

Enhancing Cloudburst Prediction System Using Bi-LSTM in Realtime: Machine Learning

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Abstract:

Nowadays Technology is enhanced, but still facing floods and toofan due to uncertain rainfall conditions and artificial rains, it is a challenging task for hydrology and meteorology. Now a new cloudburst prediction system is a requirement for hydrology and meteorology. cloudburst prediction holds significant importance in fields like hydrology and meteorology, aiding farmers, water resource managers, and emergency responders in preparing for and managing the impacts of extreme weather events like droughts and floods. One effective technique for rainfall prediction involves employing machine learning models such as Bi-LSTM (Bidirectional Long Short-Term Memory). Bi-LSTM, a neural network architecture known for its prowess in sequence modeling tasks like voice recognition and natural language processing (NLP), operates by processing data bidirectionally, facilitating a thorough understanding of sequential patterns. By analyzing historical rainfall data as a sequence, a Bi-LSTM model can effectively forecast future rainfall values with notable accuracy. In this proposed methodology, a Bi-LSTM model is trained using a CSV dataset comprising historical rainfall data. The performance of the Bi-LSTM model is then compared with that of an LSTM (Long Short-Term Memory) model, another widely used architecture for sequence prediction tasks. The results indicate that the Bi-LSTM model achieves an accuracy of 96.55%, surpassing the accuracy of the LSTM model, which stands at 94.36%. This comparison underscores the effectiveness of the Bi-LSTM approach in rainfall prediction, showcasing its potential to provide valuable insights for decision-making in various domains affected by weather variability.

Keywords: Cloudburst prediction system, Bi-LSTM, meteorology, hydrology, machine Learning, NLP, LSTM,

1. Introduction

Cloud bursts are a phenomenon that cause brief but severe bursts of rain, which makes infrastructure resilience and catastrophe preparedness extremely difficult [12]. These severe weather occurrences have the potential to cause landslides, flash floods, and other dangerous situations that could threaten lives and cause extensive property damage [13]. In order to cloud bursts on infrastructure and

communities, it is imperative to predict them effectively in advance and take prompt mitigation measures [14]. The prediction of cloudbursts involves a complex interplay of historical data, current observations, and scientific models. Traditionally, meteorologists have relied on physical and mathematical models for forecasting, but in recent years, the integration of machine learning has significantly enhanced accuracy and efficiency [15]. Machine learning algorithms leverage statistical techniques to empower computers to discern patterns and make predictions autonomously, without explicit programming. In weather forecasting, these algorithms analyze vast datasets that encompass variables such as temperature, humidity, wind speed, and air pressure, as well as past weather patterns, facilitating more accurate predictions. The integration of machine learning offers manifold benefits, including heightened accuracy, expanded prediction lead times, and swift processing of immense data volumes [16]. Cutting-edge technologies like satellite-based remote sensing and ground-based sensors supply real-time, high-resolution data, further honing prediction precision. In machine learning, features denote the attributes utilized for predictions [17]. In the context of weather forecasting, pertinent features include temperature, humidity, wind direction, and air pressure, among others. Machine learning models like regression, decision trees, random forests, and neural networks undergo training with historical weather data. Through this process, models grasp the relationships between input features and ensuing weather outcomes,

2. Problem Statement

Cloud bursts, which are episodes of unexpected, heavy rain cause grave issues for the general public safety, infrastructure resilience, and disaster preparedness. Because of the dynamic nature of atmospheric processes and our incomplete understanding of the underlying causes causing cloud bursts, precisely predicting these extreme weather phenomena remains a difficult challenge despite significant breakthroughs in meteorological science. This research investigates the cloud burst prediction problem and investigates the possibilities of Long Short-Term Memory (LSTM) neural networks as a predictive modeling technique. An overview of cloud bursts and their effects on infrastructure and communities is given at the outset of the study. It talks about how precise cloud burst forecasting is necessary to allow for prompt mitigation actions and lessen the negative consequences of these occurrences. Next, the paper explores the concept of LSTM neural networks and its suitability for time series forecasting tasks. LSTM networks are well-suited for capturing long-term dependencies in sequential information, therefore they're perfect for modeling intricate connections in meteorological data. The paper discusses the architecture and functioning of LSTM networks, emphasizing their ability to learn patterns and trends from historical weather data.

