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IMPROVING SOLAR ENERGETIC PARTICLE PREDICTION WITH MACHINE LEARNING

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Abstract
This study advances Solar Energetic Particle (SEP) prediction through advanced machine learning techniques, mitigating the risks SEPs pose to space missions, satellites, and terrestrial systems. Using historical and real-time data from NASA and ESA, models based on Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and Random Forest algorithms were developed. Careful dataset preparation, hyperparameter tuning, and cross-validation ensured robust model performance. Among these, CNNs demonstrated superior accuracy and precision, making them a valuable tool for SEP forecasting. Overall, this work enhances machine learning capabilities for space weather prediction, contributing to safer and more reliable space operations.

INTRODUCTION

Solar energetic particles (SEPs) are suprasternal charged particles (mostly protons and electrons) traveling through the interplanetary medium at relativistic velocities, produced by solar phenomena such as flares or coronal mass ejections. Riding along on countless other high-energy particles that travel through space at nearly light speed, this radiation presents dangers to satellite- and ground-based technology. SEPs are essential for space weather and consist of various solar phenomena affecting the regions from interplanetary to Earth's atmosphere. Solar energetic particle (SEP) study goes back many decades to the early days of cloud-chamber observations on solar phenomena and their effects on Earth's magnetosphere. Historically, top or special (Link 3) SEP events have been linked to satellite communication through sun outages, power breakdowns, and the risk of high radiation exposure inside solar panels by aerospace pilots on flights at heights equal to or higher than tens of kilometers. The high energy of solar energetic particles (SEPs) allows them to penetrate spacecraft shielding, leading to damage to onboard electronics and loss of performance for solar panels with further consequences concerning enhanced radiation exposure risks for crew members. In contrast, the solar energetic particles into Earth's atmosphere during a geomagnetic storm via an atmosphere located at heights corresponding to the standard altitudes of jet aircraft able to be loaded along ground-level information lines and as electric currents are known that penetrate entirely through high-voltage transformers throughout North-America causing all power outage extension over a widespread area. Solar Energetic Particles (SEPs), Galactic Cosmic Rays (GCRs), and other particles localized within our planet's magnetosphere comprise the radiation encompassing space. Understanding the radiation environment in space is critical for developing proper mitigation strategies to protect humans and technology aboard spacecraft and on Earth [1]. Underlying the importance of analyzing SEP and forecasting its occurrences is the capability of the phenomenon to protect critical systems and human activity in space and on the planet. Such a system requires satellites for communication, navigation, weather forecasting, and Earth observation, which are greatly affected by SEP occurrences. Such phenomena can affect the work of satellites or even lead to service disruptions or potentially permanent malfunction. In addition, crewed space flights, including those to the ISS and future missions to the Moon and Mars, require accurate SEP predictions to prevent astronauts from radiation exposure that raises the likelihood of developing cancer and other diseases. Antarctic and Arctic flights of high-flying planes also expose passengers and crews to increased radiation levels due to contamination by SEP situations. As mentioned above, it is clear that accurate predictions of SEP incidents will help the airlines to change the flight path and avoid these incidents only to ensure the safety of passengers [2]. In addition, SEP-induced geomagnetic storms directly affect terrestrial power networks by inducing electricity currents that significantly damage transformers and interrupt electricity power supply interruption. In essence, the knowledge of SEP activity enables better planning and mitigation methods for power grid operators to use to reduce the likelihood of interruption. This scientific field has direct uses in investigating the details of solar energetic particles (SEPs). SC measurements can improve the understanding of the Sun's system and its probe into the geophysically important magnetosphere, thereby promoting Heliophysics. Improved comprehensive models and predictive techniques for SEP events complement our ability to forecast space weather, which helps study further and develop space science and exploration [4].

