International Journal of Informatics Engineering and Computing (IJIMATIC)
Vol. 2, No.1, 2025\
E-ISSN: 3090-9112

Optimizing Sunspot Forecasts: An In-Depth Analysis of the ConcaveLSTM Model

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Abstract

This work examines how effectively the ConcaveLSTM model can forecast sunspot numbers, recognizing their importance in space weather. The model addresses the complex and changing sunspot characteristics to improve forecasting accuracy. By comparing different model variations, this research identifies optimal combinations of input steps and LSTM units that enhance forecast performance while avoiding overfitting. The study showcases the capability of specific architectures concerning detail versus computational cost, using evaluation metrics such as RMSE, MAE, MAPE, and R2. Considering factors like limited data availability and the complexity of solar phenomena, the ConcaveLSTM model could be a valuable tool for predicting solar activity. This research advances understanding of space weather forecasting through machine learning and offers guidance for further model development and future investigations.

Keywords:
ConcaveLSTM, LSTM, sunspot, space weather, machine learning

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1. Introduction

The prediction of sunspots is critically essential for understanding and anticipating their impacts on various key sectors, including telecommunications, space weather, and power systems [1]. Sunspots, which are manifestations of the Sun's magnetic activity, can cause significant disruptions to navigation and communication systems, affect satellite operations, and even lead to fluctuations in Earth's power grids [2]. However, the challenge in predicting sunspots lies in the complexity of the Sun's behavior itself, necessitating a deep understanding of solar physics dynamics and the application of advanced predictive methodologies [3]. Therefore, developing accurate prediction methods is crucial for mitigating risks associated with these phenomena and planning and managing resources in the critical sectors affected.

The study of sunspots, tracing back to observations as early as 1610 [4], has evolved significantly, underscoring their impact on telecommunications, space weather, and power systems. Beyond mere counting, these early observations offered insights into sunspots' nature [5]. Our understanding has deepened, linking sunspots to the Sun's magnetic field changes [6]. Consistency in the magnetic properties of sunspots over the past century has been highlighted through historical data, including field strength measurements [7]. Moreover, the correlation between sunspot area and magnetic flux has enabled studies on magnetic fields during periods devoid of direct measurements. Such historical datasets are pivotal for discerning long-term solar activity trends, including active region tilt and polar field evolution. The availability of these observations has been instrumental in advancing

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our comprehension of the Sun's behavior.

Solar magnetic activity, particularly sunspot activity, has been the focus of studies aiming to decipher its periodicity and patterns. Various theories and models have been proposed, including the influence of planetary gravitational effects on the 11-year sunspot cycle [8] and the existence of cycles like the biennial, Gleissberg, and Hallstatt cycles [9]. A model suggesting magnetically modified Rossby waves in the Sun's convection zone explains observed spatio-temporal patterns in solar activity [10], highlighting interactions with toroidal fields that intensify solar activity, followed by quieter periods. These insights contribute to our understanding of sunspot activity's periodicity and patterns.

Technological advancements in observational methods have enriched sunspot data collection and analysis, which are pivotal for long-term forecasting. Techniques like Topological Data Analysis (TDA) for detecting solar activity and machine learning models utilizing Fourier Transform analysis have shown promise in accurately forecasting sunspot cycles [4]. These approaches, along with statistical methods for data consolidation and anomaly identification, and the use of convolutional neural networks (CNN) for sunspot detection, enhance our analytical capabilities [11]. Furthermore, complex network techniques offer a novel perspective on the nonlinear dynamics of sunspot activity [12].

Sunspot prediction methodologies predominantly employ machine learning techniques, including neural networks, to utilize various solar activity indicators for forecasting. The performance of these models, such as the high precision of the YOLOv5 network in sunspot detection [11] and the accuracy of Random Forests in predicting sunspot cycles [4], demonstrates their potential. Moreover, LSTM-based models have shown effectiveness in forecasting using time-series data, with innovations like the LSTM-attention-LSTM model introducing attention mechanisms for enhanced prediction capabilities [13].

Despite advancements, sunspot prediction challenges persist due to the non-stationary and chaotic nature of the sunspot time series. Addressing these complexities involves deploying a range of machine learning and data analysis techniques, including neural networks for image-based sunspot tracking and two-stage models combining CEEMDAN, PSO, and ELM networks for improved prediction accuracy [14]. These methods underscore the evolving landscape of sunspot prediction research.

