tüketim Tahmini

Özet
Hızlı kentleşme, aşırı enerji tüketimi ve nüfus artışı sonucunda son yıllarda enerji ihtiyacı önemli ölçüde artmıştır. Bu durum iklim değişikliği, su ve hava kirliliği gibi çevresel sorunlara yol açmaktadır. Enerji tüketimini tahmin etmek bu sorunları azaltabilir ve enerji yönetimine ve etkinliğine yardımcı olabilir. Bu makalede, Fas'taki Tetouan şehrinde enerji tüketimini tahmin etmek için doğrusal regresyon, K-En Yakın Komşu, destek vektör regresyonu, rastgele orman, gradyan artırma ve istifleme gibi çeşitli makine öğrenimi yöntemlerinin performansını araştırılmıştır. Bu modellerin performansını değerlendirmek için MAE, RMSE ve R2 gibi değerlendirme ölçütleri kullanılmıştır. Yığınlama yöntemi, 1., 2. ve 3. bölgelerde sırasıyla %98,13, %98,11 ve %99,05 doğrulukla olağanüstü performans ve en iyi sonucu sağlamaktadır.

Anahtar kelimeler: *Makine Öğrenmesi, Topluluk Modeli, Enerji Tüketimi, Tahmin*

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1. Introduction

In terms of social and economic development in every nation, energy occupies an important place. Environmental issues have driven nations to adopt ambitious energy policies. For example, the European Union has set several goals for 2030: reduce greenhouse gas emissions by at least 55 % (compared to 1990 levels), improve energy efficiency by at least 32 %, and increase the share of renewable energy to at least 32 % [1].

The energy use in residential buildings has increased dramatically due to the use of cutting-edge technology in homes and economic development. The solution is to carefully forecast the use of energy. Forecasting is important to ensure the performance of energy. Monitoring time series energy helps to manage energy efficiency and its sustainability. Predicting energy consumption accurately reduces the demand for energy in residential buildings. The prediction may be divided into three main categories: short-term, medium-term, and long-term forecasting. Time- series models analyze the patterns of previous energy use over a period of time [2,3].

Energy plays a vital role in social and economic development in every nation [1]. Environmental concerns have driven countries to adopt ambitious energy policies; for example, the European Union plans to reduce greenhouse gas emissions by at least 55 % compared to 1990 levels, improve energy efficiency by at least 32 %, and increase the share of renewable energy production to at least 32 % by 2030 [2,3]. The proliferation of cutting-edge technologies in homes and ongoing economic growth have led to dramatic increases in residential energy consumption [4]. Accurate forecasting of residential energy use is essential to ensure effective energy management and sustainability [5]. Monitoring time-series energy data and forecasting consumption helps manage efficiency and long-term resource planning [6]. Forecasting horizons are typically divided into short-term, medium-term, and long-term forecasts, with time-series models analyzing historical patterns to predict future demand [7].

There are two primary approaches in energy-use forecasting research: statistical methods [2–4] and machine-learning methods [5–10]. Statistical techniques include autoregression (AR), moving average (MA), autoregressive integrated moving average (ARIMA), and seasonal ARIMA (SARIMA) models [2-4]. Machine-learning approaches have gained popularity due to their ability to capture nonlinear relationships and handle large, heterogeneous datasets [5–10].

Forecasting methods fall into two camps: statistical approaches and machine-learning (ML) methods. Statistical techniques—such as autoregression (AR), moving average (MA), ARIMA, and SARIMA—have a long history in load forecasting. ML methods, including both single-model learners (ANN, SVM, KNN, etc.) and ensemble frameworks (random forest, gradient boosting, stacking), offer the ability to capture nonlinear relationships and often yield superior performance [4–13]. In Table 1 advantages and disadvantages of methods are given.

Table 1. Advantage and disadvantage of statistical, machine learning

Type of Methods	Advantages	Disadvantages
Statistical Methods [4-6]	• Widely used in time series tasks. • Easy to implement and to interpret. • Provide clear statistical information. • Flexibility for different types of time series tasks. • Well-documented and widely recognized in academic literature.	• Inability to handle non-linear data. • Inability of certain models to integrate additional variables • Relies on several assumptions (normality, linearity). • Limited scalability. • Sensitivity to outliers.
Single Machine Learning Methods [7-10]	• Perform well with simple data. • Lower risk of overfitting. • Can handle multiple variables in time series forecasting. • Require less computational power. • Provide greater generalization ability than statistical approaches.	• Inability to manage heterogenic data. • Computation is more expensive than statistical approaches. • Their performance is limited to a simple data set. • Still affected by the curse of dimensionality. • Show inherent instability, even with consistent training configurations.
Ensemble Machine Learning Methods [10-13]	• Do not rely on assumptions about the nature of variables. • Ab1ility to handle large data sets. • provide stable prediction and performance than single models. • Can provide information on uncertainty. • Can reduce overfitting.	• Represent relatively new frameworks, requiring further exploration. • Learning in-series may create computationally expensive methods. • Mainly suitable for classification tasks rather than regression problems. • Training in sequence can be computationally demanding. • Require careful calibration to align with specific domains and case studies.

