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Vision-Based Smart Meter Reading and Energy Consumption Analytics Using AI

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Abstract—In this work, a deep learning-based energy consumption predictor with Long Short-Term Memory (LSTM) and Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) network models are applied to time-series data. This is aimed at enhancing the accuracy of prediction by ensuring that both short-term variation and the temporal dependencies of electricity demand are in the model. Kaggle provides public datasets such as hourly energy consumption data, which are analyzed. The cleaning, chronological sorting, Min-Max scaling, and sliding window sequence generation (24-time steps) preprocess the data. To extract temporal patterns, including trends and seasonality, feature engineering and exploratory data analysis are used. Training of models is done with the help of 80: 20 time based split to avoid the data leakages and it is also evaluated with the help of Mean Squared error (MSE), root mean squared error (RMSE) and loss curves. Experimental ablation reveals that LSTM has an ultimate training loss of approximately 0.000175 and validation loss of approximately 0.000060 whereas CNN-LSTM has 0.000176 and 0.000058 accordingly. CNN-LSTM model has a little better performance because it has an enhanced feature extraction and noise reduction. Both models demonstrate stable convergence, low overfitting, and good generalization. Additionally, 24 hours recursive forecasting creates smooth and realistic forecasts that are consistent with the historical trends. On the whole, the suggested CNN-LSTM method is a more appropriate solution to short-term energy consumption forecasting due to its higher accuracy and strength, which is why it can be used in smart grid and energy management.

Keywords—Smart meter, energy consumption, computer vision, artificial intelligence, deep learning, optical character recognition (OCR), image processing.

Introduction

The swift development of the modern infrastructure, city growth, and rising reliance on the electric energy have preconditioned the emergence of efficient energy management as one of the most significant world issues of the twenty-first century. Electricity has increased tremendously with the increase in population density and industrialization, generating a huge burden to power distribution systems. Conventional energy monitoring and billing systems that depend heavily on the use of manual meters are gradually becoming insufficient because of their inaccuracy and

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inefficiency as well as lack of scalability [1]. Human reliant meter readings processes are not only time consuming but are also subject to errors, billing cycles delays and may be subject to inconsistencies during data recording. These problems can cause losses of revenues to utility providers and dissatisfaction to consumers. Consequently, automated, intelligent, and scalable solutions are highly demanded to have the capacity to transform the energy monitoring ecosystem [2].

Vision-Based Smart Meter Reading and Energy Consumption Analytics Using Artificial Intelligence (AI), therefore, becomes a revolutionary pattern, which combines computer vision, machine learning, and Internet of Things (IoT) to make electricity meter readings and energy utilization analysis automated. Compared to the traditional systems, where a manual intervention is necessary, vision-based systems capture real-time images of electricity meters with the help of cameras or other imaging equipment [3]. These images are then analysed with advanced AI algorithms to obtain numerical readings with accuracy. This method allows physical inspection to be avoided and allows round-the-clock, remote, and automated energy consumption monitoring [4].

Computer vision techniques are the key building blocks of vision-based smart metering as they enable machines to process and understand visual information. Image preprocessing, edge detection, segmentation, and feature extraction are techniques which are employed to improve the quality of images and isolate acceptable meter regions. After detecting the meter display, Optical Character Recognition (OCR), and deep learning models, specifically Convolutional Neural Networks (CNNs), are used to detect and read the digits shown on an analog or digital meter. CNN-based architectures are very effective in acquiring spatial hierarchies in images and hence are applicable in the recognition of intricate patterns, even in distorted or noisy environments. This guarantees high degree of accuracy in reading extraction, even in different lighting conditions, camera angles as well as different meter designs [5].

In addition to simple identification of digits, AI-based applications can facilitate more powerful energy consumption analytics, which can be of great value in utility management. Machine learning algorithms have the capacity to process the data on the historical consumption to determine the patterns of usage, highest demand times, and seasonal changes in electricity consumption. These lessons can enable utility providers to streamline the distribution of energy, minimize imbalances in loads, and enhance grid stability. Also, anomaly detection models can detect abnormal consumption patterns, which can be used to report technical faults, energy leakage or electricity theft [6]. The ability becomes especially crucial in terms of establishing fair billing practices and minimizing non-technical losses in power distribution networks [7].

