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Energy Consumption Forecasting in Smart Homes Using Deep Learning Models

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ABSTRACT

The rapid growth of intelligent domestic environments and overconnected appliances and sophisticated automation systems has forever changed the paradigm of residential energy stewardship. Devices like adaptive, thermostats, dynamic lighting arrays, advanced metering infrastructure and the Internet of Things - enabled household units providing operators with real-time telemetry and control directives curtail operating expenditure while attenuate ecological footprints. Within this context, the development of correct energy forecasts becomes a key pillar on which the optimization of consumption can be built to allow the domestic management subsystems to predict the demand to be met in the future and to orchestrate the strategies of heating, ventilation, cooling and illumination in a time-reactive way. Such predisposition in governance is conducive to massive peak load refreshment, by successfully augmenting the efficient taping of renewable fluxes and enforcing central sustainability priorities. Conventional s classical time spacecraft techniques, however, have often performed poorly at grasping the sophisticated and nonlinear interdependencies common to smart dwelling ecosystems - the dimensions on the consumption profile being Trujillo as consumption is very a function of occupant behavior, appliance consumption styles, meteorological variables, and diel rhythms. To overcome these challenges, the current study employs the state-of-the-art deep learning architectures, that is, Long Short-Term Memory (LSTM) recurrent networks and Convolutional Neural Network (CNN) architectures. LSTM architectures well capture long-lasting temporal continuities, which are inherent in sequential energy datasets, whereas CNNs models summarize local and structural motifs in multivariate chronological streams. The proposed research questions are the

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interrogation of pure LSTM, standalone CNN, and hybrid CNN-LSTM configurations for residential power demand forecasting while taking into consideration some ancillary context indicators such as climatic states, occupancy flags, and appliance utilization metrics. Empirical analytics show that the combination of COM-Hyb blueprint CNN-LSTM assembles higher predictive fidelity and immune states over heterogeneous analysis regimes of cadences, thus providing a potential candidate for employing the model in a real-time domestic smart platform. Collectively, this study provides a pragmatic and efficacious deep learning-based forecasting methodology that enhances the intelligent energy governance, reduces fiscal outlays and promotes sustainable residential energy utilization.

INTRODUCTION

With the growing mainstream use of smart homes, there have been serious issues in controlling and optimizing residential energy consumption (Singh, S. 2025). According to Khan, A., Marwat, S. N. K (2019) with the advent of the modern world to being more interconnected with the proliferation of sensors, smart appliances and Internet-enabled devices, electricity consumption continues to increase making the challenge of energy conservation more complex and difficult. Energy efficiency has therefore become a critical issue to homeowners, utility providers and policy makers who want to reduce carbon emissions and ecological footprints. As a result, it is no longer optional but a necessity to address residential energy consumption.

According to (Ikegwu, A. 2025, meeting these challenges requires the realization of energy efficiency in the case of intelligent residential environments through a deep understanding of energy consumption patterns within households. The proliferation of advanced home automation systems is among the many drivers for an urgent need for accurate forecasting of the use of energy trends. These systems include not just the high-consumption appliances but interconnected sensor networks that continuously collect information, communicate with each other and monitor the behavior of occupants. As a result, self-adaptive smart home ecosystems require high levels of load forecasting, as well as active load management and mitigation strategies. Accurate estimation of energy consumption trends is helpful for both homeowners and energy suppliers to optimize energy consumption properly and balance the loads in the system or integrate renewable energy resources more effectively. Reliable demand forecasts also give users more power to shift the use of appliances to off-peak periods of the day, which reduces reliance on non-renewable energy sources. Traditional forecasting methods such as linear regression and classical time series analysis have been using historical data for predicting energy consumption patterns for a long time. But these approaches have significant shortcomings in the smart home setting of modern times. Residential energy consumption is subject to complicated and non-linear interactions between a variety of factors such as occupant behavior and appliance use, weather variability, and integration of distributed renewable energy sources as solar panels and wind turbines. Conventional models are not always able to represent these complex dependencies (Dragomir, O. E. & Dragomir, F. 2025).