Integrating machine learning and artificial intelligence into sunspot prediction models has diversified forecasting approaches, from employing Fourier Transform analysis for periodicity detection to recursive feature elimination for solar irradiation estimation [15]. Exploratory techniques in artificial intelligence also unveil the decision-making processes of neural networks, offering insights into features associated with solar activity [16].

Considering external factors like solar irradiance and geomagnetic activity in forecasting models has improved sunspot prediction accuracy. For instance, ensemble models like XGBoost-DL and the incorporation of periodicity attributes into forecasting models exemplify this integration [17]. These enhancements, along with investigations into the impact of climate change and external phenomena on sunspot patterns, underline the multifaceted nature of sunspot prediction research.

Previous research in sunspot prediction has significantly improved our understanding, but a persistent gap remains in developing models that balance high accuracy with computational efficiency. This research aims to fill that gap by proposing to create and apply the ConcaveLSTM Algorithm, a new approach designed to boost prediction accuracy while keeping computational demands manageable. The main contribution of this study is its potential to significantly enhance sunspot prediction accuracy, providing a more efficient computational model that can be practically used in real-world settings. Additionally, by utilising the ConcaveLSTM Algorithm, this research seeks to offer deeper insights into the dynamics of sunspot activity, thereby supporting the broader field of solar physics and its real-world applications in telecommunications, space weather forecasting, and power grid management. Through this dual focus on advancing the theoretical understanding and practical use of sunspot prediction, the study aims to achieve a notable progression in the field.

2. Methods

Dataset

The phrase pre-processing data refers to activities planned to prepare the dataset for analysis by ensuring it is free of noise and consistent. When analysing a dataset of monthly mean total sunspot numbers between January 30, 1749, and January 30, 2023, sourced from Kaggle, we focus on a dataset with 3265 records. Such a time series history enables the investigation of solar activity over many centuries, aiding in studying the cyclical variability in sunspot numbers.

Data Preprocessing

The primary tasks in the data preprocessing stage involve irreversibly removing records that will influence how analyses are conducted. Specifically, records with attributes indicating a zero value are discarded since they could be outliers. Additionally, it is crucial to delete fields containing blank spaces or no values, as this is important for ensuring data quality. After this cleansing process, the dataset undergoes a weighting procedure, where attribute values are adjusted to appropriate scales. This normalization process, often called pre-processing normalization, is essential for practical analysis and model training in data fitting, and it is performed using the formula shown in Equation 1.

$$\text{Normalized Value} = \frac{\text{Original Value} - \text{Minimum Value}}{\text{Maximum Value} - \text{Minimum Value}} \tag{1}$$

Applying this formula normalizes the attribute values to a range between 0 and 1, facilitating a standardized dataset ready for deeper analysis.

Data Splitting

After the data pre-processing step, which produced a refined dataset of 3265 entries, the dataset is divided into two parts to support practical training and evaluation of the model. The central part contains 3225 entries, with 80% (or 2580 entries) used for training and the remaining 20% (645 entries) reserved for validation. This division provides a robust training dataset while allowing the model's performance to be tested on a separate validation set. The secondary segment includes 40 entries, assigned explicitly for further training activities to enhance the model’s predictive accuracy. This deliberate split aims to balance training and validation phases, aiming to develop a model that performs well and is generally applicable.

ConcaveLSTM Architecture

The ConcaveLSTM architecture uses both stacked LSTM layers and a Bidirectional LSTM layer, which allows for the use of the architecture for time series. This design is particularly made to use the forward and backward dependencies in the data, improving the accuracy of such models in time series predictions. The LSTM units are designed to alleviate the vanishing gradient problem associated with other recurrent neural network

(RNN) designs. This is done by having a memory cell that stores information for long periods. The forget gate f_t, the input gate i_t, and the output gate o_t constitute the key interacting parts of the LSTM unit with the cell for the respective commands. Such operational updates for each LSTM layer are systematically explained in Equations 2-5 to unravel the model's internal movements.

Forget Gate: Determines parts of the cell state to discard.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{2}$$

Input Gate: Decides which new information to store in the cell state.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{3}$$

Cell State Update: Updates the old cell state C_{t-1} into the new cell state C_t.

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C_t} \tag{4}$$

Output Gate: Determines the next hidden state.

$$\begin{gathered} o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\ h_t = o_t * \tanh(C_t) \end{gathered} \tag{5}$$

In the LSTM framework, every single gate x_t, in particular, the output gate is vital in regulating the circulation of data. In particular, the output gate o_t is the one that combines the current external input x_t, the preceding hidden state h_{t-1}, and a bias term b_o and outputs the next hidden state. The computation in the gate is captured mathematically in Equation 5, with a sigmoid function σ, which acts to normalize the simulated state towards a range confined by the numbers zero and one and W_o, which are the coefficients of the output gate.