IoT technologies allow expanding the functions of smart metering systems based on the vision. Smart cameras and sensors with IoT are able to constantly record and send meter data to centralized cloud platforms. It allows processing of data in real time and accessing remotely, which means that utility companies can effectively monitor the use of energy over large geographical areas. Scalable storage and computational capabilities are also aided by cloud-based systems, which means that huge amounts of data produced by millions of smart meters can be handled. Moreover, mobile and web-based dashboards will enable consumers to have access to their energy usage in real-time which will encourage awareness and lead to energy saving behaviour [8].

Artificial Intelligence is pivotal in converting raw energy data into insights to action. The models of predictive analytics as Long Short-Term Memory (LSTM) networks can be used to predict the future trend in energy consumption based on the past data. It assists utility companies in demand planning, infrastructure planning, and effective resource planning [9]. In addition, reinforcement learning methods can be used to optimize energy distribution strategies in smart grids to minimize energy wastage and enhance performance of the system. All these AI-based solutions work towards creating intelligent and adaptive, efficient and self-learning energy ecosystems [10].

Although it has many benefits, there are challenges associated with the implementation of vision-based smart meter reading systems. It is one of the main problems because environmental conditions include the presence of light and shade, reflections, etc., which may influence the image quality. Moreover, varying meter designs, digit fonts, and display types may make the process of digit recognition difficult. Other factors that can decrease system accuracy are camera misalignment, image blur, and occlusion. Powerful preprocessing algorithms like image enhancement, noise removal, as well as perspective correction, are needed to address these problems. Moreover, AI models trained on large and heterogeneous sets will have a better generalization ability and can work well in practice.

Security and privacy is also another factor that is crucial to the implementation of such systems. Energy consumption data may contain sensitive information concerning user behavior and therefore, it is necessary to have secure transmission and storage of data. The data integrity and unauthorized access prevention should be ensured by applying encryption and secure communication protocols. Also, the ethical implications of using data should be considered in order to ensure that users trust the data and that it is not used in a way that contradicts regulations.

The other notable feature of smart metering systems based on vision is that it encourages sustainable energy use. These systems also enable consumers to make well informed decisions regarding their energy consumption by giving them specific information regarding their usage patterns. Live feedback spurs energy saving behaviors, which eventually leads to less carbon emission and environmental protection. Aggregated data also enable governments and utility providers to develop effective energy policies and implement strategies that manage demand-side.

To sum up, the Vision-Based Smart Meter Reading and Energy Consumption Analytics Using AI is one of the most promising steps in the sphere of smart energy management. It uses computer vision, deep learning, and IoT technologies to provide a highly scalable, efficient, and accurate alternative to the traditional manual metering systems. In addition to automation, it facilitates smarter energy analytics, which aid in predictive forecasting, anomaly detection, and optimized resource management. Despite the issues with the environmental variability and the complexity of the system, the aforementioned limitations are being overcome by the constant improvement of AI and sensor technology. In the end, this would not only make the operations of utility providers more efficient, but also encourage sustainable energy consumption habits, which will lead to a more intelligent and more robust energy infrastructure system.

Literature Review

Wazirali 2025et.al close the gaps by showing how using sensor, artificial intelligence, and human-centered design can be used to integrate perception, decision-making, and feedback in smart cane systems. It deals with sensor-laden architectures with technologies like Simultaneous Localization and Mapping (SLAM), computer vision, and machine learning to improve mobility support. Multimodal feedback allows real-time localization, context awareness, dynamic obstacle avoidance and user-specific navigation, depending on their preferences. It examines the major hardware parts such as ultrasonic, infrared, LiDAR, RGB-D cameras, inertial sensors and viable sensor fusion approaches to enhance spatial perception. The human factors, including usability, cognitive load, and ergonomics, are also highlighted to guarantee the practical adoption. It also suggests an embedded smart cane system, including edge AI, indoor positioning (using Bluetooth), secure 5G/6G connectivity, cloud-based health management, and a solar-powered energy system. This combined strategy facilitates scaled intelligent mobility support and enhances smooth adjustment in smart city landscapes towards inclusive city living [11].

Patria 2025et.al Report describes a tomato ripeness detection on a mobile robot with Artificial Neural Networks (ANN) as the design of the vision-based system. The objective of the system is to automate the process of monitoring and sorting tomatoes into three groups namely: ripe, unripe and partially ripe thus enhancing efficiency and accuracy in farming. The ESP32-CAM module helps the robot to take images and extract features of the visuals using color and texture when it traverses farm environments independently. ANN model is trained using a set of 1,000 tomato images with tomato ripeness labels. The performance in navigation and classification was tested by field testing in varying environmental conditions. The system got an accuracy of 94.5% with RGB features, and best accuracy with 200 training epochs and low variation in validation loss. 0.15 seconds per frame Real-time processing was attained. The robot was able to complete 95% of test paths at 0.8 m/s, showing that robotics, computer vision and ANN have been effectively integrated to create smart agriculture [12].