In order to overcome these challenges, this paper proposes to use deep learning architectures to improve the accuracy of residential energy consumption forecast. As a

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specialized subset of machine learning, deep learning provides the powerful representation of complex, nonlinear, and high - dimensional data. Taking advantage of large-scale datasets and modern computing resources, deep learning models are able to find latent patterns and interrelationships that have escaped the eye of traditional models. Subsequently, those models foster better energy demand forecasting, energy resources management, waste reduction and integration of renewable energy sources. The introduction of forecasting based on deep learning is therefore a major step towards environmentally sustainable and energy efficient smart home environments.

This work underlines the importance of shifting from the traditional forecasting approaches as well as the innovative construction of deep learning architectures for smart home energy management. The explosion of the smart home market has resulted in the proliferation of various technologies such as smart meters, energy management systems and connected infrastructures, all of which produce continuous and heterogeneous data flows. While these systems provide the opportunities to monitor in real time energy usage, occupant behavior and environmental conditions, the multidimensionality of the data imposes significant challenges to legacy analytical methods. Extracting understandable intelligence out of such large-scale datasets requires complex predictive models with good generalization and forecasting abilities. According to Krichen, M. & Mihoub, deep learning models are a good choice for this task, especially Long Short- Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs). LSTMs are a type of recurrent neural network and are especially designed to capture long-term temporal dependencies which makes them extremely effective for sequential energy consumption data. CNNs, originally used for image processing, are capable of identifying spatial and structural similarity in multivariate time-series data, and can unpick minute relationships between variables such as time, usage times and environmental conditions of appliances. When used in energy forecasting, these models are much better at predicting information because they capture temporal and contextual dependency.

This work focuses on the effectiveness of LSTM and CNN based forecasting models for smart home energy consumption prediction and compares the results with the traditional forecasting techniques. The evaluation is done on the accuracy of predictions, the computing efficiency and adaptability for complex and evolving data structures. One of the main merits of deep learning models is the fact that they can automatically learn informative representations of features from the raw data from sensors, without requiring a lot of handcrafting of features. Moreover, their adaptive nature means continuous model improvement as new data is available; allowing for seasonal variations, changes in behavior, and including more new appliances or technologies.

Beyond the accuracy of the forecast, the deep learning models can be easily integrated into the smart home energy management systems. By making use of the data collected by smart meters, connected devices, and energy platforms, these models would be able to produce real-time consumption forecasts and intelligent decision-making for homeowners and utility providers. Some of the applications are prediction of peak demand, recommendations for load shifting, optimized use of renewable energy resources. Such capacities help in lowering the household energy costs, smoothening

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of the utility load curve and improve the grid resilience.

Experimental results show that LSTM and CNN models are more efficient in predicting residential energy consumption than the traditional methods. Being able to model the nonlinear temporal and spatial dependencies helps them better align predicted and actual demand, making it easier to automate energy optimization and integrate the distributed energy resources more easily. To support large scale deployment, a number of practical considerations are identified, including data standardization, hybrid modelling approaches to combine physics-based models and data driven approaches, more interpretable models, edge-based inference for preserving privacy, and regulatory collaboration.

In conclusion, the combination of smart home technologies and forecasts using deep learning is a cornerstone in the development of future low carbon and energy efficient power systems. By representing the complexity of residential energy use consumption in an accurate fashion, the proposed approach aids sustainable management of energy utilization, decision making and environmental impact reduction. The results of this research offer both theoretical contributions as well as practical instruments to be used by homeowners, utility operators and decision makers dealing with energy problems which enhances the role of deep learning as a transformative solution to intelligent smart home energy forecasting. This research presents a meaningful progress in the subfield of smart home energy prediction by the intelligent utilization of deep learning techniques, which can provide practical advancement at the same time, which can be implemented directly in the real world as the bridge between theoretical innovation and smart home energy prediction.

