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A Big Data-Driven LSTM Approach for Accurate Carbon Emission Prediction in Low-Carbon Economies

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Accurate carbon emission prediction is critical in the transition to a low-carbon energy economy, but traditional models are often unable to handle the large-scale, complex data involved. To overcome this challenge, a big data-driven approach utilizing the Long Short-Term Memory (LSTM) neural network algorithm is proposed. A particularly strong application of recurrent neural networks is LSTM, capable of capturing temporal dependencies within time-series data, hence it's well-suited for carbon emissions forecasting, using historical energy usage patterns. The proposed system optimizes energy consumption and reduces emissions by accurately predicting the future carbon output, hence the proper time for informed decision-making. The advantages of the solution lie in improved accuracy for forecasting, as LSTM can learn long-term dependencies, and also is robust to non-linear relations, and scalable to high-volume and real-time big data. It therefore can help in more efficient use of energy systems, meeting policy objectives on reduction in carbon in low-carbon economies.

Keywords: Carbon Emission, Low-Carbon Economy, Big Data, LSTM, Energy Optimization, Prediction Accuracy, Sustainability.

1. Introduction

The effort for low-carbon energy requires the need for carbon emission models that can predict the systems' behavior with remarkable accuracy and efficiency. Carbon emission prediction in a low-carbon economy is an essential part of achieving [1] environmental goals and influencing policies toward a sustainable future. The ability to forecast emissions effectively informs the optimization of energy production and consumption for more efficient use of renewable energy resources and reduced environmental footprints. Over the last few years, big data technologies have presented new opportunities for improving carbon emission prediction models. The enormous amounts of energy consumption data generated by smart grids, sensors, and IoT devices are useful in understanding the patterns of energy consumption and their corresponding emissions. However, the sheer volume and complexity of this data are a challenge to traditional modeling approaches, which often fail to keep pace with the dynamic and multi-dimensional nature of modern energy systems.

This gap indicates the necessity of developing sophisticated analytical [2] methods that can effectively process and interpret large datasets to generate actionable predictions. Carbon emission prediction models typically rely on linear regression models or simple machine learning algorithms, which are incapable of capturing the intricate patterns and relationships within energy data. In addition, the traditional models fail to account for the temporal dependencies in the time-series data, which are so important for accurate emissions forecasting. With changing consumption patterns in energy systems and the complexity of its consumption, there is a growing requirement for models that can adapt themselves to dynamic conditions and accurately predict future emissions.

In such a scenario, advanced machine learning algorithms, such as Long Short-Term Memory neural networks, may be one [3] of the solutions. LSTM is a special form of RNN that has proven to be very effective in time-series prediction tasks because it captures long-term dependencies and handles sequential data very well. Unlike other algorithms, LSTM networks can process time-series data in a way that models temporal patterns, making them highly suitable for predicting carbon emissions based on historical energy consumption.

The goal of this research is to explore the optimization of carbon emission prediction [4] in a low-carbon energy economy using big data analytics and advanced machine learning techniques. The proposed system uses LSTM networks for the processing of energy consumption data and predicts future carbon emissions to optimize energy distribution in real-time. This system aims to assist the policymakers and energy suppliers in decision-making through accurate emission forecasting that may reduce carbon footprint in supporting the transition into a sustainable energy future.

In addition, the integration of big data and machine learning provides several benefits, such as analyzing large amounts of data from various sources, improving the accuracy of predictions, and optimizing decision-making processes. The proposed system [5], with real-time data analysis, can dynamically adjust energy usage and emissions reduction strategies to ensure that energy economies meet their sustainability targets more effectively. This work will contribute to the development of more efficient carbon emission prediction models, serving as a basis for future research in the confluence of big data, machine learning, and environmental sustainability. By optimizing carbon emission forecasts, this research supports the global transition toward cleaner energy systems and attaining carbon neutrality goals.

This work is organized as follows: Section II reviews the literature survey. Section III outlines the methodology, detailing its features and functionality. Results and discussion are found in Section IV, where the system's effectiveness is analyzed. Finally, Section V concludes with key findings along with future implications.