The proposed architecture is further enhanced by incorporating the Bidirectional LSTM (Bi-LSTM), where input is processed in forward and backward directions using separate LSTM layers. This dual processing enables the model to access information from both past and future states, significantly increasing the available context at any given timestep. The forward layer handles data from the past to the future, while the backward layer considers data from the future to the past, providing a comprehensive view of temporal dependencies. At each timestep, outputs from both layers are combined into a single, rich feature vector. This vector is essential for building the final output through subsequent dense layers, thereby boosting the model's temporal predictive capabilities.

Parameter Settings

To forecast the following 40 steps, fine-tuning parameter settings is crucial for optimal results. Selecting the correct number of input steps is essential; in this analysis, 30, 50, and 70 were chosen to represent the latest data points. Different numbers of neurons in each LSTM layer—specifically 100, 200, and 300—were tested to evaluate their effect on model performance. The choice of the 'adam' optimizer and the 'mse' (mean squared error) loss function was made to enhance the training process. Training for 100 epochs with a batch size of 32, these configurations form a strategic framework for parameters aimed at delivering accurate and reliable forecasts for the next 40 steps.

Model Evaluation

The ConcaveLSTM model is evaluated using extensive parameters for sunspot prediction. However, these assessment methods include the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination, R-squared (R2). Several of these involve RMSE, MAE, MAPE, and R2 formulas, which demonstrate the efficiency of the models built. A comprehensive quantitative analysis of all these metrics is also carried out, as detailed in Equations 6 to 9.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{6}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{7}$$

$$\text{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{8}$$

$$\text{R2} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{9}$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value, $\bar{y}$ is the mean of the actual values and n is the number of observations.

Evaluating the ConcaveLSTM model using these metrics allows for a nuanced understanding of its effectiveness in sunspot prediction, considering both the magnitude and direction of prediction errors and the model's explanatory power.

3. Results and Discussions

Performance Evaluation

In the model's architecture, stacked LSTM layers and a separate bidirectional LSTM layer are used, thus making it possible to learn and recognize patterns in the input string in both forward and backward directions. Such a sophisticated construction of the model makes it remarkably efficient in tasks involving continuous prediction, that is, in regression tasks. However, the raw data to be fed to the model should be organized to optimize the utilization of the said model. The assessment of the ConcaveLSTM model presented in Table 2 is through several parameter configurations aimed at forecasting the sunspot number for the next 40-day period. This overall setup allows the model's forecasting abilities to be examined in crossed conditions.

Table 1. Performance Evaluation of the ConcaveLSTM Model for Sunspot Prediction

prediction	n_steps_in	n_units	RMSE	MAE	MAPE	R2
1	30	100	0.0228	0.0182	5.42%	0.8650
2	30	200	0.0202	0.0153	3.88%	0.8666
3	30	300	0.0230	0.0184	5.30%	0.9063
4	50	100	0.0193	0.0134	1.83%	0.9137
5	50	200	0.0196	0.0132	1.77%	0.9366
6	50	300	0.0198	0.0141	2.25%	0.9444
7	70	100	0.0191	0.0136	2.73%	0.9175
8	70	200	0.0205	0.0163	5.37%	0.9580
9	70	300	0.0202	0.0157	4.28%	0.9650

The assessment of the ConcaveLSTM model for predicting sunspot numbers, focusing on how the model's configuration affects its predictive ability, is shown in Table 2. This helps explain, at least partly, the performance of all configurations and why, in some cases, increasing input steps further results in higher performance metrics such as RMSE, MAE, MAPE, R2, and others. Notably, better predictions are achieved with 50-70 input steps compared to 30, emphasizing the importance of using historical data when forecasting sunspot numbers. Additionally, while performance generally improves with a moderate increase in LSTM units, our results show an optimal number beyond which additional increments lead to diminishing returns and potential overfitting, as seen in configurations with up to 300 LSTM units. This reaffirms the importance of tuning the number of LSTM units to improve model effectiveness without sacrificing performance.

Optimal model performance is reached with `n_steps_in=50` and `n_units=300`, balancing input complexity and LSTM capacity. This setup achieves the highest R2 value of 0.9444 while keeping error rates low. It indicates efficient use of historical data points and LSTM processing power for accurate sunspot activity forecasting. However, the slight rise in RMSE and MAE at higher LSTM unit settings for specific input steps suggests potential overfitting, where the model might fit the training data too closely, reducing its ability to generalize to new data. These results highlight the importance of careful parameter selection in the ConcaveLSTM model to improve predictive accuracy and avoid overfitting.