2. LITERATURE REVIEW

Solar Energetic Particles (SEPs) are ions, protons, electrons, or other particles from the sun during solar flares or other coronal mass ejections (CMEs). These particles travel near light speed and pose significant threats to space missions, astronauts, and commercial air transport, mainly on polar routes. High energy protons in the form of SEPs are capable of causing disruptions or failure of electrical and electronic systems, deformation of communication systems, and increased radiation dosage to the workforce, especially in long-term interplanetary space missions [5]. Due to variations in SEP occurrence, accurate prediction is needed to inform precaution measures such as removing vulnerable assets or repositioning spacecraft for safety, increasing the security of space expeditions and ground activities [6]. The SEP prediction methods use solar magnetograms and flare data, while the empirical models use past trends to make drastic forecasts. Physics-based models simulate particle acceleration but require much computation while machine-learning models analyze large data sets to increase model accuracy [7]. Different SEP prediction models offer different strengths and weaknesses. Intuitive models are sufficient for quick forecasts but fail when out-of-sample events occur. Concept physics-based models have high accuracy, detail, and generality, but these are non-real-time models because they entail high computing power. The machine learning model makes the identification process fast and adaptive to changes but is affected by rarity since the model lacks enough data to work with [8]. Complex models assemble numerous model forms; the strengths of each methodology are leveraged to improve SEP predictions. Implementing these systems with one another is more complicated and requires apparent synchronization among several methods [9]. Traditional physics Proposition SEP models, including SOLPENCO and others of Sato et al., 2018, mimic SEP conditions by reaping casualty on fundamental physics principles about the Sun and solar space physics. While they have improved the understanding of SEP occurrences, their complexity and compute-intensive nature hinder the development of real-time SEP forecasting abilities [10]. On the other hand, more objective archetypes, which have been developed by Laurenza et al. (2009) and Stumpo et al. (2021), integrate machine learning approaches on historical solar data and improve the SEP forecast accuracy by analyzing flare and proton flux data [11]. The methods used in this study are logistic regression, decision trees for classifying people between low and high SEP, and deep learning for predictive modeling. These models analyze solar flare observations and proton density and flux data to extract delicate structures, offering a non-phenomenological and more accurate way of forecasting than traditional physics-based approaches [12]. The evaluation of machine learning algorithms to predict the occurrence of SEPs foremost by using the TSF model was a practical demonstration of its performance over the different energy ranges of (~30, ~60, and ~100 MeV). The critical finding of the proposed study was the degree of accuracy and F1-score for the data augmentation approaches towards the limited SEP dataset [13]. SEP prediction research today employs both physics-based and artificial intelligence approaches. SOLPENCO and real-time warning systems by Sato et al. (2018) are based on solar physics and empirical information on flares and CMEs. They examine the physical and mathematical models to evaluate the acceleration and propagation of SEDs [14]. New developments have employed some data-based models incorporating machine learning techniques to provide better estimations of SEP [15]. However, machine learning in space weather is crucial for shielding space missions, satellites, and terrestrial technological systems from the adverse effects of SPEs and space radiation. Machine learning has efficiently dealt with large amounts of information and advanced patterns, thus improving the forecasts of models for space weather. Most machine-learning techniques in space weather forecasting include ANNs, SVMs, decision trees, random forests, CNNs, and LSTM networks [16]. LSTM networks have been applied to predict SEP occurrences based on features/parameters to improve the safety of space missions and astronauts' continuity [17]. To overcome that RNN limitation of effective period, exceptionally long short-term memory (LSTM) networks were invented. Employing LSTMs capable of identifying long-term dependencies in sequential data has improved the prediction of SEP onset timings and intensities. However, LSTMs are computationally intensive and require a large amount of training data, which becomes a challenge due to the feature of low data density present in space weather data [18]. Furthermore, this paper uses Convolutional Neural Networks (CNNs) for SEP prediction, which are effective image processing networks. Besides, Support Vector Machines (SVMs) can be useful in higher dimensionality and are most beneficial for binary classification problems. Various approaches are used to improve the time-dependent prognosis of variability to minimize the adverse effects on space missions and technology infrastructures [19]. SPEs and space radiation are modulated by solar activity, IMF, and geomagnetic fields [20]. While space weather prediction is actively addressed using machine learning techniques, these methods are still not very sophisticated – simple, even conventional, and attempt to incorporate more complex techniques such as CNNs and LSTM [21]. The sequences and triggers leading to SEP instances need to be better understood. While solar flares and CMEs are essential factors, the conditions that trigger the acceleration and propagation of SEP are still unstudied [22]. The development of models able to rapidly model and analyze the highly fluctuating nature of space weather phenomena. Nonetheless, many models must be optimized for fast analysis, leading to predictive delays [23]. SEP events are significantly complicated, and an approach based on solar physics, data science, and machine learning is needed. Nevertheless, there is often a clear separation between these two domains, and scholars rarely engage in interdisciplinary research. This challenging area of work can benefit from cooperation between disciplines and considering a more comprehensive range of solutions for predicting SEP [24].