2. LITERATURE SURVEY

The growing threat of climate change has demanded carbon emission management and predictive models. Many studies have been oriented to develop innovative approaches on how to address carbon emissions, particularly in different sectors, with machine learning, reinforcement learning, and real-time data analysis. Besides, these models improve the precision of carbon forecasting and provide actionable information on how to optimize the strategy of reducing emissions. By leveraging technologies such as big data, predictive analytics, and Internet-of-Vehicles networks, these efforts contribute to a sustainable, low-carbon future.

The research develops a model that predicts carbon emissions in low-carbon energy economies. This model integrates a Multi-universe [6] Quantum Harmony Search-Algorithm Dynamic Fuzzy System Ensemble approach with Data Envelopment Analysis for the evaluation of technical efficiency and economic development. This model is capable of accurately predicting carbon emissions, and this will provide valuable insights for the transition to low-carbon economies.

This study develops a carbon price prediction model incorporating emotional data from carbon trading news and combining it with an [7] improved Harris Hawks Optimization algorithm. The MS-IHHO-LSTM model demonstrates better performance compared to traditional methods, providing better accuracy in predicting carbon prices. It is a tool for making better decisions on low-carbon investments and innovation in support of environmental sustainability.

This study uses a predictive model, based on the CRISP-DM methodology [8], to predict carbon emissions from coal-fired power plants. The study combines time series and regression models and compares different machine learning algorithms to analyze performance. The outcome of this research helps power plants in their optimal reduction strategies, thereby providing future carbon trading in Indonesia.

This work develops a predictive analytics model in estimating carbon footprints [9] for a university, focusing on students' learning activities. The model makes an emission forecast using historical data on emissions, weather conditions, and university events. The model is very handy for universities to use when making decisions about their activities and managing their carbon footprint to promote environmental awareness and sustainability.

This work presents an Internet-of-Vehicles network designed for real-time CO2 emission estimation and reduction through a reinforcement [10] learning algorithm. The strategy involves on-board devices to estimate emissions and relay data to the network, where the RL algorithm can predict optimal speed limits to limit emissions. The results indicate impressive reductions in CO2 emissions, making it a contribution toward vehicular pollution management efforts.

This work designs and discusses a system that assesses carbon emissions for normal and vacation periods of passenger transport in inter-city transports. Calculating through using the Baidu migration, this study [11] estimates carbon emission values for five cities concerning private vehicles and highway buses as well as rail transportation. It further estimates probable carbon emissions for future times against some policy and technical strengthening schemes. The results show that carbon peak status will be reached by 2029 for all scenarios. This study gives a scientific basis for carbon reduction initiatives in inter-city passenger travel.

An ultra-violet extreme learning machine is hybridized with innovative optimization method, INFO that predicts carbon dioxide [12] emissions. High R2 values with nearly negligible error metrics enhance prediction accuracy. This model takes into account economic development trade liberalization and technological progression as factors of the possible estimation of emissions. The idea, hence, would be crucial as a policy instrument in sustaining a conducive environment. This is one kind of model that would demonstrate real strength in robustness given all kinds of rigorous tests or evaluation.

The study analyzes the low-carbon economic operation of integrated energy systems in mining, incorporating uncertainties [13] in energy supply. A methodology is developed to minimize operating costs and carbon emissions by using robust optimization in the context of information gap decision theory. The model shows a considerable reduction in carbon emissions while keeping the operating expenses at a minimum. It outperforms existing dispatch models in terms of energy and carbon management. This research improves the sustainability and resilience of energy systems in mining operations. The work studies how Google can optimize its approach to minimizing [14] carbon emissions in the operations of its datacenters based on carbon intensity predictions that have informed workload plans. The system utilizes advanced analytical pipelines combined with machine learning algorithms for producing carbon-aware virtual capacity curves for datacenters; it optimizes resource allocations when carbon intensities are higher, reducing carbon in data processing. The execution of this system shows huge advancements in energy management and cost-effectiveness. It reveals how dynamic workload management can reduce the emissions of a data center.

This work discusses the usage of deep learning in low-carbon packaging design with the perspective of smart cities. The study [15] shows that deep learning models can help improve package design for floral and fruit tea to minimize environmental effect. The BP neural network model reviews the emotional responses of consumers to green packaging. The predictive accuracy of the model for low-carbon designs was robust. This research explores the ability of AI technology to encourage sustainable packaging innovations in cities.