Ashraf 2024et.al reviews the design and development of an AI-based data sensing and prediction model to enhance smart home control systems. It concentrates on the optimization of the lighting and HVAC activities based on the information about the sensors monitoring occupancy, movement, temperature, and humidity. The proposed AI system will increase energy efficiency and decrease electricity costs, as well as occupant comfort, especially in people with limited mobility or disabilities. It allows adaptive learning to change the lighting and climate settings automatically depending on users, and preferences, thus reducing wastage of energy. The system will also foster sustainability and the creation of intelligent and easy to use smart homes by responding to real-time environmental data. The key goals are independent automation of homes, effective use of energy and green living. The research shows that AI has the potential to substantially change smart home technologies into more efficient, cost-effective, and accessible systems, and the future research will focus on enhancing the performance of the system and its integration in the real world [13].

Plathottam 2023et.al discusses the use of an AI-based sensing and prediction model to enhance smart home control systems. It maximizes lighting and HVAC controls based on sensor data (occupancy, motion, temperature, and humidity). The system proposed will result in increased energy savings and decrease in the cost of electricity, as well as, increased comfort of occupants particularly persons with disabilities. It is adaptively learned and adapted to adjust environmental settings according to user behavior and preferences, reducing energy wastage. The system facilitates intelligent and sustainable home automation with real-time data processing. Its primary goals are self-regulation, the use of energy efficiently, and eco-friendly living. The paper demonstrates that AI can turn smart homes into more convenient, cheaper, and accessible places, and there is further work aimed at enhancing the performance of the system and its utilization in the real environment [14].

Tu 2023et.al introduces a three-fold exploration to enhance transparency in deep learning on multiple edge devices of energy consumption. It is concerned with the measurement of energy consumption, prediction of power demand as well as the creation of efficiency rating. First, it measures on-device deep learning energy consumption in detail, leading to the generation of three large-scale energy datasets of a variety of kernels, recent deep neural network (DNN) models, and common AI applications. Second, it presents kernel-level predictors of energy that have been trained on this dataset and can make correct predictions on unseen DNN models of edge devices. The experiments indicate that the proposed predictors provide consistent and reliable energy estimations. Lastly, the research suggests two scoring measures, PCS and IECS, to transform the complicated energy consumption data into straightforward, easy-to-understand marks to end-users. In general, this work can advance sustainability in edge computing through increased awareness and facilitating the creation of AI systems with efficient energy usage [15].

TABLE 1: LITERATURE SUMMARY

Authors/Year	Method	Research Gap	Findings
Vanky /2023[16]	Uses Geertz theory, case studies, urban vision framework development	Lack of contextual, cultural understanding in	Proposes interpretive framework improving semantic

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		urban AI vision systems	awareness in urban AI
Flammini /2022[17]	Develops digital railway architecture with AI and digital twins	Existing train systems lack explainability, autonomy, and optimization	AI integration improves safety, energy efficiency, and operational capacity
Liao/2022[18]	IoT-based AMR system uses BIF-MSP network for real-time meter reading.	Existing methods fail to handle dial meters and embedded deployment efficiency.	BIF-MSP improves accuracy for cyclometer and dial meter reading systems.
Chukkapalli /2021[19]	IoT-based smart fisheries with ontology and ABAC security model	Weak security, interoperability, and access control in smart fisheries	ABAC and IoT integration improves security and decision-making efficiency
Ishizu/2021[20]	Low-resolution smart meter data used with balanced random forest classifier.	Household activity recognition lacks robust models for unseen homes variability.	Method achieves 70% accuracy using low-resolution aggregated power consumption data.

Research Methodology

This paper aims at creating a smart energy consumption predictor system based on time-series and deep learning models. Conventional approaches lack scalability to complex and dynamic consumption patterns, thus machine learning and deep learning are more appropriate solutions. The suggested methodology involves the LSTM and CNN-LSTM models in predicting the future electricity demand using past data. It involves data collection, preprocessing, feature engineering, and exploration data analysis to enhance model performance. Time-based splits are used to train the models, and RMSE and validation metrics are used to evaluate them. Lastly, a multi-step forecasting is carried out so that the future energy consumption can be predicted and the two models are compared to determine the most suitable model.