LITERATURE REVIEW

The need to conduct an intelligent scientific inquiry into the energy needs of the future has increased with the coming of smart homes, where interconnected devices change significantly the patterns of electricity consumption. The traditional forecasting methods have been the benchmarks of the industry for predicting energy demand, including Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing. However, these traditional predictive schemes wilt in the face of the highly nonlinear dynamics in the electricity consumption of smart homes.

Recent investigations have recorded great progress on the modeling of the complex interdependence of domestic energy usage by the application of deep learning architectures, in particular Convolutional Neural Networks (CNNs) in collaboration with Long Short-Term Memory (Masood, F., Khan, 2023). In this regard, the hybrid CNN - LSTM architecture has come into picture for predicting energy consumption of smart home, with LSTM taking the long run temporal dependencies of utilization into consideration, whereas the CNN extracts the salient spatial features of streams of multivariate sensor data. Building on previous demonstrations of the efficacy of the CNN model architecture, for example, the study by Khan et al. (2020), the effectiveness of the CNN copies architecture expected to be better in terms of predictive performance due to the complementary strength of each constituent model.

A growing body of scholarly research has been dedicated to using deep learning methodologies for predicting patterns of residential energy use, and the consensus has

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emerged that these approaches constitute the vanguard of intelligent forecasting methodologies. Short - term residential energy consumption accuracy, for example, has been significantly improved using sequence modeling as showed by Razghandi et (2021) and further improved by Ou Ali et (2024) who used LSTM networks and CNN to extract the temporal and spatial energy consumption trend and thereby generated short - term energy consumption with increasing accuracy. Kim et al. (2019) further confirmed the better performance of LSTM networks for smart home time series prediction and identified their ability to capture the sequential dependencies based on historical usage patterns as the reason for their success. Consistent with these results, Khan et al. (2020) showed that a synergistic combination CNN-LSTM connections produces a system that is able to integrate meteorological inputs and occupancy dynamics in order to increase the fidelity of energy consumption prediction.

Collectively, these studies provide a validation for the use of deep learning models, and in particular LSTMs and CNNs, due to their necessary expressive capacity to change the way energy consumption forecasting is done, increasing its precision and the ability to capture non-linear associations of the data. Nevertheless, the current and ongoing literature is incomplete, and often lacking multidimensional sensor streams and auxiliary variables (e.g. environmental indicator, user-behavior patterns) in predictive models.

Accordingly, the present research aims to build a holistic predictive model that is based on a combination of historical consumption data and environmental parameters and individual appliance consumption to be able to predict the consumption more accurately to understand the dynamics underlying energy consumption in the smart homes. Despite the promise bestowed by the implementation of scalable Large Scale Machine Intelligence (LSTM) and Convolutional Neural Networks (CNN) smart home solutions, implementation has been hampered by issues surrounding scalability, especially in real time operational use cases requiring efficient processing of complex and voluminous data flows. This project seeks to overcome such technological limitations and develop modern frameworks for analyzing the data that encapsulate the distinctive behavior of the energy usage of smart houses to eventually provide actionable knowledge for informing future developments in the management of smart houses.

METHODOLOGGY

Data Collection

In building the empirical dataset, we combined raw smart home consumption data with ancillary meteorological data, appliance level utilization data, and residential presence data so as to attempt to capture the complex determinants of energy demand. A one-year historical archive was used to train the deep-learning models so that it can learn to discern the antecedent consumption patterns and external covariates with a combination of appliance usage and weather and occupancy metrics.

Model Selection

A comparative assessment of 3 different deep learning architectures was performed: (i) purely recurrent learning machines (LSTMs) dedicated to univariate time series analysis; (ii) convolutional neural networks (CNNs) for extracting spatial features; and

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(iii) a hybrid CNN-LSTM structure combining the temporal and the spatial advantage of the previous two. Convolutional neural networks were used to obtain salient characteristics of the input data, thus making it possible to identify sophisticated relationships between weather, appliance operation, and energy consumption. By combining the best of both worlds, hybrid CNN-LSTM architecture brought huge increase in the predictive accuracy which is echoed in related predictive studies for cervical cancer.