Figure 1 compares the sunspot numbers and nine forecasts for the next 40 days from the ConcaveLSTM model. The real sunspot numbers are shown with a blue line. The predictions are depicted with different colored lines, each representing a forecast from Prediction 1 to Prediction 9. This visual makes it easy to see how closely the model's predictions match the actual sunspot activity. It provides a clear view of its forecasting ability and overall accuracy during the forecast period.

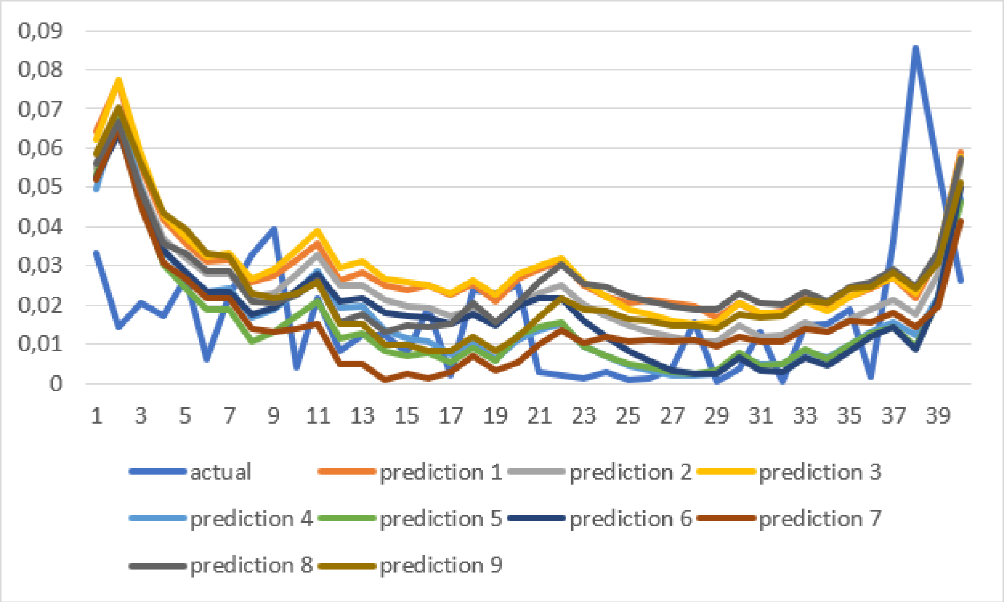

Figure 1. Comparison of Actual and Predicted Values

The trends shown in Figure 1 indicate that while some of the model's forecasts closely match the actual sunspot numbers, demonstrating good accuracy in capturing sunspot fluctuations (notably Predictions 2 and 5), others show significant deviations (such as Predictions 7 and 9). This highlights potential limitations in the model's ability to accurately predict more complex patterns or sudden changes in sunspot activity. This variation in predictive accuracy emphasizes the need to improve the ConcaveLSTM model's performance, especially in forecasting intricate or rapid variations in sunspot numbers. The insights from comparing these predictions with actual data are valuable for guiding adjustments to the model, with the intention of increasing its precision and reliability in sunspot forecasting.

Summarization of Key Findings

The research uses the ConcaveLSTM model with a prediction horizon of up to 40 days, considering the complexities of modeling sunspot activity dynamics. Results show that model settings, particularly the number of LSTM units and input steps, impact the predictions most. Historical input step configurations (50 and 70), where extensive historical data is fed into the model through the time series interface, outperform shorter configurations like (30). These setups also enhance understanding of historical processes and help overcome inaccuracies in short-term dependencies. Additionally, exploring the optimal number of LSTM units offers insights on avoiding under- and over-modeling, thus improving forecasts. While some models produced forecasts closely aligned with actual sunspot activity, others had lower accuracy, underscoring the need for further improvements to better capture the complex patterns of sunspots. Overall, the ConcaveLSTM model shows great potential for forecasting sunspot numbers and provides valuable ideas for enhancing solar activity predictions in future research.