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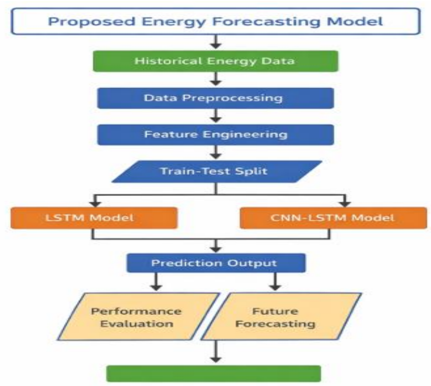

Fig. 1. Proposed Flow Chart

A. Data Collection

Data collection is a crucial step in developing any data-driven system, where quality of data directly influences model performance and reliability. This research has used time-series energy consumption data that are publicly available to make it authentic and applicable in real-world settings. The major dataset is the Kaggle smart meter energy consumption dataset that includes hourly energy consumption data and time and context. Also, the PJM hourly energy consumption data was incorporated to introduce several regional patterns of consumption, enhancing the strength of the analysis. These data are formatted as a CSV and have important fields like date and energy usage in kilowatt-hours or megawatts. The datetime index allows time series analysis and feature derivation like hour, day and month. Before modelling, data quality tests were conducted to deal with missing data, duplicates and inconsistencies. The datasets gathered in general give a solid base to reliable and reproducible energy forecasting with the deep learning models.

B. Data Preprocessing

Preprocessing of data is very crucial to enhance the accuracy of the forecasting since the raw energy data is usually full of noise, missing and irregularities. The paper has used a systematic preprocessing pipeline to transform time-series energy consumption data into a clean and model-ready format. The datetime column was then changed into the correct time format and arranged in the chronological order keeping the time sequence intact, which is vital to LSTM and CNN-LSTM models. Interpolation was used to fill in values where there was no data. It was then scaled up to feature scaling using Min-Max normalization, to normalize the values to 0-1, enhancing model stability and convergence. The data was converted into sequence-based form with a sliding window method (e.g. 24 time steps) to generate input-output pairs to deep learning models. Lastly, the data was divided into training and testing sets chronologically to avoid leaking of data. In general, preprocessing guaranteed us with clean, consistent and structured data to have accurate forecasts.

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C. Exploratory Data Analysis

Exploratory Data Analysis (EDA) is one of the important steps to analyze time-series energy consumption data before model development. It assists in determining the trends, seasonality, variability, and anomalies that influence the forecasting performance. In this experiment, the EDA allowed to represent a visual depiction of energy consumption over time and comprehend daily, weekly, and long-term patterns. Line plots data visualization, offered information on the peaks of demands and variations in consumption. Data distribution was described using statistical summaries like mean, standard deviation and range. Missing values and outliers were also examined so as to ensure data reliability. To extract time based variables, hour, day and month were extracted in order to capture seasonal trends. Rolling statistics were used to even out noise and bring out the underlying trends whereas correlation analysis was used to determine relationships between variables. In general, EDA helped to gain a clear picture of how the dataset behaved and preprocessed and developed models to perform proper energy forecasting.

- **Data Visualization**

Data visualization: Time-dependent energy consumption through line graphs to see trends, fluctuations and anomalies. It is useful in interpreting real world demand trends and proper time indexing.

- **Total Energy Consumption Analysis**

The total energy consumption is computed regionally in order to examine the general demand patterns. This assists in determining growth trends, periods of stability and abrupt fluctuations in energy consumption with time.

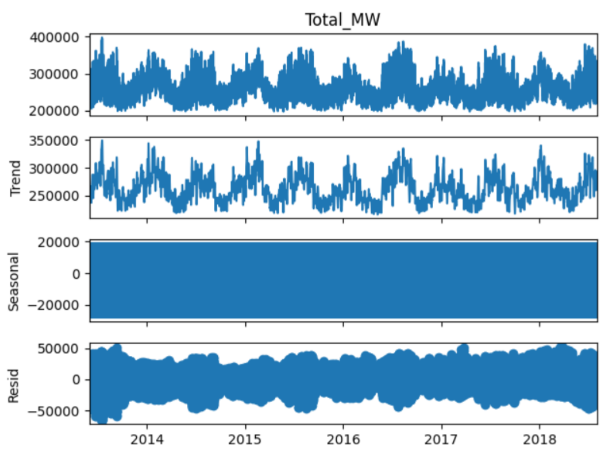

Fig. 2. Time series decomposition of energy consumption showing original data, trend, seasonal patterns, and residual components for detailed temporal analysis.