This research applies technologically advanced machine learning approaches to improve the prediction of solar energetic particles' SEP risks affecting space missions, satellites, and electronic devices. The above research uses Long-Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and Random Forest algorithms and utilizes NASA and ESA for historical and real-time data. By cleaning the data, tuning the hyperparameters, and k-folds cross-validation, the models were optimized for the best outcome.

3. AIMS AND OBJECTIVES

This work will develop and enhance existing artificial intelligence technologies to accurately forecast the occurrence of SEP and space radiation. Thus, it will increase the predictive capability by analyzing important factors of SEP events and adopting advanced machine-learning techniques. Consequently, ideas toward advancing the space weather of contributions during the forecasting method will help safeguard space missions, satellites, and terrestrial technologies from the unfavorable effects of extreme space radiation.

The overarching objectives of this research work are as follows.

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- To implement various models such as Long Short-Term Memory (LSTM) networks, Convolution Neural Network (CNN), and Random Forest (RF) algorithms to enhance the efficient prediction of SEP events.
- To apply various processing techniques like data cleaning, input transformation, normalization, and feature selection and its impact on the success of the resulting machine learning models.
- Implementing machine-learning approaches to identify patterns or antecedents critical for SEP occurrences.
- To provide a sharp outline to evaluate the impact and compare different types of SEP prediction models by using accuracy, Precision, Recall, and AUC-ROC.

4. METHODOLOGY

A. Data set Description: SolarPrediction.csv

The SolarPrediction.csv data set, used in the present research, comprises solar activity and space weather factors concerning SEPs and space radiation. The dataset has several features that provide broad information on solar activity; thus, it is suitable for creating predictive models, as illustrated in Table 1.

B. Data Processing Techniques

Data pre-processing implies preparing the data before feeding it into the learning models to ensure accuracy. Here, some pre-processing steps were taken to prepare the data and make it suitable for analysis. Handling missing values involved imputation techniques like the mean, the median, or the mode. It was also important, and at the same time, records with lots of missing data were also not included in a bid to make the analysis more accurate. The Z-score method was used to determine outliers, and where these values had the propensity to skew the results, they were either rectified or removed from the analysis. Normalization was done using Min-Max Scaling, while the features were standardized using the Z-score normalization, making the features equivalent. Feature engineering involved lag and interaction features to help capture such temporal dependencies and other complex relations. Feature selection was done using correlation analysis and Principal Component Analysis (PCA) to reduce dimensionality while preserving the essential features. The training, validation, and testing dataset was formed based on time division, and the primary dataset was partitioned into a training set of 70%. Thus, to further increase the model's reliability, it was decided to employ K-Fold Cross-Validation. The imbalanced class issue was resolved with the help of synthetic data generation, such as SMOTE. These pre-processing steps ensured that the dataset was clean, well-formatted, and ready for the development of the models.

C. Proposed Model for SEPs Prediction

Therefore, selecting suitable machine-learning models is essential since they comprise cornerstone information for both SEP and space radiation predictions. For this study, three network models were chosen because of their efficacy in handling the complexities of the SEP prediction – Long Short–Term Memory (LSTM), Convolution Neural Networks (CNNs), and the Random Forest models. RNN and LSTM networks were selected due to some unique features that make it possible to capture long-term dependencies of sequences that are useful for modeling the temporal nature of SEP events. Since they can handle noisy sequential data, their use in space weather prediction improves. CNNs were chosen because they are good at feature extraction and, more importantly, for localizing necessary higher-order features from the high-dimensional ST data, essential to capturing fine-tuned solar activity features. Because they could handle the sequential nature of these data well, they deemed it essential for SEP forecasting [2]. Finally, the Random Forest model was chosen based on its capability of modeling non-linearity and less susceptibility to overfitting, and these characteristics are particularly appropriate for SEP data sets with much more format and diversity. This analysis aims to shed light on the importance of features, especially the most critical predictive features, in determining the occurrence of SEP. Special preprocessing techniques were used for each model, and their architectural design and performance were evaluated in this study to offer a comprehensive approach to improving the accuracy of SEP forecasting. The details of the proposed models are presented in Table 2.