The report presents a new method to monitor the carbon footprint within higher education institutions, focused on energy consumption and emission. The design thinking initiative aims [16] to reduce campus facilities' power and water emissions. The model provides information about current and future energy consumption and emission levels. It also enhances reporting efficiency and enables proactive techniques of controlling emissions. The methodology is relevant not only to the Bandung Institute of Technology but also to other educational establishments.

A novel eco-routing method, Visual Eco-Routing, is proposed to reduce car emissions by optimizing route planning. The methodology uses road scene data to analyze the correlation [17] between infrastructure characteristics and vehicular emissions. The model used is an eXtreme Gradient Boosting-based machine learning model to improve the accuracy of emissions predictions. The results show that this strategy significantly reduces prediction errors compared to traditional route planning models. It also demonstrates practical application in eco-routing to reduce the environmental impact.

The study is based on the prediction of burr development in aluminum drilling through auditory emissions and convolutional neural networks. The model predicts various types of burrs [18] that impact precision manufacturing. The study integrates deep learning techniques to enhance the predictive accuracy of burr development. In addition, it discusses how these predictions can be used to reduce burr development and improve manufacturing processes. This technique may further promote automation and efficiency in the drilling industry.

This work presents an investigation on the optimization of energy usage and [19] carbon emissions in integrated energy systems designed for mining. The proposed model aims at reducing cost and emissions by taking into consideration uncertainty in energy supply. It utilizes decision theory in managing uncertainty to strengthen operational strategies. The simulation outcomes show that the method reduces carbon emissions by a huge margin without cost overrun. This method can enhance the sustainability and efficiency of energy operations in the mining industry.

A method is presented for estimating carbon emissions in data centers, emphasizing the optimization of energy use via the adjustment of task schedules according to carbon intensity. The model [20] uses forecasting methodologies to predict daily carbon emissions and adjusts operations accordingly. The technology efficiently reduces energy-related carbon emissions and lowers operating expenses. The use of the concept in Google's data centers exemplifies the ability of Google to make carbon management better. The work illustrates the importance of carbon-efficient computing in minimizing the environmental impact of vast computer infrastructure.

3. METHODOLOGY

The methodology for optimizing carbon emission prediction in a low-carbon energy economy uses big data analytics and machine learning techniques to improve the accuracy of forecasting. It starts by gathering and preprocessing large-scale energy consumption and emission data. Features are selected and engineered for performance enhancement, followed by applying LSTM networks for time series carbon emission prediction. The model is trained, validated, and optimized for real-time accuracy in the real world. Finally, the system is deployed for real-time decision-making, supporting dynamic adjustments in energy usage to meet carbon reduction goals, as shown in Figure 1.