The main contributions of this study are summarized as follows: (1) a comprehensive comparison of six machine learning models, including both single learners and ensemble approaches, for energy consumption prediction using real-world data from Tetouan City; (2) the development and implementation of a stacking ensemble model that integrates SVM, KNN, and Random Forest as base learners with a linear regression meta-learner, providing superior prediction performance compared to individual models and other ensemble techniques; (3) a detailed evaluation using multiple performance metrics (MAE, RMSE, R^2) across three separate consumption zones, highlighting the robustness and generalizability of the proposed method; and (4) empirical evidence demonstrating that the proposed stacking framework significantly outperforms traditional ensemble methods like Random Forest and Gradient Boosting in this application domain.

2. Literature Review

Numerous studies have applied statistical models to short-term electricity forecasting. Chujai and Kerdprasop used ARIMA and ARMA to predict household consumption, finding ARMA superior over very short horizons based on RMSE and AIC metrics [1]. Mahia evaluated several ARIMA configurations, concluding that ARIMA(1,1,1) minimized AIC and delivered the best fit [2]. Erdogdu applied ARIMA to Turkish national demand data, reporting satisfactory performance in both in-sample fitting and out-of-sample forecasts [3].

More recent work has combined ARIMA with signal-processing techniques. Lee and Ko embedded a lifting-scheme wavelet transform into ARIMA to enhance short-term load forecasting performance [4]. Benli benchmarked nineteen classical methods—including decomposition, regression, exponential smoothing, and ARIMA—across five Turkish households, revealing substantial variation in model performance by series characteristics [5]. Che and Zhai proposed a WT-ARIMA hybrid that decomposes non-stationary data into components before ARIMA modeling, demonstrating improved stability and lower MAPE compared to vanilla ARIMA [6].

Artificial intelligence and ML techniques have become increasingly popular due to their ability to model complex, nonlinear patterns. Ahmad et al. reviewed the use of ANNs and SVMs for building energy forecasting, noting that each method has unique strengths and that hybridization (e.g., GMDH–LSSVM) shows promise for future work [7]. Neto and Fiorelli compared a detailed EnergyPlus simulation to an ANN model for building load prediction, finding that the ANN provided comparable accuracy with far lower computational cost [8]. Raza and Khosravi surveyed AI-based load-demand forecasting for smart grids and buildings, highlighting the crucial role of feature selection and parameter tuning [9]. Pham et al. predicted multi-building energy use using a range of ML regressors, reporting strong generalization across heterogeneous datasets [10].

Ensemble learning methods have delivered state-of-the-art results in many forecasting competitions. Taieb and Hyndman applied gradient boosting machines to the Kaggle load-forecasting challenge, achieving top-tier accuracy [11]. Salam and El Hibaoui designed a deep-inception-ResNet hybrid with LSTM layers, yielding significantly lower RMSE on Moroccan city-level data [12]. Wang et al. proposed a two-level ensemble combining clustering, LSTM, and a fully connected cascade network for urban load forecasting, demonstrating superior performance to single-model baselines [13].

Energy consumption forecasting has attracted substantial research interest, encompassing a variety of modeling paradigms. Liu et al. [14] conducted a comprehensive evaluation of nine machine learning algorithms for predicting building energy consumption, initially considering 52 features such as room count and lighting parameters. By applying mutual information–based feature selection, they distilled the input set down to eight key predictors, achieving a significant reduction in model complexity while preserving R^2 and RMSE performance on held-out data. Their results demonstrate that careful feature curation can simplify deployment without compromising accuracy.

Ou et al. [15] proposed a hybrid model combining Discrete Fourier Transform (DFT)–based decomposition with bidirectional LSTMs (BiLSTMs). By separating time series into trend, seasonal, and residual components via DFT and feeding each into specialized BiLSTMs, they outperformed baseline techniques across ten real-world datasets for both short- and long-term horizons, showcasing the utility of signal-processing enhancements in deep temporal models.