Result Interpretations

The analysis of the ConcaveLSTM model's performance in sunspot prediction has shown that as the number of input steps increases, one can discover many more trends and relationships that improve the predictions quite significantly [18]. This implies that expanding the temporal range for which the model is attempting to make a prediction will help make that prediction more accurate [19]. Such findings were generally as expected and showed how efficient the model was in capturing the successive time-series behavior of sunspots [20]. However, there were some surprises, too. For example, the model's performance with LSTM units did not follow any pattern due to the overfitting of larger configurations of LSTM, suggesting that overfitting is also present [21]. Towards that end, it highlights the importance of carefully selecting parameters since the model performance depends on the sunspot production's temporal and nonlinear dynamics [22]. Differences in predictive power illustrate the assumptions' frailty and potential gains that would be made by enhancing the modeling through other types of data or different data to emphasize and model the multilayered aspects of sunspot activities [23]. All these interpretations are to the effect that even though the ConcaveLSTM model is remarkably improving in sunspot prediction, there is still a need for additional improvements and seeking other models to adequately address the problem of solar weather prediction more effectively.

Research Implications

This study on the use of the ConcaveLSTM model for sunspot prediction significantly contributes to the fields of solar physics and space weather forecasting, underscoring the critical role of advanced predictive models in understanding and mitigating the effects of solar activities on Earth's technological systems [24]. By delving into the specifics of LSTM configurations and their impact on forecasting accuracy, the research not only aligns with but also extends the existing literature by offering empirical insights into optimizing LSTM-based models for solar phenomena [25]. The findings highlight the importance of incorporating extensive historical data and pinpointing an optimal range of LSTM units to balance model complexity and overfitting risk, presenting a nuanced approach to enhancing predictive accuracy [26]. These insights not only reinforce the potential of machine learning in solar activity prediction, as suggested by previous studies, but also introduce practical guidelines for model development, thereby paving the way for more accurate, robust forecasting tools [27]. This contribution is particularly relevant for improving the predictive capabilities of space weather models, with broader implications for protecting communication networks, power infrastructure, and navigation systems from solar-induced disturbances, ultimately advancing our collective ability to predict and respond to the dynamic behavior of the Sun [28].

Research Limitations

This study has definitively established the ability of the ConcaveLSTM model to predict sunspots, with sculpted watering of the LSTM architecture configuration being the key to achieving high prediction. In addition, some analysis of various configurations of the model has raised several issues regarding how LSTM models can be improved to increase the accuracy of the forecast. The model is quite robust and can be applied widely; however, it has some drawbacks, like any other model, such as a limited dataset and, in some cases, overfitting phenomena with some configurations. Learning from these constraints and benefits in a systematic manner of how these configurations have been evaluated has enhanced our knowledge of both the model durability and its limitations and prospects, especially the impact of machine learning on improving understanding of solar physics. The findings not only support the application of the ConcaveLSTM model in predicting solar weather phenomena but also provide a solid basis for further studies toward enhancing the accuracy and reliability of sunspot forecasts in the future.

Recommendations for Future Research

To enhance the practical application and effectiveness of the ConcaveLSTM model in predicting sunspots, optimizing model configurations by focusing on configurations with higher input steps and a balanced number of LSTM units to mitigate overfitting risks is recommended. Incorporating additional solar activity indicators through data augmentation and advanced feature engineering can provide a more nuanced understanding of sunspot dynamics, potentially improving predictive accuracy. Implementing regularization techniques and exploring hybrid modeling approaches could refine the model's performance. Future research should consider rigorous cross-validation across solar cycles, comparative analyses with other models, and exploring the impacts of specific solar phenomena on prediction accuracy. Investigating advanced feature selection methods and the model's interdisciplinary applications could uncover new insights into solar activity's broader impacts. These steps aim to solidify the ConcaveLSTM model's role in space weather forecasting, providing a roadmap for future advancements.

4. Conclusion

Developing the ConcaveLSTM model for sunspot number prediction has added to the existing works, significantly improving the accuracy of solar activity forecasting via the more complex LSTM architectures. Through the systematic testing of many configurations, this research has emphasized the importance of the optimal input steps and the quantity of LSTM units in modeling the complexity associated with solar data. Aside from reducing the risk of overfitting, these measures boost the model’s performance. The ConcaveLSTM model also performs pretty well in predicting the sunspot numbers despite the limitation of data, particularly on the solar phenomena, along with the Conceive structure providing new solutions to forecasting weather using machines.

In the future, this research will provide a foundation for subsequent activities focused on improving the prediction of solar events. It specifies the possibilities of advancement in data augmentation, regularization methods, and combinatorial modeling. The bottom line of the present results is essential as it provides a good ground for further enhancement of forecasting instruments necessary for assessing the consequences of solar variations on Earth’s systems and climate technology. This study adds to the available information on solar physics, the use of machine learning technology, and the development of new products to help understand and forecast solar events.

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