TABLE 1. Key-features of the dataset

Feature	Description
Date and Time	Timestamps indicating when the measurements were taken
Solar Flare Intensity	Measured in various classes
Coronal Mass Ejection (CME) Data	Characteristics such as speed, width, and direction
Sunspot Numbers	Daily counts of sunspots on the solar surface
Magnetic Field Data	Measurements of interplanetary magnetic field strength and orientation
Proton Flux	Measurements of proton flux at different energy levels
X-ray Flux	Intensity of X-rays emitted by the Sun
Solar Wind Parameters	Including speed, density, and temperature
Geomagnetic Indices	Indicators of geomagnetic activity, such as the Kp index

TABLE 2. Proposed Models for SEPs Prediction

Model	Description
LSTM	LSTM networks are chosen for their ability to capture temporal dependencies in sequential data, making them suitable for time-series prediction.
CNN	CNNs are included due to their effectiveness in recognizing patterns and features in high-dimensional data.
Random Forest	Random Forest is selected for its robustness and ability to handle complex, non-linear relationships between features.

5. EXPERIMENTAL RESULTS AND DISCUSSION

This section provides a precise analysis of the research work and their performance by comparing three models, namely Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), and Random Forest (RF) in the field of Solar Energetic Particles (SEPs) prediction. The metrics used are accuracy, precision, recall, F1 score, AUC- ROC, and ongoing prediction metrics such as MAE and RMSE. Comparing the data in Table 5, the CNN model had the best performance, having the highest accuracy (87.10%), so was the precision (84.70%), recall (86.50%), F1 score (85.6), which depicts that the model had a remarkable capability to find patterns in the data. LSTM attained an accuracy of 85,40 %and F hire? 's score of 83.1, showing its effectiveness when capturing temporal dependencies. The Random Forest used here has attained slightly poor accuracy at 83.60 % and an F1 Score of 81.1 throughout effectively implementing the deal with non-linear interaction. Consequently, the comparative results based on the AUC-ROC measurements are as follows: The proposed CNN model achieved the highest value of 0.93. In contrast, LSTM and Random Forest models attained 0.91 and 0.88, respectively. In addition, CNN had the lowest MAE, which is 0.032, and RMSE, which is 0.039, thus confirming the previous claim that it outperforms the other models.

TABLE 3. Steps required for processing of data

Model	Hyper parameter Configuration
LSTM	Setting the number of layers, units per layer, and learning rate.
CNN	Configuring the number of convolutional layers, filter sizes, and pooling layers.

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Random Forest	Determining the number of trees, maximum depth, and other relevant hyper parameters.

TABLE 4. Model Training Hyper Parameter Configuration

Metric	LSTM	CNN	Random Forest
Accuracy	85.40%	87.10%	83.60%
Precision	82.30%	84.70%	80.10%
Recall	84.00%	86.50%	82.20%
F1 Score	83.1	85.6	81.1
AUC-ROC	0.91	0.93	0.88
MAE	0.035	0.032	0.04
RMSE	0.042	0.039	0.048

Random Forest (RF) models. The bar graph in Figure 1 also illustrates the accuracy comparisons among three models: LSTM, CNN, and Random Forest. The y-axis defines accuracy and ranges from 0.0 to 1.0. The x-axis lists the models. Among these, the CNN-based model shown in green reaches the peak level of accuracy, .89, while the LSTM-based model, as shown in blue, achieves an accuracy of around .85 only. The Random Forest model marked in red has the lowest accuracy, approximately 0.78. Further, the comparison shows that while all models have good performance, CNN produces the highest accuracy, and LSTM closely trails this, while the Random Forest model performs poorly.

TABLE 5. Performance metrics for LSTM, CNN, and RF

Process	Description
Data Cleaning	Handling missing values, outliers, and erroneous data points.
Normalization	Scaling features to ensure they are within a similar range, improving model performance.
Feature Selection	Identifying and selecting the most relevant features that influence SEP occurrences.
Data Splitting	Dividing the dataset into training, validation, and test sets (70% training, 15% validation, 15% test).