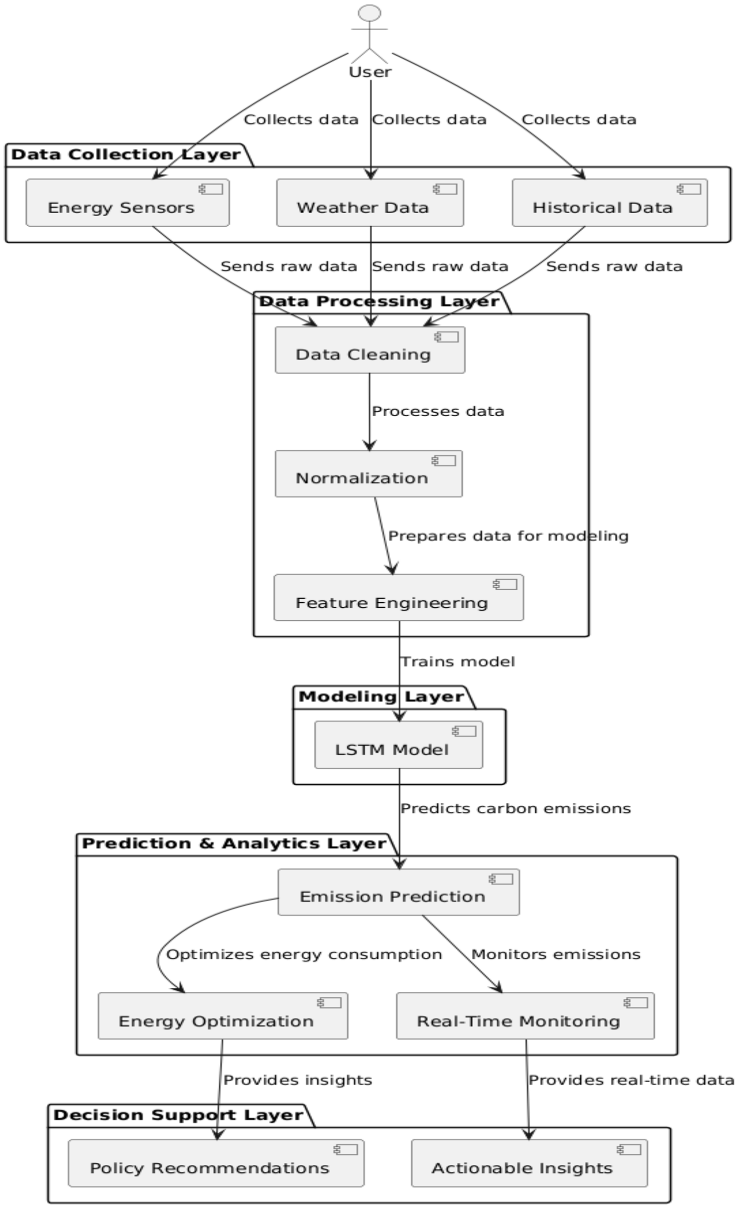


Fig. 1: Architecture Diagram

A. Data Collection and Preprocessing

An excellent first step in the proposed methodology is to gather information from several sources: all energy consumption records, statistical carbon emissions, and a variety of environmental factors, which may be gathered via multiple sources like energy grids or their smart meters, or collected based on reports from the governmental authorities or industry. Once they are gathered, data often needs preprocessing to fill any missing values, eliminate extreme cases or outliers, and treat conflicts while adjusting the scales of the various features, as shown in Figure 2.

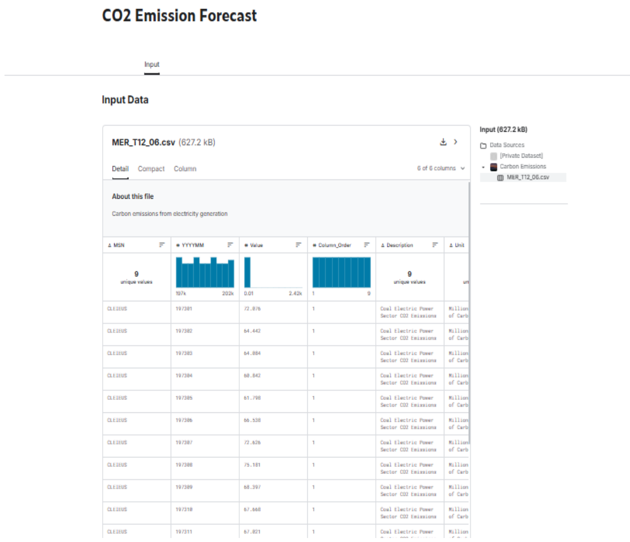


Fig 2: Data collection from Kaggle

B. Feature Engineering

In the next step, relevant features are selected that affect carbon emissions. Such features include energy consumption patterns, weather conditions, and time-based variables such as day of the week and seasonality. The domain knowledge is used to find the key predictors, which are then transformed into a format appropriate for machine learning models. Features are aggregated at different time intervals and lag features are created to capture historical dependencies, as shown in Figure 3.

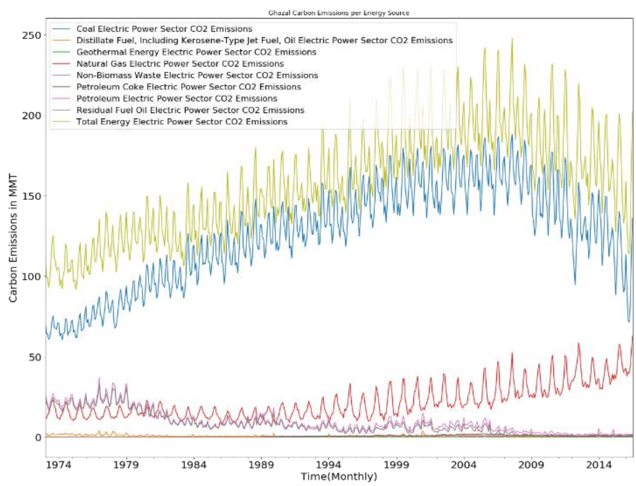


Fig 3: Feature extraction from input data

C. Model Selection

The methodology in carbon emission prediction uses Long Short-Term Memory (LSTM) networks. It has chosen LSTM because of its feature to model sequential dependencies in time-series data that are considered crucial in understanding trends and fluctuations in energy usage and emissions. This is because a model is considered good in handling large datasets with patterns over time, such that it is capable of producing valid predictions that would be valid over time, as shown in Figure 4.