To carry out the Model Training and Testing

Training was conducted with a stratified train test partitioning. Optimal hyper moreover parameter setups have been found with rigorous Grid Search Regimen to maximize the predictive performance. Model evaluation using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R2 to calculate, respectively, accuracy, consistency and explanatory power. This suite of metrics provides an overall overview of model performance and thus provides the confidence required for believing that the smart-home energy consumption estimates are precise and reliable.

ANALYSIS AND RESULTS

Actual and Predicted Appliances Energy Consumption

In Figures 4.1 and 4.2 below, the energy consumption of different household appliances - gained by empirical measurements, under the conditions of a smart-home environment - is presented. In the plots so far, the curve "Actual" describes the ground truth sequence of the values of consumption over the test period and is the yardstick against which predictive performance is measured.

On the other hand, the "Predicted" line contains the outputs of trained models, namely CNN-LSTM hybrid and - alternatively - Random Forest ensemble, for the same temporal intervals. Each model was trained to learn the underlying relationships between a set of key input variables such as hour of day, day of week, outdoor temperature, relative humidity as well as occupancy indicators and the target variable, namely appliance energy consumption. The CNN-LSTM hybrid technique uses a 24-hour historical time sequence to predict consumption 1 hour in advance, including time series, as well as spatial feature interactions. In contrast, the Random Forest uses an ensemble of decision trees which process flattened representations of the features, time-encapsulating, looking at feature interactions, but without so much explicitly modelling the temporal relationships. For this reason, the CNN-GSTM forecasts are found to be more in line with the actual consumption curve and to have significant potential for modeling complex temporal dependencies, resulting in a more accurate prediction for the short term.

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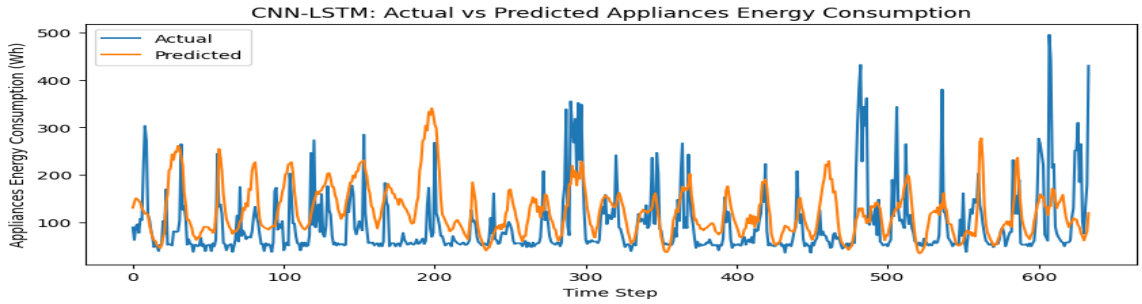