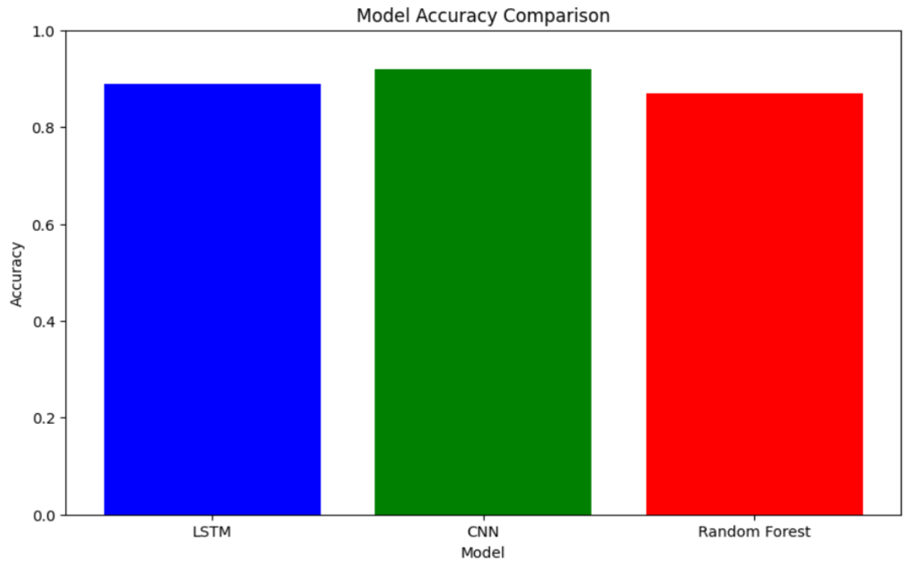

Fig. 1. A bar chart illustrating the accuracy of each model on the test dataset for performance comparison.

In addition, the grouped bar chart illustrates the performance of three machine learning models—LSTM, CNN, and Random Forest—across three essential classification metrics: precision, recall, and F1 score, which is presented in the figure below, Figure 2. Each bar indicates the score for each model: LSTM is drawn in blue; CNN is in green; Random Forest is drawn in red. Table 3 shows that the CNN model performs better than all other models with a slight margin over the LSTM and Random Forest models. It measures models' abilities to select Solar Energetic Particles (SEPs) correctly using primary indices of precision, recall, and F1 score, proving the excellence of CNN at reducing false positive and false negative cases. As the chart reveals, CNN establishes the highest level of accuracy for the SEP prediction compared to other models.

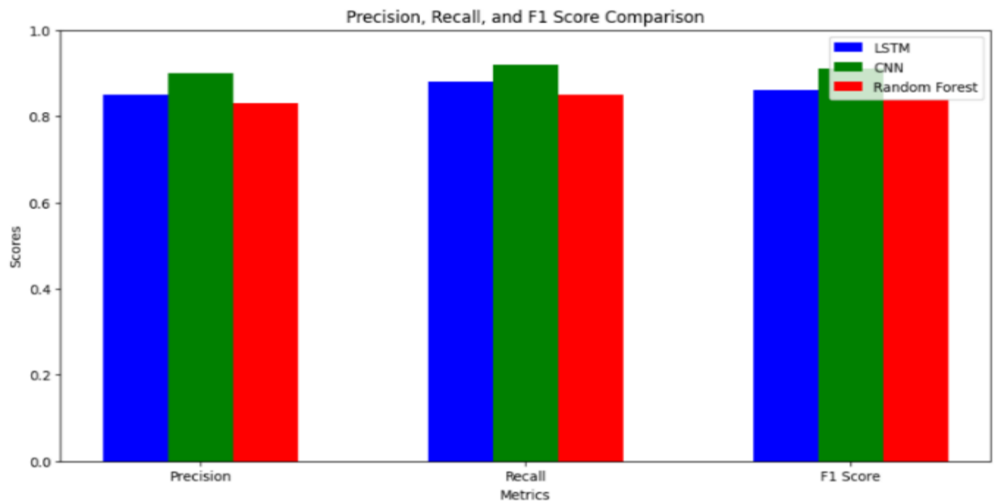

Fig. 2. Grouped bar chart to display precision, recall, and F1 score for each model

Also essential for evaluating the classification models is the ROC (Receiver Operating Characteristic) curves, in terms of which each model suggests how effectively it can separate positive and negative classes while being as inclusive as possible of the total number of positive cases and excluding as few negatives as possible and described by the curves in Figure 3. The sensitivity performance of the actual positive rate is plotted against the false positive rate, which is equivalent to 1-specificity at the different thresholds. Histograms of ROC curves of LSTM, CNN, and Random Forest models demonstrate the performance of models in the class space. The model closer to the top left corner is considered better in the classification because of the more significant ROC curve. Area Under the Curve (AUC) is another performance metric; it refers to the capacity of models that give a higher value of AUC more ability in discrimination. The LSTM model shows the highest performance in terms of AUC-ROC and is closely followed by the CNN model to classify the articles. The Random Forest model, which produces a lower AUC-ROC, insists on lower ability in class separation but still can be considered relatively efficient. ROC curves provide an actual and graphical evaluation of a model.