Yoon et al. [16] advanced this direction by integrating convolutional neural networks (CNNs) with LSTM layers to capture spatial and temporal dependencies in multi-utility time series (electricity, water, heating, etc.). Through systematic hyperparameter tuning, their CNN-LSTM architecture delivered superior accuracy relative to traditional statistical and pure-LSTM approaches, particularly when exploiting the spatial correlations inherent in multi-channel consumption data.

Munir et al. [17] leveraged LightGBM, a gradient-boosting decision-tree framework, augmented with SHAP (SHapley Additive exPlanations) values to forecast household energy usage. Their model achieved the lowest RMSE among competitors and, critically, provided transparent feature-importance insights—identifying HVAC sub-metering as the dominant driver of consumption variability. This work illustrates the growing trend toward interpretable, high-performance ensemble predictors in the energy domain.

Chen et al. [18] addressed the challenge of electric-vehicle (EV) range prediction by fusing plug-in EV driving data with real-time traffic flow information. Their model reduced RMSE and MAPE by over 66%, effectively mitigating “range anxiety” through context-aware energy estimation. The integration of external traffic signals marks a notable step toward more holistic, situationally adaptive forecasting for mobile energy systems.

Yang et al. [19] introduced an Autoregressive Kalman Filtering (AKF) approach tailored to hierarchical equipment structures in industrial settings. By combining AR modeling with Kalman filters, they outperformed both LSTM and back-propagation neural models on real ceramic-manufacturing electricity data, demonstrating that classical state-space methods remain competitive when structured around domain knowledge.

Collectively, these studies underline the diverse strategies—ranging from feature selection and signal decomposition to explainable boosting and domain-specific hybrids—available for energy consumption prediction. Yet, gaps remain in unifying interpretability with deep, multi-modal architectures and in scaling these methods to greener, real-time control applications. Future work may focus on integrating causality-driven feature discovery and online learning to further improve adaptability and transparency in operational settings

3. Material and Methods

The methodology used in this study is based on three single models (LR, KNN, SVM) and three ensemble model (RF, GB, stacking) (Figure 1). Using these methods, we can determine which is suitable for predicting energy consumption by Quads, Smir, and Boussafou zones in Tetouan City [20].