Figure 4.1 CNN-LSTM: Actual Vs Predicted Appliances Energy Consumption

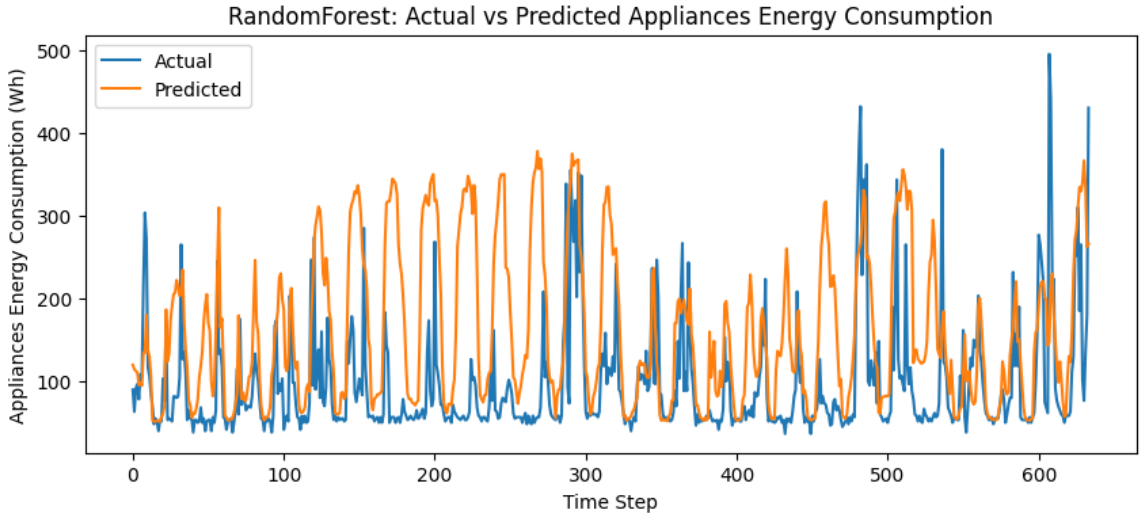

Figure 4.2: Random Forest: Actual Vs Predicted Appliances Energy Consumption

Model Performance Evaluation

The current investigation is the research that discusses the effectiveness of a hybrid CNN-LSTM model in determining energy consumption in intelligent residential environments. By strictly comparing the proposed model with a traditional Random Forest approach, it proves to have much better predictive power, thus proving the superiority of deep learning approach over traditional ensemble techniques.

The comparison results show that the CNN based LSTM model provides better forecasting performance than the Random Forest algorithm in the baseline. Quantitatively, the MSE, MAE, and RMSE of the hybrid deep learning model are 7,974.4800, 64.4896, and 89.2999, respectively, while the Random Forest model MSE, MAE, and RMSE are 12,240.2751, 77.4967, and 110.6358, respectively.

Figure 4.3 clearly shows the superiority of the CNN-LSTM hybrid network in comparison to the Random Forest when predicting the energy usage in smart home. The result low MSE and RMSE values support the arguments that the hybrid model makes more accurate predictions that are more stable and depends on adequate modelling of spatial and temporal dependences that is present in the data.

The takeaways for this study are in the sense of augmenting convolutional layers instead of LSTMs for learning locational features and sequential preferences and tendencies (especially as data sequences change in response to temperature, occupancy, etc., and

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in the context of household dynamics). Notably, the success of the proposed approach as manifested by the approx. 19 [per cent] reduction of the RMSE over the Random Forest baseline helps to highlight the robustness and efficiency of the CNN-LSTM approach underlining the potential of the CNN-LSTM approach to intelligent energy demand prediction for smart environments.