- **Hour-wise Consumption Analysis**

The amount of energy used in various times of the day usually fluctuates greatly. In order to examine this behavior, the dataset will be clustered according to the hour feature and the mean

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consumption per hour will be determined. This analysis indicates how it was used daily with high use in the morning or the evening hours and low use in the late-night hours. It is quite essential to know these patterns in order to predict models as they are able to learn periodic behaviour.

- **Outlier Detection**

Outliers are unusual data, not typical of the typical range of values. These can be due to the error of measurement, system failure or unexpected events. Such outliers in the dataset are detected using boxplots. Outliers ought to be identified and addressed to avoid having an impact on the model training process negatively.

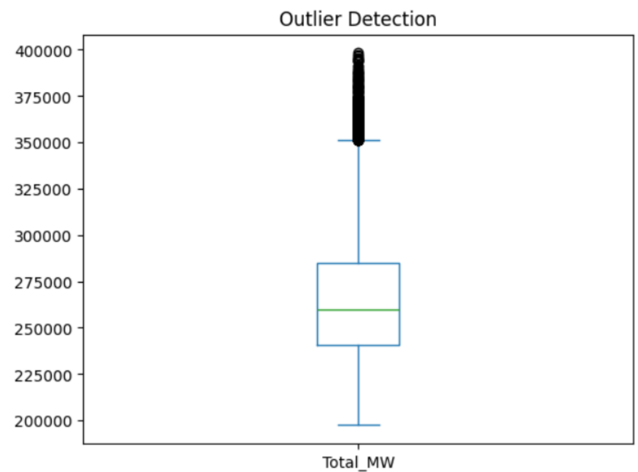

Fig. 3. Boxplot visualization of energy consumption highlighting distribution, median values, interquartile range, and presence of outliers affecting data variability and analysis.

D. Feature Engineering

Feature engineering is a crucial step in improving model performance by transforming raw data into meaningful inputs. Time-based characteristics, including hour, day, and month, derived on the index of date and time in this study, were used to include daily, weekly, and seasonal energy consumption trends. Lag features (e.g., lag-1, lag-24, lag-168) were added, in order to add the dependency of the past, allowing the model to learn historical trends. Smoothing of short-term fluctuations and emphasis on long-term trends were done using rolling statistics like rolling mean and standard deviation. Min-Max normalization was also used as a feature scaling method to normalize the values between 0 and 1 to enhance the stability of training. Caution was observed to prevent leakage of data such that the past data was only used to develop features. All in all, feature engineering improved the learning capabilities of the model to learn temporal patterns.

E. Model Development

The theme of model development revolves around creating deep learning models to predict energy based on time-series data. Two models are put into use in the study LSTM and CNN-LSTM. A sliding window method is used to transform data into fixed-length sequences to capture the temporal relationship. The LSTM model is also applicable to sequential data by learning the long-term dependencies with memory cells and gating, thus suitable in sequential data. CNN-LSTM hybrid model is a combination of CNN to extract local features and LSTM to learn over time, enhancing the accuracy of predictions. These two models are trained onTensorFlow and Keras with Adam optimizer and MSE loss functionalities. Training is conducted on several epochs and batch processing is used, validation loss is also monitored to avoid overfitting. Time based splitting provides real time forecasting and recursive multi-step prediction is employed to estimate energy demand in the future.

- **LSTM Model**
  LSTM model is a recurrent neural network that helps to obtain long-term dependencies in time-series data. It has memory cells and gating mechanisms (input, forget and output gates) to regulate the flow of information. This enables it to keep valuable historical data and disregard useless data. The model is composed of layers of LSTM that are stacked and dropout layers to avoid overfitting, and finally, the dense output layer. The LSTM is suitable to forecast tasks since it is useful at modeling nonlinear relationship and dynamic trends in energy consumption.
- **CNN-LSTM Hybrid Model**
  CNN-LSTM model is a combination of convolutional neural networks and LSTM layer to enhance forecasting. CNN component is used to extract local patterns and short-term variations by convolution and pooling layers, whereas LSTM is used to capture long-term temporal dependencies. To minimize the overfitting, it has dropout, and a dense layer generates the final output. This hybrid method improves the feature extraction and temporal learning which makes more stable and accurate prediction than standalone models.