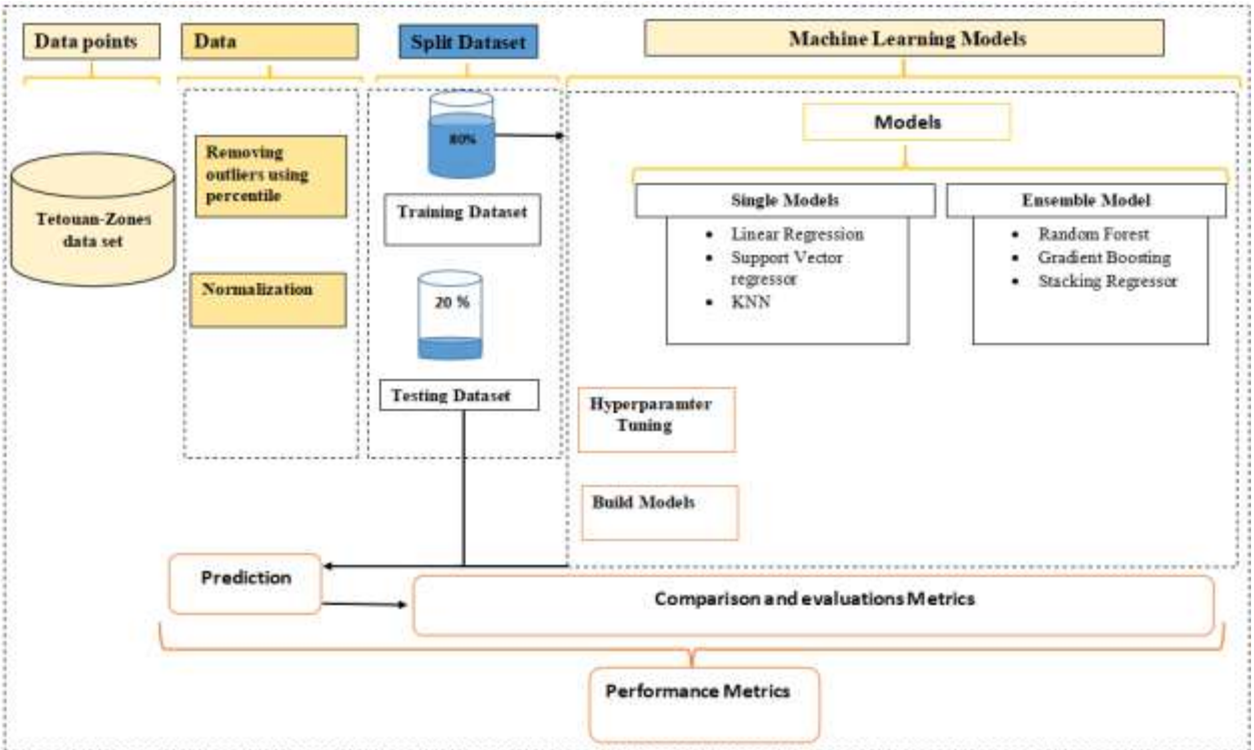

Figure 1. Structure of proposed methodology

3.1. Proposed Methods

In this section, we implemented five methods such as linear regression, support vector regressor, K-Nearest Neighbor, Random Forest, Gradient boosting to predict energy consumption. The main objective of these methods is to determine which model accurately predicts energy use. This helps to evaluate and understand the pattern of energy use over a period.

Random forest is an ensemble learning model that belongs to bagging ensemble methods. This approach is based on decision trees that consist of several trees and each tree has node and leaf. Random forest combines the prediction of different trees, then it makes a prediction. This method is useful for reducing overfitting and handling large and complex relationships between data points.

Linear regression model is a classical machine learning method which is based on linear relationships between features. The main purpose of this method is to find the best line which means finding the best coefficient of intercept and slope that minimizes the error between actual values and predicted values. Linear regression excels when there is a linear relationship between independent variables and dependent variables.

Support vector machine is a supervised machine method which can be used for classification and regression. Support vector regressor is designed to solve regression tasks such as energy consumption. The purpose of this method is to find the best margin which maximizes the hyperplane. Margin is the distance between boundary and closest data points. A major advantage of using this method is that it can handle both linear and non-linear relationships by using different kernel functions, such as linear, polynomial, Radial Basis Function (rbf), and sigmoid.

K-Nearest Neighbor is also supervised ML model which can be used both classification and regression problems. KNN makes predictions based on the k-nearest data point by applying Euclidean distance, cosine similarity, Manhattan distance.

Gradient Boosting is an ensemble learning method that belongs to the boosting family. It builds a series of models sequentially, where each model attempts to correct the errors made by the previous model. A significant advantage of using gradient boosting is that capture complex patterns of data points by applying different hyperparameters.

Stacking is an ensemble learning method which combines the prediction of different single learner models. The stacking method has level 0 models which is also known as base model and level 1 model is called meta-model. As we can see from the Figure 2, we used SVM, RF, KNN as base model and linear regression as meta-model because this combination provides the best performance after conducting different combinations.

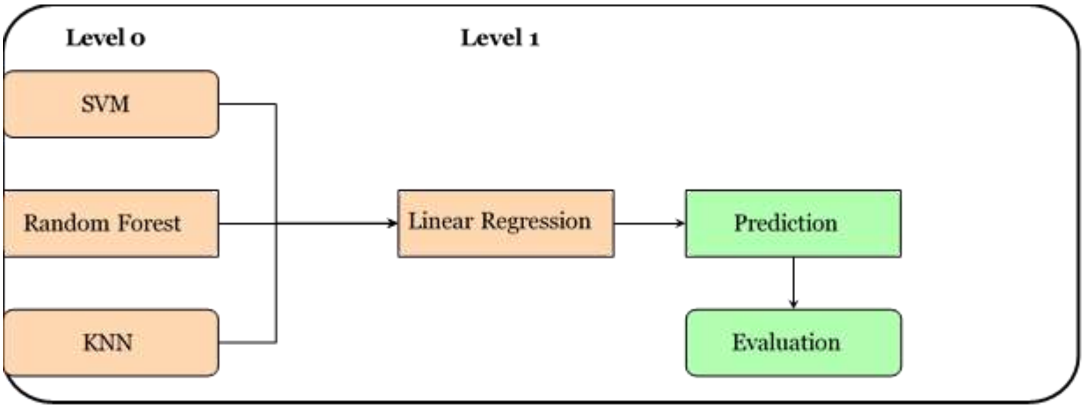

Figure 2. Structure of stacking method

3.2. Data Collection and Description

In this paper, we used an open dataset which is titled "Tetouan-Zones data set" and collected every ten between 2017-01-01 and 2017-12 from Supervisory Control and Data Acquisition System (SCADA). The data contains five weather attributes (temperature, wind speed, humidity, general diffuse flows, and diffuse flows), and energy consumed by three zones (Boussafou, Quads and Smir) [21].