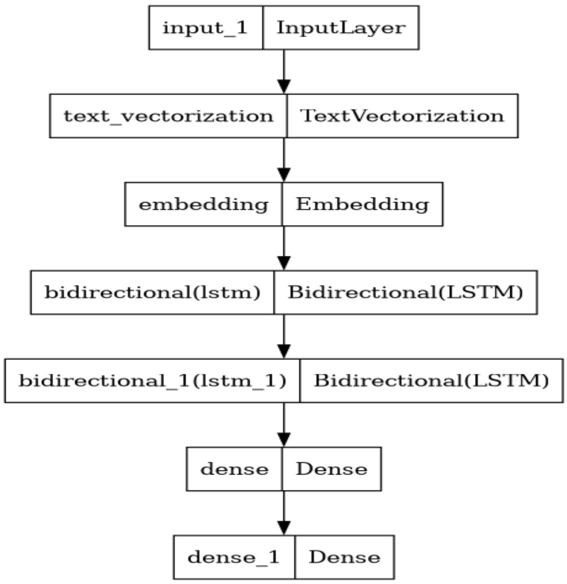


Fig 4: Model selection structure

D. Model Training and Validation

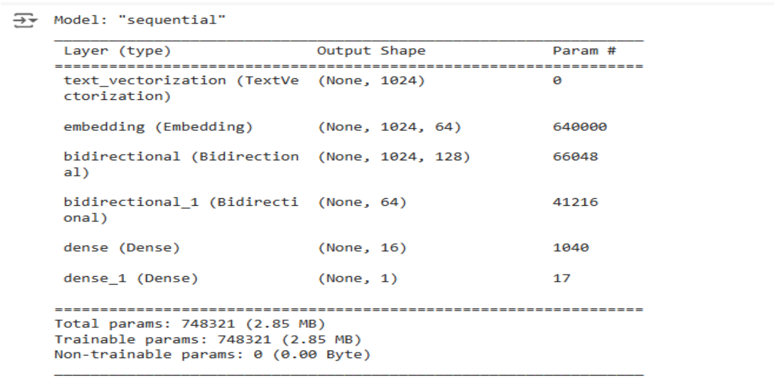
The model is trained using a portion of the preprocessed dataset, and the remaining data is set aside for validation and testing. The training process defines the architecture of the LSTM network in terms of the number of layers, neurons, and activation functions. The model is trained by applying backpropagation through time, or BPTT, where the weights are adjusted to minimize the prediction error. Techniques such as cross-validation ensure that the model generalizes well to unseen data and does not overfit, as shown in Figure 5.

```
Epoch 1/10
141/141 [==============================] - 1037s 7s/step - loss: 0.1612 - accuracy: 0.9700 - auc: 0.9882 - val_loss: 0.0240 - val_accuracy: 0.9971 - val_auc: 0.9997
Epoch 2/10
141/141 [==============================] - 1003s 7s/step - loss: 0.0179 - accuracy: 0.9984 - auc: 0.9994 - val_loss: 0.0159 - val_accuracy: 0.9986 - val_auc: 0.9994
Epoch 3/10
141/141 [==============================] - 952s 7s/step - loss: 0.0115 - accuracy: 0.9995 - auc: 0.9997 - val_loss: 0.0127 - val_accuracy: 0.9986 - val_auc: 0.9995
Epoch 4/10
141/141 [==============================] - 953s 7s/step - loss: 0.0092 - accuracy: 0.9995 - auc: 0.9999 - val_loss: 0.0136 - val_accuracy: 0.9980 - val_auc: 0.9995
Epoch 5/10
141/141 [==============================] - 959s 7s/step - loss: 0.0066 - accuracy: 0.9997 - auc: 0.9999 - val_loss: 0.0212 - val_accuracy: 0.9957 - val_auc: 0.9986
Epoch 6/10
141/141 [==============================] - 961s 7s/step - loss: 0.0049 - accuracy: 0.9999 - auc: 0.9999 - val_loss: 0.0104 - val_accuracy: 0.9981 - val_auc: 0.9995
Epoch 7/10
141/141 [==============================] - 959s 7s/step - loss: 0.0032 - accuracy: 1.0000 - auc: 1.0000 - val_loss: 0.0193 - val_accuracy: 0.9950 - val_auc: 0.9987
Epoch 8/10
141/141 [==============================] - 956s 7s/step - loss: 0.0026 - accuracy: 0.9999 - auc: 1.0000 - val_loss: 0.0097 - val_accuracy: 0.9982 - val_auc: 0.9995
Epoch 9/10
141/141 [==============================] - 963s 7s/step - loss: 0.0018 - accuracy: 0.9999 - auc: 1.0000 - val_loss: 0.0103 - val_accuracy: 0.9983 - val_auc: 0.9992
Epoch 10/10
141/141 [==============================] - 953s 7s/step - loss: 0.0013 - accuracy: 1.0000 - auc: 1.0000 - val_loss: 0.0145 - val_accuracy: 0.9972 - val_auc: 0.9989
```