F. Model Training

The model training allows deep learning models to be trained on patterns based on past energy data. Time-series sequences are used to train LSTM and CNN-LSTM models with the preservation of the temporal order. A time based method is used to partition the dataset with 80 and 20 percent normally used as training and testing respectively to prevent data leakage. The input sequences are created using sliding windows. Epochs, batch size, learning rate and LSTM units are hyperparameters that are selected carefully. They are optimized using Adam optimizer and MSE loss function. Validation loss is used to monitor training to avoid overfitting and methods such as dropout and early stopping enhance generalization. Future energy forecasting is carried out with the trained models.

- **Train-Test Split**
  The data are chronologically arranged into training and testing sets to ensure time sequence and eliminate data leakage. Training and testing with 80 percent and 20 percent respectively are usually considered. Input-output pairs are created by sliding windows sequences that are used in forecasting.

- **Hyper parameters**
  Epochs, batch size, learning rate, and LSTM units are important hyperparameters. The best performance of the model is 50-100 epochs with a batch size of 32. To guarantee stable convergence and precise predictions, Adam optimizer and MSE loss function are applied.
- **Training Process**
  Training is done by feeding the model with input sequences to give predictions and reducing the error by backpropagation. The loss of training and validation is observed to tell whether it is overfitting. Generalization is enhanced with methods such as dropout and early stopping. The training process of both models is the same, but CNN-LSTM offers better feature extraction followed by LSTM processing.

G. Performance Evaluation

Performance assessment is necessary in order to assess the effectiveness of the trained models on unknown data. The LSTM and CNN-LSTM models are compared in this research both numerically and visually. Root Mean Square error (RMSE) is the main measure of the difference between the actual and predicted values with lower RMSE being an indicator of higher accuracy. Training and validation loss (MSE) is also examined to monitor the learning behavior and identify overfitting. Also, actual and predicted plots are plotted to visually estimate the extent to which the models track actual trends in energy consumption. Realism and stability are also tested with recursive multi-step forecasting (24-hour prediction). In general, CNN-LSTM tends to be more effective because it is characterized by enhanced feature extraction and temporal learning abilities.

H. Model Evaluation Metrics (Shortened)

Forecasting models are evaluated by the model evaluation metrics to determine the accuracy and reliability of the forecast. In this research, the RMSE, MSE, and MAE are used to quantify the errors in prediction of energy consumption. RMSE and MSE are more penal to bigger errors, whereas MAE is more stable to the error. Besides numerical measures, visual aids like actual vs predicted plots are employed to assess the model performance. Training and validation loss curves are used to identify overfitting or underfitting in order to have good generalization. Prediction errors are also analyzed using residual analysis. The use of these metrics to compare the LSTM and CNN-LSTM models will enable the detection of the most precise and reliable model to use in making predictions.

- **Mean Squared Error (MSE)**
  Mean Squared Error (MSE) is a typical statistic used to assess regression and time-series models. It computes the mean squared error between observed and predicted values with the higher errors being more severely penalized. This research compares LSTM and CNN-LSTM models using MSE with smaller values representing greater accuracy in prediction.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad (1)$$

- **Loss Function Analysis**
  The loss function analysis is used to check the effectiveness of the model in learning. In this work, the loss function of both models is the Mean Squared Error (MSE). Training loss demonstrates the quality of the model on the training data, and validation loss demonstrates the quality of the model on unseen data. The declining pattern of both losses is an indication of good learning and the variance is an indication of overfitting. When the two losses are large, then it is underfitting. These curves can be monitored to maintain model stability and appropriate generalization.
- **Actual vs Predicted Comparison**
  Actual vs predicted comparison graphically measures forecast performance by charting actual and predicted values. The quality model shows well-matched curves, which means that learning the temporal patterns is correct. Minor deviation is a norm as per the variability in the real world but big gaps are indicative of bad performance. Another benefit of this comparison is to determine the accuracy of trends, like daily or seasonal energy consumption patterns. The overall trends are well represented by the models in this study, with a close match to the actual energy consumption data.

Result & Discussion

In this chapter, the results of LSTM and CNN-LSTM models in energy consumption forecasting based on time-series data are presented and analyzed. Training models are done on preprocessed sequences via a sliding window method and assessed with a time-based train-test split. To investigate learning behavior and generalization, MSE and RMSE and training and validation loss are used as measures of performance. Accuracy in trend and the removal of seasonal pattern are assessed with visual tools like the actual vs predicted plots and forecasting graphs. LSTM model exhibits good temporal learning whereas CNN-LSTM makes better performance by extracting combined features and modelling sequence. Both models are employed in 24-hour recursive forecasting and their outputs are compared to see which one is more accurate and stable.