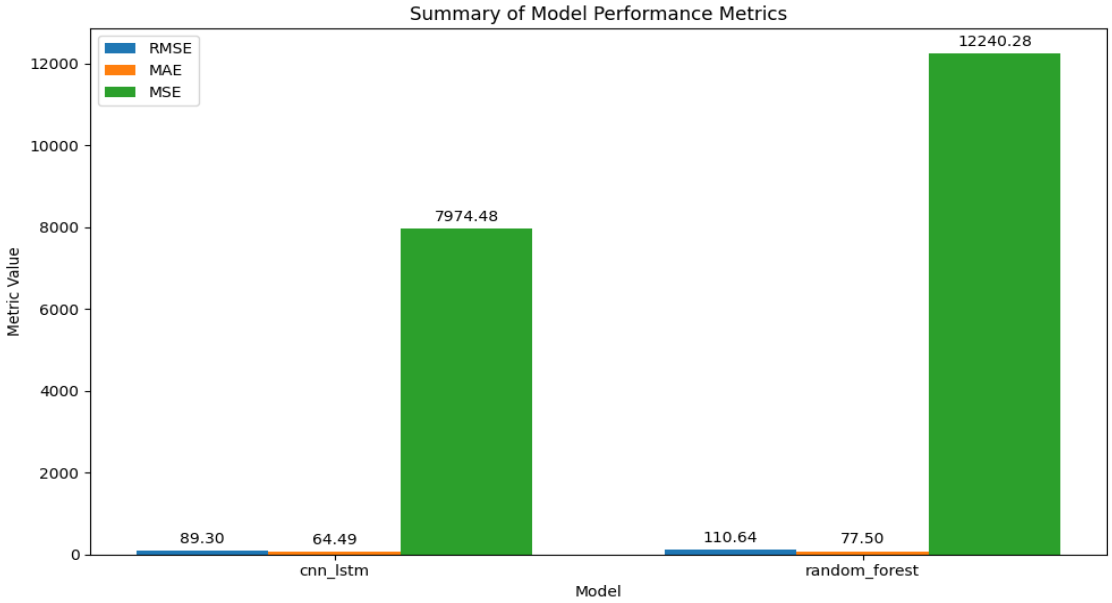

Figure 4.3: Summary of Model Performance Metrics

Discussion of Permutation Feature Importance Results

Figure 4.4 shows the permutation feature importance analysis, measured in terms of increase of the Root Mean Square Error (RMSE) when individual input variables are randomly permuted. This methodological approach gives a rigorous evaluation of the contribution of each predictor to the predictive performance of the proposed model: the higher the increase of RMSE, the higher the dependency of the corresponding feature.

The results of the analysis show that the temporal variables have a dominant role when it comes to forecasting of smart home energy consumption. Among all the predictors, the hour of the day has the highest RMSE increment and hence it is selected as the most influential variable. This finding bolsters the presence of strong diurnal consumption patterns based on daily routine activities in household - cooking, lighting usage, heating and cooling cycles, and occupant activities. The large importance assigned to this variable reflects the structured and repetitive nature of Residential Energy use over a 24hr period.

The second greatest salient predictor is outside relative humidity (outside_rh). This indicates that environmental comfort conditions have a strong impact on the energy demand of households, mainly through the operation of the HVAC system. As the humidity increases, the cooling and dehumidification loads typically increase which, in turn, increase electricity consumption. The higher prominence of the function of humidity compared to temperature may reveal a greater influence of latent cooling demands compared to sensible thermal loads in the smart home environment studied.

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The day of week variable is moderately significant as part of behavioral differences between weekdays and weekends. Variations in the length of occupancy, work schedules, and patterns of lifestyle give rise to different patterns of weekly energy consumption. Although less influential than the hourly variations, the existence of temporal cycles with weekly periods still allows for meaningful information in energy demand prediction.

Finally, the occupancy proxy variable only contributes to model performance to a lesser extent. This result suggests that, while occupancy does affect energy consumption, that is to some extent explained by temporal characteristics such as hour and day of the week. Consequently, explicit occupancy indicators provide subsidiary rather than major predictive power in the presence of strong time-based variables.