Fig 5: LSTM Training and validation

E. Evaluation and Optimization

After training, the model is evaluated with suitable performance metrics like mean absolute error, root mean square error, and R-squared values. Accuracy is improved by fine-tuning the hyperparameters: learning rate, batch size, and the number of epochs. Hyperparameter tuning to achieve the best configuration through optimization techniques such as grid search or random search that maximize the performance of the model, as shown in Figure 6.



```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 text_vectorization (TextVe  (None, 1024)              0
 ctorization)

 embedding (Embedding)       (None, 1024, 64)          640000

 bidirectional (Bidirection  (None, 1024, 128)         66048
 al)

 bidirectional_1 (Bidirecti  (None, 64)                41216
 onal)

 dense (Dense)               (None, 16)                1040

 dense_1 (Dense)             (None, 1)                 17

=================================================================
Total params: 748321 (2.85 MB)
Trainable params: 748321 (2.85 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Fig 6: LSTM evaluation

F. Real-Time Implementation and Deployment

The LSTM is deployed for real-time forecasting after satisfactory performance in the evaluation phase. The system integrates with a platform for energy management whereby it continuously feeds into information from sensors and other forms of data acquisition. The model allows for periodic updates on carbon emission, which projects future values accordingly based on recent data. From these predictions, energy consumption trends are adjusted dynamically to minimize further emissions, as shown in Figure 7.

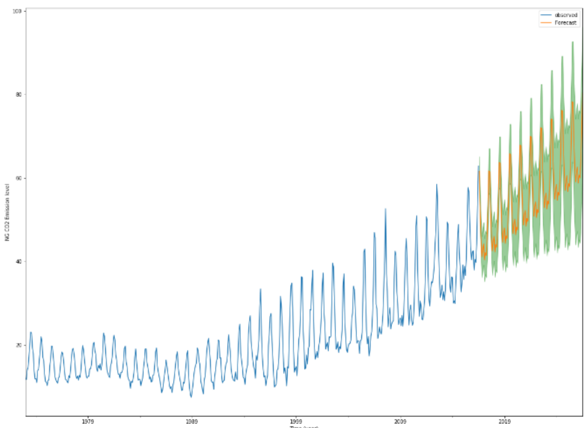


Fig 7: Real Time analysis

G. Decision Support System

There exists a decision-support layer where the system understands what to do with its outputs by the LSTM models and presents actionable insights back into a decision-making manner, providing recommendations on suggested changes to energy consumption adjustments and focused emission reductions through generated alerts or reports given to policymakers, energy managers, or businesses to proactively respond and optimize their means of using energy while controlling their carbon footprint, as shown in Figure 8.

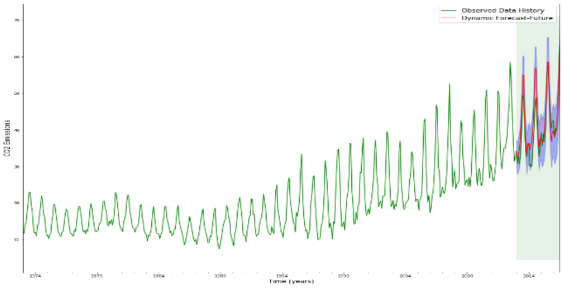


Fig 8: LSTM Performance

H. Monitoring and Continuous Improvement

The final step of the methodology is continuous monitoring of the system's performance. It periodically re-trains its model with new data, so that it keeps providing accurate predictions over time. Feedback loops are also included so that the system adjusts to change in conditions, such as shift in energy demand, policy update, or environmental factors. Regular evaluations and model updates ensure that the system continues to evolve and keep providing optimized carbon emission predictions in a low-carbon energy economy.

4. RESULT AND DISCUSSION