Table 2. Data description

Variables	Description	Class	Type
DateTime	Collected period for each 10 minutes	Temporal	Object datetime
Temperature	Temperature of Tetouan city	Continuous	float64
Humidity	Weather Humidity of Tetouan city	Continuous	float64
WindSpeed	Wind speed of the city	Continuous	float64
GeneralDiffuseFlows	General diffuse flows	Continuous	float64
DiffuseFlows	Diffuse flows	Continuous	float64
PowerConsumption_Zone1	Power consumption of Quads	Continuous	float64
PowerConsumption_Zone2	Power consumption of Smir	Continuous	float64
PowerConsumption_Zone3	Power consumption of Boussafou	Continuous	float64

GridSearch was applied to optimize each model’s key hyperparameters: for the SVM, three kernels (linear, poly, RBF), five regularization strengths ($C \in \{0.001, 0.01, 0.1, 1, 10\}$) and two gamma settings (scale, auto) were tested, yielding an RBF kernel with C = 10 and gamma = scale; the k-nearest neighbors model evaluated neighbor counts (5, 11, 15), Minkowski distance orders (p = 1, 2) and weight schemes (uniform vs. distance), selecting 5 neighbors with p = 1 and distance weights; the random forest searched over tree counts (50–400), tree depths (4–20), minimum samples per leaf (2–10) and split thresholds (5–15), choosing 400 trees, max depth = 20, min_samples_leaf = 2 and min_samples_split = 5; and the gradient boosting model considered 50–400 estimators, max depths (2, 4, 6) and leaf sizes (3, 6, 9), settling on 400 estimators, max_depth = 6 and min_samples_leaf = 9 in Table 3.

Specifically, the Tetouan-Zones dataset includes approximately 52,560 observations, recorded at 10-minute intervals throughout the year 2017. Key descriptive statistics of the input features are as follows: the temperature ranges from 4.0°C to 35.6°C, with a mean of approximately 18.5°C and a standard deviation of 5.4°C; humidity varies between 10% and 99%, with a mean of 72.4%; wind speed ranges from 0 to 9.8 m/s, averaging 2.6 m/s. For the energy consumption variables, Zone 1 (Quads) shows power consumption ranging from 200 to 18,500 kW, with a mean around 8,200 kW. Zones 2 (Smir) and 3 (Boussafou) show similar distributions, with average consumption values approximately 7,900 kW and 8,400 kW respectively. This statistical overview provides a clearer understanding of the dataset used for model development and evaluation.

Table 3. Hyperparameter tuning with GridSearch

Model	Parameter	Range	Best
SVM	Kernel	*‘linear’, ‘poly’, rbf’*	*rbf*
	C	*[0.001,0.01,0.1, 1, 10]*	10
	gamma	*’scale’,’auto’*	*scale*
kNN	n_neighbors	*[5, 11, 15]*	5
	p	*1,2*	*1*
	Weights	*‘uniform’, ‘distance’*	*distance*
RF	n_estimators	*50, 100,150,200,300,400*	400
	max_depth	*[4,6,8,10,15, 20]*	*20*
	min_samples_leaf	*[2, 4,6,7,8,10]*	*2*
	min_samples_split	*[5, 8,10,15]*	*5*
GB	n_estimators	*[50, 100,150,200,300,400]*	400
	max_depth	*[2, 4,6]*	*6*
	min_samples_leaf	*[3, 6,9]*	9

3.3. Data Preprocessing

Data preparation is a fundamental step to ensure high-quality datasets, effective models, and accurate predictions, since model performance depends on data quality. Data preprocessing is time-consuming, but necessary. The data were standardized, which means that the data have a standard deviation of one and a mean of zero. It is calculated by subtracting the mean feature from each value and then dividing by the standard deviation.

Outliers are one of the problems which affect the performance of models. Handling outliers effectively is crucial in order to improve the performance and scores of methods. To detect outliers, several methods are available. In our case, we used a percentile method to detect outliers and then remove with a lower threshold of 1% and upper threshold of 99%.

After cleaning and normalizing the data points, 80% were used for training and the remaining were used for testing.

$$\acute{x} = \frac{x-\mu}{\sigma} \quad (1)$$

Here , x′ defines standard value, x shows original value, μ defines mean of the values of x, σ shows standard deviation of the value of x.