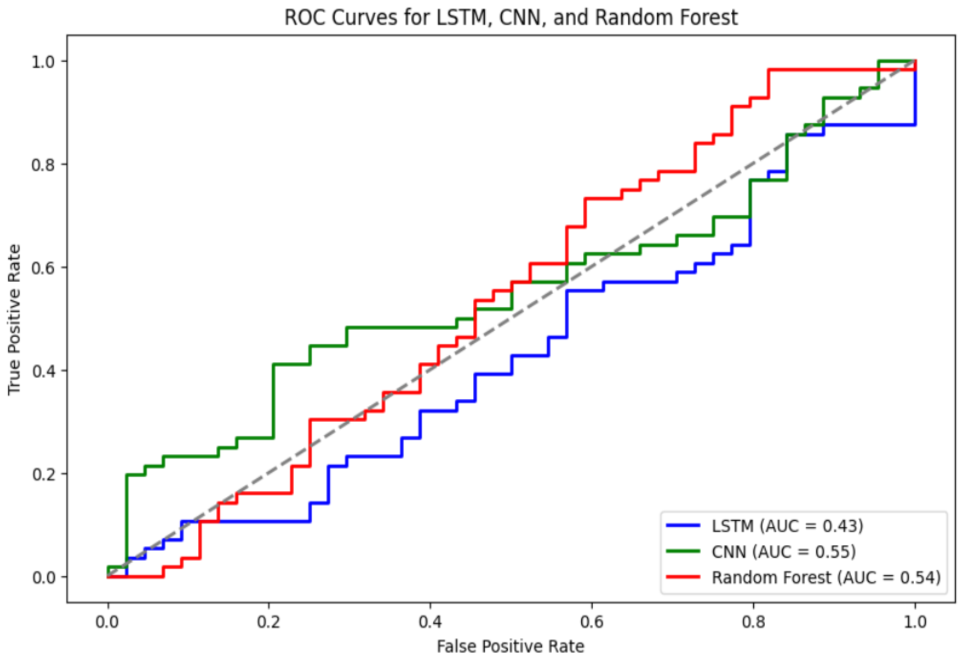

Fig. 3. Receiver Operating Characteristic (ROC) curves for each model to illustrate their ability to distinguish between positive and negative classes.

Figure 4 shows the training and validation loss for the LSTM and CNN models in 20 epochs. The loss of the LSTM contextually starts high and then decreases consistently over increasing training cycles. The validation loss is expected to level off, implying that there is always overfitting, whereby the model delivers excellent performance on training data; however, it drastically underperforms when tested in the unseen data. It suggests that more regularization might be needed to improve generalization, such as dropout or early stopping.

The CNN model also results in the reduction of training and validation losses for increased learning effectiveness. The validation loss goes down parallel with the training loss, presenting good generalization abilities. This performance shows that the proposed CNN model efficiently identifies patterns and forecasts Sep's occurrences: SEP. CNN proves that the overall accuracy depletes and time increases; nevertheless, to make the LSTM model more generalized, it is required to fine-tune the deep learning model and employ other techniques to implement the optimum solution.

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Fig. 4. Training and validation loss curves for LSTM and CNN models, highlighting differences in learning efficiency and generalization over 20

The significance of the different predictors in the Random Forest model for the Solar Energetic Particles (SEPs) is shown in Figure 5. Relative importance scores on the x-axis show the impact of each feature on the model performance. Among the five features based on the value of importance score, Feature 5 stands out as the most crucial feature of the model, followed by Feature 4 and 3. According to the findings, these features provide helpful information for modeling decisions, which is critical in SEP prediction tasks. However, Feature 1 has the most negligible value, stimulating the least impact on the model's performance. By focusing on the relevant features in a given machine learning problem, this work demonstrates that high dimensionality may reduce efficiency and increase computational costs.