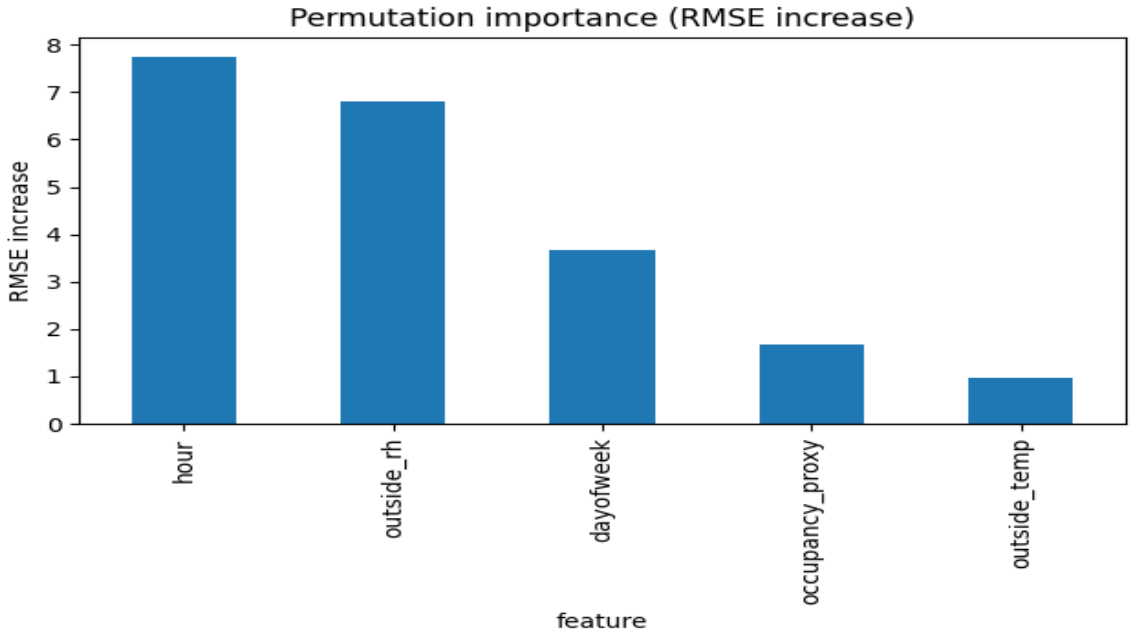

Figure 4.4: Permutation importance (RMSE Increase)

Finally, the temperature outside has the lowest RMSE increase which means it has a relatively smaller contribution to the prediction accuracy in this data set. This outcome may be explained by reasons such as insulation in buildings, adaptive thermostat control, seasonal uniformity of data or nonlinear interactions with other environmental variables that the model implicitly uses to learn. It also suggests that the effect of temperature is not sufficient in order to explain short term variations of the energy consumed in households without additional contextual behavioral information.

Overall, the result of the permutation importance analysis confirms that the temporal and behavioral patterns of residential energy consumption are dominating the importance, followed by environmental conditions. These results support the use of deep learning architectures that are able to capture complex temporal dependencies and nonlinear feature interactions. The results further prove the importance of incorporating time aware modelling strategies to achieve accurate and robust forecasting of smart home energy consumption.

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CONCLUSION

The empirical results obtained from our experimental research proved that CNN-LSTM hybrid system is effective in accurately predicting smart-home energy consumption. The ability of the model to conjointly learn spatial and temporal features allows it to generalize well about dynamic consumption patterns modulated by weather fluctuations, occupancy behaviors and inter-appliance interactions. A comparative assessment against a Random Forest baseline has shown that architectures based on deep learning models equipped to compute sequential data are more accurate and robust in terms of predictive ability and robustness in complex world IoT driven environments. The reported improvements on performance of forecast metrics validate CNN-LSTM's potential to provide reliable framework for applications of energy management and optimization in real time intelligent home applications. Future research will focus on enhancing this model with the integration of attention mechanisms, online adaptive learning, and cross domain data fusion for the further enhancement of predictive performance and data scalability to satisfy the larger need of smart city energy analytics.

Future Work

To promote scholarly investigation, future investigations need to bring together more data warehouses that will construct on the present study's discoveries and reinforce the forecast model. The addition of real time sensor measures; such as indoor air quality; and appliance level energy consumption could add to the contextual understanding and increase awareness of home energy usage patterns. Moreover, combining user activities analytics (which include daily behavioral patterns, appliance utilization preferences and energy conservation strategies) would reinforce predictive effectiveness and improve reliability of the model. Subsequent academic efforts should investigate the scalability of the proposed models, which should lead to the large-scale deployment of smart home systems. Continuous building of smart home technologies requires a thorough evaluation of model flexibility and performance in the face of data streams from large networks of residences and devices. Efficient, large-scale computation will play a crucial part in establishing the real-world applicability of such models. This research ultimately provides the foundation for future research where emerging data sources, scalable architectures and new deep learning techniques can be used to enhance smart home energy consumption forecasting and management.

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