4. Results and Discussion

In ML, there are several evaluation metrics that allow to measure the performance and quality of the models. It is essential to choose the appropriate evaluation metrics based on the objective of the model and regression problems. However, using multiple metrics provides a more comprehensive view of the model’s performance and helps in decision-making. To identify which model predicts energy consumption well, statistical methods such as MAE, RMSE, and R^2 were used.

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_i^n (yi-\widehat{yi})^2} \tag{2}$$

$$\text{MAE}=\frac{1}{n}\sum_i^n |yi-\widehat{yi}| \tag{3}$$

$$R^2= \quad 1-\frac{\sum_i^n (yi-\widehat{yi})^2}{\sum_i^n (yi-\overline{yi})^2} \tag{4}$$

Here, yi is real values and $\widehat{yi}$ shows predicted values

4.1. Evaluation of Proposed Method

The results obtained from the analysis of models are displayed in Table 4. Metrics, such as MAE, RMSE, R^2 were used to evaluate the performance of the methods. As shown in Table 3, stacking ensemble provided outstanding performance and the best result with an R^2 of 98.13%, 98.11% and 99.05% in zone 1, 2, 3, respectively while linear regression provided the worst result with an R^2 of 62.40%, 57.11%, and 57.91% respectively.

It can be seen from the results in Table 4 that the K-Nearest Neighbors model performed well, achieving better RMSE values of 1005.8160, 749.3821, and 671.7094 for Zone 1, Zone 2, and Zone 3 respectively, compared to the Random Forest and Gradient Boosting ensemble models, linear regression, and support vector regressor.

The results of this study are presented in Table 4. Metrics, such as R^2, MAE, MSE, and RMSE, were used to evaluate the performance of models. As shown in Table 3, The stacking model achieved the best results and the highest R^2 for all the zones, while linear regression provides the worst results with RMSE of 1005.8160,749.3821, 671.7094 respectively. The results indicate that KNN is the second-best model and effective model for predicting energy consumption.

Table 4. Comparison of model performances by regions

Models	Zone	MAE	RMSE	R2
Random Forest	Zone 1	738.8876	1081.7107	0.9750
	Zone 2	523.2798	774.5810	0.9750
	Zone 3	406.7600	637.4048	0.9888
SVM	Zone 1	3 138.33	4041.71189	0.6512
	Zone 2	2 270.9567	2948.1579	0.6375
	Zone 3	2 693.7751	3738.7078	0.6142
Linear Regression	Zone 1	3 364.21	41196.2301	0.6240
	Zone 2	2 561.8995	3206.6607	0.5711
	Zone 3	3 124.2646	3738.7078	0.5791
KNN	Zone 1	652.0277	1005.8160	0.9784
	Zone 2	471.4066	749.3821	0.9766
	Zone 3	396.8386	671.7094	0.9875
Gradient Boosting	Zone 1	895.1722	12218.5628	0.9683
	Zone 2	671.3325	899.9585	0.9663
	Zone 3	511.9833	721.8659	0.9856
Stacking	Zone 1	**631.9995**	**774.5810**	**0.9812**
	Zone 2	**450.3186**	**672.4319**	**0.9811**
	Zone 3	**370.7818**	**589.0824**	**0.9905**

What stands out in Table 4 is that stacking model achieved improved performance compared to both bagging ensemble (Random Forest) and boosting ensemble learning (gradient boosting). Stacking combines the prediction of two single models, such as support vector regressor, KNN, and one ensemble model (Random Forest) with a linear regression as the meta-model while the prediction of Random Forest relies on averaging the outputs of several decision tree and gradient boosting relies on adding decision tree model sequentially that correct error made by the previous one.

The line-plot in Figure 3 contrasts each model's RMSE across Zones 1–3. In all three zones, the stacking ensemble (gold stars) achieves the lowest RMSE (≈937, 672, 586), closely followed by KNN (≈1006, 749, 672) and Random Forest (≈1082, 775, 637). Gradient Boosting sits in the middle (≈1219, 899, 722), whereas SVM (≈4042, 2948, 3739) and Linear Regression (≈4196, 3207, 3905) perform worst. Errors are consistently highest in Zone 1 and decrease through Zones 2 and 3, indicating Zone 1's consumption time series is the most challenging to predict. Overall, stacking markedly outperforms individual learners, shaving off roughly 70–300 RMSE points versus the next best (KNN).