A. Model Training Results

According to the model training results, LSTM and CNN-LSTM models are efficient to learn patterns of time-series energy consumption. The two models have been trained on scaled and preprocessed data by sliding window and performance measured by training and validation loss. The loss curves of both models demonstrate the effective learning and convergence, which is a constant downward trend. The LSTM model shows a gradual decrease in the loss, which proves that it is able to learn the temporal relationship, and the validation loss is also close to zero, which shows that it has good generalization and does not overfitting. On the same note, CNN-LSTM model demonstrates consistent convergence, where CNN layers are used to extract local features and LSTM layers are used to learn long-term dependencies, leading to a steady performance. There are no indications of overfitting or underfitting as the training and validation losses are equal. The use of dropout layers is used to enhance generalization and the Adam optimizer to guarantee

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efficient updates in parameters and accelerated convergence. In general, the two models are efficient in picking up patterns using the data and can be used to make reliable energy predictions.

TABLE 2: COMPARISON TABLE OF LSTM AND CNN-LSTM MODELS SHOWING TRAINING LOSS, VALIDATION LOSS, CONVERGENCE BEHAVIOR, AND IMPROVED PERFORMANCE OF HYBRID MODEL.

Model	Initial Training Loss	Final Training Loss	Avg Validation Loss
LSTM	0.000195	0.000175	0.000060
CNN-LSTM	0.000195	0.000176	0.000058

B. *LSTM Model Results*

The LSTM model is trained on the time-series data and then it is tested on the test data. It creates predictions using the previous sequences, which are transformed back to the original scale. The findings indicate that the model can generate consistent and stable forecasts that are very close to real energy consumption patterns. Small deviations are experienced as a result of the real world variability, although the overall accuracy is high. The graphical comparison between the actual and predicted values reveals that there is a close correspondence between the model and the actual values, which implies that the model is capable of capturing both the short-term variations and the long-term trends. The curve is realistic and smooth without abrupt changes as predicted. MSE and RMSE are also used to assess model performance and ensure that the error of prediction is low and that it predicts well.

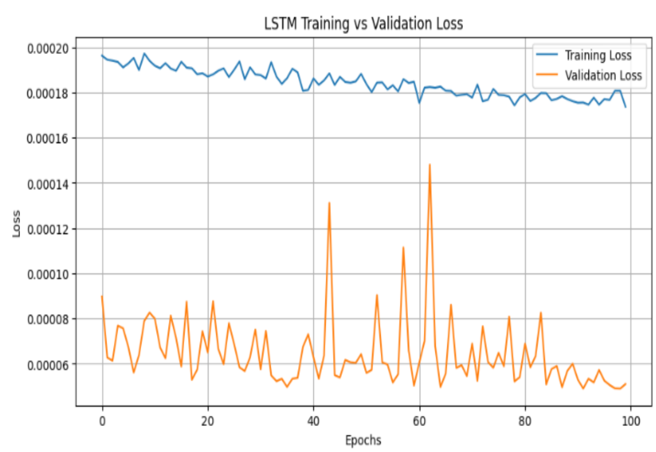

Fig. 4. LSTM model training and validation loss curves showing stable convergence, minimal overfitting, and effective learning across epochs for energy consumption forecasting task.

C. *CNN-LSTM Model Results*

The CNN-LSTM hybrid model enhances prediction by integrating CNN to obtain local features and LSTM to learn long-term temporal patterns. Upon training, they make predictions on test data,

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which are inverse-transformed, and present smooth and stable predictions that are similar to real energy consumption. The convolutional layers eliminate noise and boost short-term patterns, whereas LSTM is effective to capture the general trends. Graphical analyses of real vs forecasted values ensure high convergence and good trend follow-up. MSE and RMSE are used to assess the model with lower error values as compared to LSTM alone. In general, CNN-LSTM provides more precise and consistent results owing to the joint capability of extractions and sequence learning.

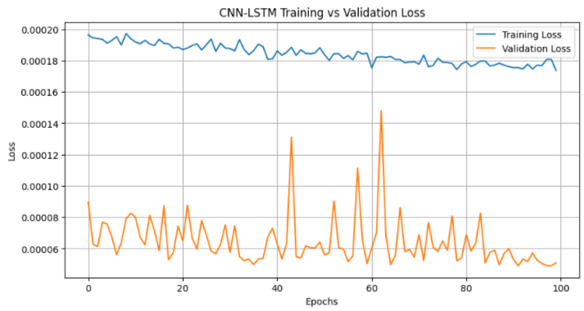

Fig. 5. CNN-LSTM model training and validation loss curves indicating stable convergence, reduced error, improved generalization, and effective feature learning across training epochs.