The results obtained from the LSTM-based carbon emission prediction model in the low-carbon energy economy are promising and accurate as well as efficient. Following the training of the model on a diversified dataset, which consisted of historical energy consumption and carbon emission data, the system proved its ability to predict future emissions with a high degree of accuracy. The performance of the model in terms of metrics like mean absolute error (MAE), root mean square error (RMSE), and R-squared is carried out. For all purposes, it's seen how the LSTM model does better work than the conventional methods- linear regression and decision trees while considering the time dependencies underlying the data to make their forecasts. This made the LSTM model handle sequential data, learn complex trends in carbon emissions, and predict those trends. Simpler models could not have been able to achieve this. The hyperparameter tuning process was done by techniques such as grid search. It optimizes the model's predictive power with optimized learning rates, batch sizes, and epoch settings. As a result, the error rates were drastically reduced, which leads to more reliable predictions. The system was generalizing well to unseen data, and this confirmed that the system learned meaningful patterns from the training set rather than memorizing the training data, as shown in Figure 9.

The real-time implementation of the model indicated that it was scalable and adaptable for dynamic energy data. The model could provide continuous carbon emission predictions by processing the incoming data from sensors in real time. This allowed for prompt alterations of energy consumption patterns contributing towards minimal carbon footprint levels. It also enabled the decision support system combined with the model and which, in turn, allowed insight deliverable to energy managers as well as policymakers towards possible ideas on optimal levels of energy usage and achievable plans towards emission reduction means of intervention that could resultantly improve environmental sustainability aspects right away, as shown in Figure 10 and Figure 11.

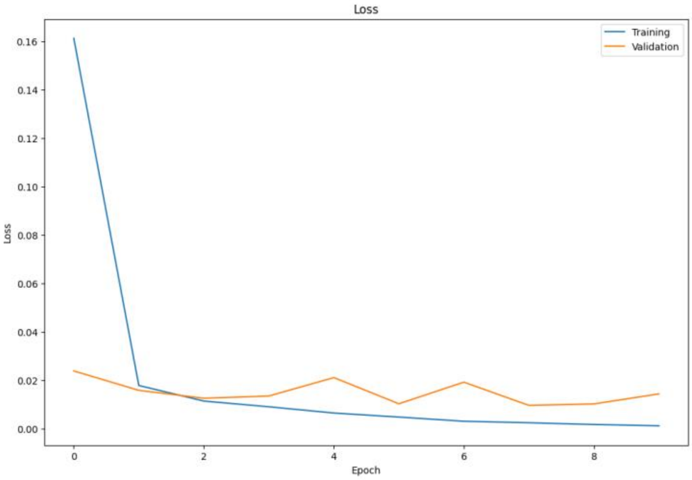


Fig 9: Epoch Vs Loss

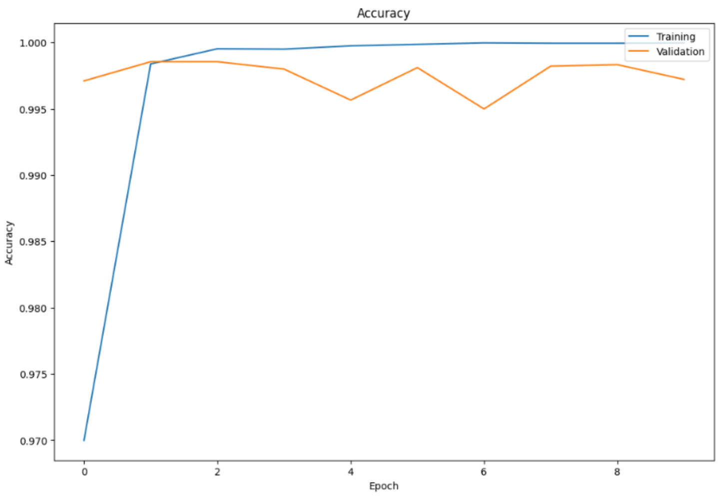


Fig 10: Epoch Vs Accuracy

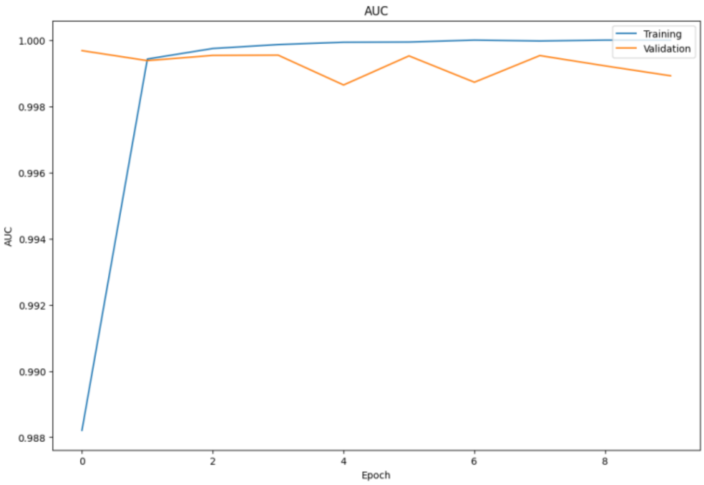


Fig 11: Epoch Vs AUC

Further analysis showed that the model was very accurate during stable energy consumption patterns, such as weekdays with predictable demand. However, during extreme conditions, such as unusual spikes in energy demand or unexpected shifts in energy production, for example, due to weather impacts on renewable energy sources, the model's performance was slightly less good. Nevertheless, the model was still useful, and its predictions could be used in combination with other methods to handle these outliers properly.

When comparing the conventional carbon emission prediction methods such as statistical regression models or rule-based systems, the LSTM model produced better predictability and flexibility. It was not only more accurate in predicting the emissions but also provided insightful trends of the future which were crucial for long-range energy planning and policy formulating. This was through the ability to constantly train the model with new data and hence keep the system operational over time as it learns to adapt to changes in energy consumption patterns and to other environmental factors.