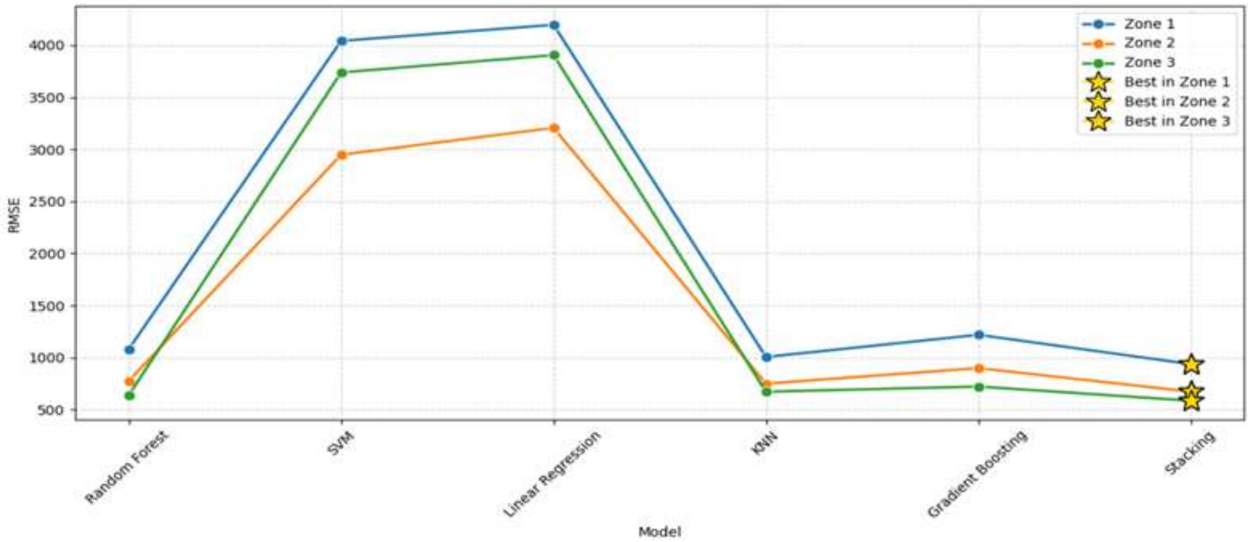

Figure 3. RMSE comparison across models

The heatmap recasts the same RMSE data with a color-intensity scale: darker blues highlight high errors (Linear Regression, SVM), and pale greens denote low errors (stacking, KNN, RF) in Figure 4. Stacking produces the lightest cells across all columns (Zones), underscoring its uniform superiority. KNN and Random Forest also appear in the lighter quadrant for each zone, while Gradient Boosting occupies the mid-tone band. Zones trend from darker shades in Zone 1 toward lighter hues by Zone 3, visually reinforcing the pattern of decreasing prediction difficulty from Zone 1 to 3.