D. Future Forecasting Results

One of the primary outcomes of the study is future forecasting, which shows that LSTM and CNN-LSTM models are practical in predicting energy consumption. Both models are used to produce 24-hour ahead forecasts by using recursive multi-step forecasting with each result as an input in the next step. The forecasts are inverted and exhibit realistic smooth trends that are in line with the historical data. The gradual variations with no sharp spikes are predicted by forecast graphs, which proves that temporal patterns are learned. Historical and future plots indicate a great continuity between real and forecasted data. In general, both models come up with stable and reliable forecasts that can be used in real world energy management.

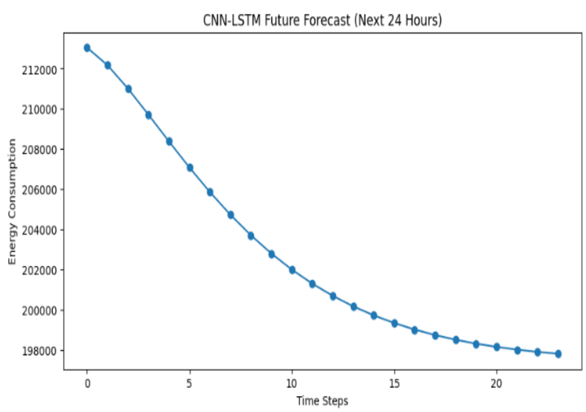

Fig. 6. CNN-LSTM future forecast for next 24 hours showing gradual decline in energy consumption with smooth trend and stable predicted values over time.

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E. Past vs Future Comparison

Comparison of the past and future is a necessary step to assessing the time-series forecasting models by testing the degree of its ability to predict the future based on the patterns learned previously. This paper compares the recent historical energy usage with 24-hour recursive predictions to test the use of LSTM and CNN-LSTM models. Past data constitute the most recent measured values whereas future data involve forecasted outputs. An excellent model will have continuity between these two segments without abrupt jumps and breaks. This study has good forecasts which are close to the historical trends meaning there is a good temporal learning. The two models are consistent with trends, showing gradual increases, decreases, and seasonality. CNN-LSTM is more stable with less noise and smooth predictions. In sum, the comparison establishes that both models produce realistic, continuous and reliable forecasts that could be applied to real-world tasks of energy prediction.

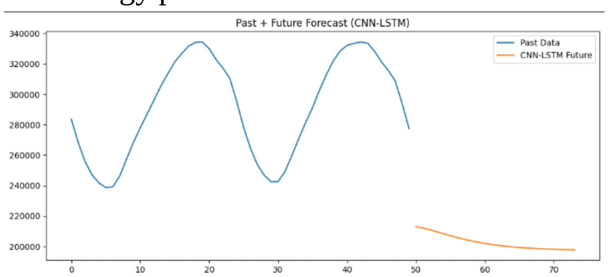

Fig. 7. Past and future energy consumption comparison using CNN-LSTM model showing trend continuation, smooth transition, and stable forecasted values over time.

Conclusion

To sum up, this paper was able to create an intelligent energy consumption predictive algorithm based on LSTM and CNN-LSTM deep learning models on time-series data. The methodology involved a combination of data gathering through publicly available datasets, cleaning and chronological sorting as well as Min-Max scaling and sliding window sequence creation (24 time steps) to model the data. Temporal patterns including trends and seasonality were important patterns that were captured using feature engineering and exploratory data analysis. The 80:20 time-based split was used to train the models and data was not leaked. The results of performance analysis on MSE, RMSE, and loss curves were strong with LSTM having a final training loss of approximately 0.000175 and validation loss of approximately 0.000060 and CNN-LSTM having a final training loss of approximately 0.000176 and validation loss of approximately 0.000058. Both models exhibited steady convergence, low overfitting and good generalization power. Recurring 24-hour predictions The 24-hour recursive forecasting produced a smooth and realistic future predictions in accordance with the historical patterns. In general, CNN-LSTM marginally outperformed LSTM because of its superior feature extraction and reduced validation error rendering it the best choice to forecast energy demand with accuracy and reliability in real-life use.

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