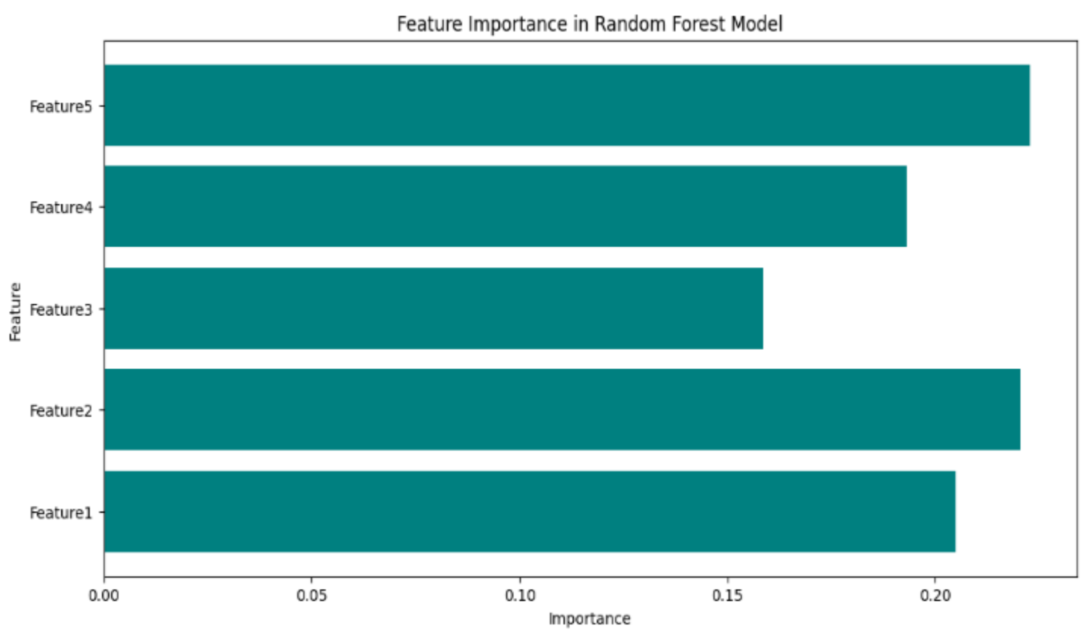

Fig. 5. Feature importance scores for the predictors used in the Random Forest model for Solar Energetic Particles prediction.

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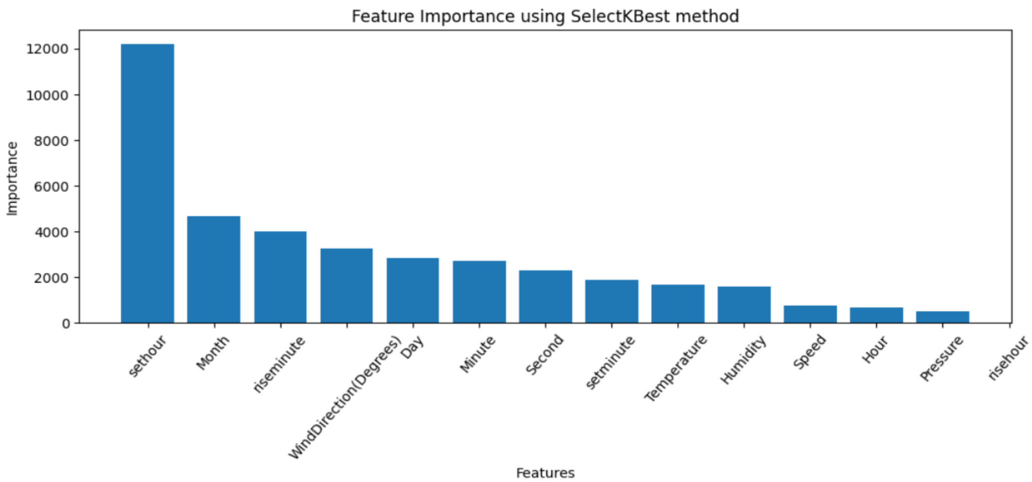