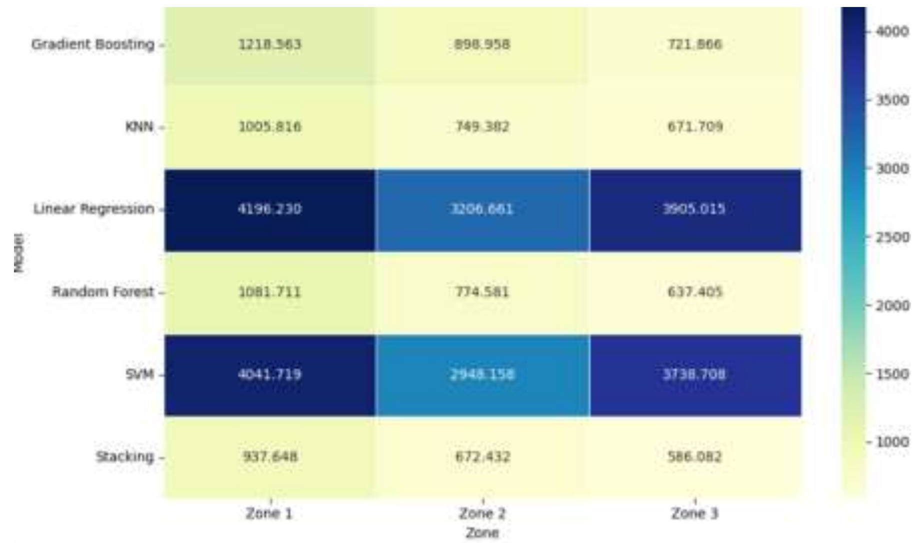

Figure 4. Heatmap of models' RMSE scores

Three radial plots display each model's MAE, RMSE (lower-is-better toward the center) and R^2 (higher-is-better toward the rim) for Zones 1–3 in Figure 5. In every chart, the stacking ensemble's polygon is closest to the center on both MAE and RMSE axes and reaches furthest on R^2, reflecting its lowest errors and highest explained variance. KNN again ranks second, with compact error radii and strong R^2. Random Forest and Gradient Boosting occupy intermediate positions, while Linear Regression and SVM exhibit large error "spikes" and the smallest R^2 lobes. These plots succinctly confirm stacking's balanced, top-tier performance across all metrics and zones.

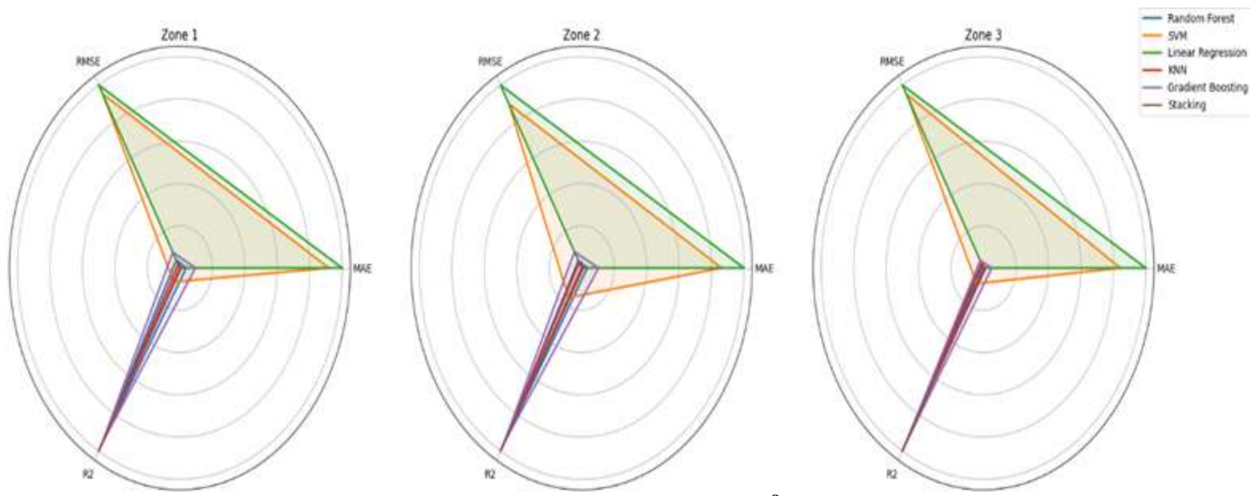

Figure 5. Radar charts of MAE, RMSE and R^2 metrics of models

5. Conclusion

This study investigates energy consumption using machine learning algorithms. Predicting energy use has emerged as a critical aspect of energy management and sustainability. The RMSE, MAE and R2 of the six learning approaches were used to identify models that accurately forecast energy consumption. Stacking ensemble model provided the highest results in terms of prediction energy use. K-Nearest Neighbor achieved the second-best values while linear regression performed poorly compared to other models. This indicates that stacking model is the most effective model in predicting energy use in Tetouan City, in Morocco. In this field, the use of machine learning methods to predict energy consumption is rapidly expanding, with several studies already being conducted on this topic.

Symbols

ANN	Artificial neural network
AR	Autoregressive model
ARIMA	Autoregressive Integrated Moving Average
GBR	Gradient boosting regressor
GRU	Gated recurrent unit
LR	Linear regression
LSTM	Long short-term memory
MA	Moving Average model
MAE	Mean absolute error
MLP	Multi-layer perceptron
MLR	Multiple linear regression
MSE	Mean square error
R2	Coefficient of determination
RF	Random forest
RMSE	Root mean square error
RNN	Recurrent neural network
SARIMA	Seasonal Autoregressive Integrated Moving Average
SVM	Support vector machine

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Declarations and Ethical Standards

The author(s) declare that they have no potential conflict of interest regarding the research, authorship, and/or publication of this article. The author(s) also state that the materials and methods used in this study do not require ethics committee approval and/or any legal-special permissions.

Author Contributions

T.E. conceptualized the presented idea, supervised the findings of this study and developed the theory. M.A.A. performed the calculations, prepared visualizations and conducted the experiments. All authors discussed the results and finalized the manuscript.

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