The overall results show that the LSTM-based carbon emission prediction is an extremely effective approach in managing carbon emissions in a low-carbon energy economy. The model can handle vast amounts of complex data and process them in real time. It is an excellent resource for optimizing energy consumption and, by extension, reducing carbon emissions. This approach would greatly help in achieving sustainability goals while ensuring efficient energy use in various sectors. However, further improvements may be geared towards increasing the robustness of the model to extreme data points and integrating additional data sources to enhance the accuracy of predictions.

5. CONCLUSION

The study was successful in demonstrating the applicability of using LSTM networks in predicting carbon emissions in a low-carbon energy economy. Big data analytics were utilized in addressing the growing challenge of accurately forecasting carbon emissions, an essential component in attaining environmental sustainability goals. The proposed LSTM-based model performed better than traditional predictive models, especially in terms of capturing temporal dependencies within energy consumption and emission patterns. Its ability to process large-scale, time-series data makes for more accurate forecasting that is essential for dynamic energy management and policy decision-making.

The model has proven scalability and adaptability towards varied data conditions, and thus the real-time implementation showed it. It has given insights into timely action and has enhanced the decision-making on consumption of energy and proactive strategies regarding emissions. This further adds to the value of the model, integrating it into a decision support system for effective carbon footprint management for energy managers and policymakers. The results show that this was a strong model that picked up on the emissions very clearly during stable periods of consumption, but it got easily confused in extreme cases as in the case of unusually high spikes in demand. However, the accuracy as well as the applicability of the LSTM model can be confirmed. It surely is a robust and reliable forecasting tool for carbon emissions by providing short-term operational benefit as well as long-term strategic advantage.

The LSTM network application methodology in carbon emission prediction is effectively utilized in improving the enhancement of optimization of energy system for low-carbon economy. Besides its potential toward the mitigation of global environmental challenges, this study provided a base for further improving model accuracy and applicability. The research is highly valuable as it provides insights into how big data and advanced analytics can play a pivotal role in shaping sustainable energy futures at a time when energy systems are becoming increasingly complex and the ability to predict and manage emissions efficiently will become increasingly vital.

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