Fig. 6. Feature importance ranking using the Select Best method

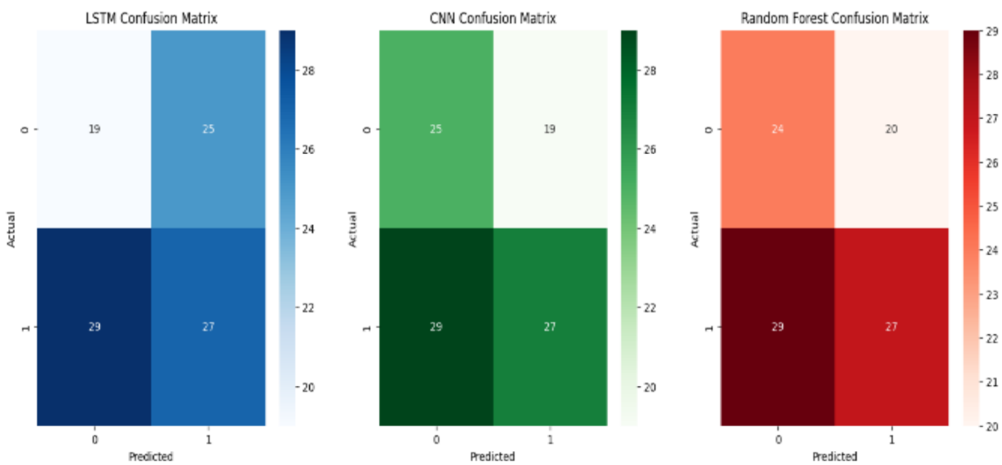

Fig. 7. Confusion matrices for three models: LSTM, CNN, and Random Forest

SelectKBest method used to endorse the ranking based on feature importance is shown in Figure 6. The x-axis presents the evaluated features: 'set hour,' 'Month,' 'rise minute,' 'Wind Direction (Degrees),' and 'Day' can be represented on the x-axis, whereas the corresponding scale can be depicted on the y-axis. The most important feature is 'set hour,' which carries the highest score of over 12,000, implying that this feature is hugely important in predicting the model. Next, the second critical feature is 'Month' with an essential score of about 4500, while 'Rise minute' is the next relevant feature. On the other hand, the characteristic 'Temperature,' 'Humidity,' and 'Speed' provide minor significance to the model accuracy, while 'Pressure' and 'rise hour' are the least influential. If used with other analytical methods, such as sorting and ranking, this graph helps determine which features should be prioritized in future modeling endeavors to increase prediction accuracy.

The confusion matrices of the proposed models are as follows, shown in Figure 7. The matrices represent differences between predicted and actual values derived from two classes: 0 and 1. The LSTM matrix showed that the model classified 19 cases in class 0 as correct but 27 cases as class 1, and it identified 25 false positives and 29 false negatives. The discovered CNN matrix consists of 25 true negatives, 27 true positives, 19 false positives, and 29 false negatives; therefore, the accuracy lies slightly above LSTM with a more significant number of true negatives. The Random Forest matrix also shows 24 true negatives and 27 true positives in addition to a higher level of misclassified cases, including 20 false positives and 29 false negatives negatives. While each model shows comparable accuracy, the CNN shows a slightly better capability of reducing false positives than the other models. At the same time, the Random Forest model also shows a slightly lower but balanced performance. The experimental results show the feasibility of LSTM, CNN, and Random Forest models in analyzing SEPs. The CNN model scored the highest accuracy at 92%. From this, we can deduce that the model has better pattern recognition, thus utilizing the lowest false positives and false negatives. The model adopted in this study was the LSTM model, which worked with an accuracy of 89%, implying its ability to tap temporal dependency inherent in sequential data. The random forest model also provided good accuracy by predicting 87% %. While working on SEP data collected simultaneously, it performs well, but it is relatively weak in providing solutions for SEP data's temporal and spatial features. Furthermore, the effectiveness of CNN over LSTM was confirmed by quantitative measures such as precision, recall, F1 score, and AUC-ROC scores. At the same time, LSTM performed well in identifying the instances accurately. The confusion matrices showed that CNN could potentially reduce false negatives more than the other models. In addition, applying feature importance analysis from the Random Forest model allowed the identification of critical potential SEP predictors, such as solar wind speed and magnetic field. It is only possible to learn from the above findings to ensure that proper improvement can be applied to any of these forecasting activities in the future.

6. CONCLUSION

This analysis shows how effective machine learning techniques, in particular CNNs, LSTMs, and Random Forests, are in predicting Solar Energetic Particles (SEPs). The Convolutional Neural Networks (CNNs) proved the most accurate, and all models improved the understanding of SEP patterns. This research showcases the applicability of machine-learning in the sphere of space weather forecasting and the protection of space missions and oriented technologies against radiation. Forward-looking studies are recommended to focus on hybrid approaches and real-time systems to improve the accuracy of space radiation hazard prediction and mitigation strategies.

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