3. LITERATURE SURVEY

YUN LIN (Member, IEEE), KEPING ZHOU, AND JIELINLI [1]. The classification outcomes of the RS-CM are June 26, 2018. in contrast to those of the Bayes, KNN, and RF methods.

M W Moncrieft, Someshwar Das, and Raghavendra Ashrit [2]. To lessen the effects of the following flash floods on society, early forecasting and warning of such extreme local weather systems are essential (2006)

On January 28, 2017, Yukio Ogawa [3], Go Hasegawa, and Masayuki Murata presented a novel idea to improve cost effectiveness using cloud bursting. When demand outpaces available resources, this

method smoothly transfers a private cloud's capacity to a public cloud, optimizing resource use. By letting businesses scale their infrastructure in response to changing workloads, cloud bursting provides a flexible option that lowers operating costs while maintaining service continuity. Through the utilization of cloud resources' scalability and flexibility, Ogawa, Hasegawa, and Murata's concept transforms cost management tactics and enables companies to effectively respond to changing market needs.

Machine learning algorithms have been developed by applied by Singh et al [4]. to forecast the weather based on rhythms. They predicted the weather occurrences using several machine learning methods. Using soft computing techniques, Khajuria and Mohod have deployed the future weather forecasting. The use of soft computing techniques has been used by Bhardwaj and Duhoon for weather forecasting.

Deep subsurface rock mass engineering excavation frequently involves the risk of rock explosions. Rock bursts are classified and evaluated in this study using a cloud model. An index system for evaluation is established by considering factors such as elastic energy index, stress coefficient, rock brittleness coefficient, tangential stress, uniaxial compressive strength, and tensile strength. An RS-cloud model is established and normalization is used to achieve classification. The weights of these indicators are established using the rough set approach, which is based on 246 rock burst samples. Rock burst classification and prediction can benefit from the simplicity and great discriminatory ability of the RS-cloud model, which outperforms Bayes, KNN, and RF approaches in terms of accuracy, Kappa, and within-class classification metrics [11].

Drawback: *Reliance on A comparatively tiny sample size could limit generalizability.*

This paper [5] presents a cloud bursting technique that makes use of public data center resources during capacity spikes to increase the capacity of a cloud-based service housed in a private data center. The best way to allocate resources across private and public data centers is to use both long- and short-term projections of system requests. This considers both total cost and response time limits. Numerical simulations show that the method works well with notable cost savings and acceptable response occasions, even in cases where there forecast errors.

Drawback: However, reliance on prediction accuracy and the requirement for cooperation between private and public data centers may introduce operational complexities and potential risks in real-world implementations.

Predicting the likelihood of rock bursts is essential for preventing disasters in underground engineering. Current mathematical models often lack accuracy due to shortcomings in determining the comprehensive weight of rock burst indices. An enhanced cloud model is proposed to address this issue by incorporating cloud atomization conditions, improving prediction accuracy by obtaining a more reasonable comprehensive weight. However, the proposed model's effectiveness may be limited by its reliance on theoretical frameworks, potentially hindering its practical applicability in real-world scenarios [6].

Drawback: The proposed model's reliance on theoretical frameworks may limit its practical applicability in real-world scenarios.

In order to effectively handle varying workloads, a lot of businesses increasingly use pay-as-you-go cloud computing. Hybrid cloud models enable companies to use private resources primarily and "burst" into the cloud when needed. However, to ascertain which applications should be migrated to the cloud during bursts and when, current methods frequently depend on human intervention [9]. We are pleased to present Seagull, a technology that greatly reduces burst time and overall expenses by automating cloud bursting decisions and optimizing application deployment into the cloud. However, although Seagull presents significant gains over conventional approaches, its dependence on heuristics might lead to marginally increased expenses in contrast to more accurate methods such as ILP[7].

Drawback: Although Seagull provides significant efficiency gains, its reliance on heuristics may lead to slightly higher costs compared to more precise optimization techniques like ILP.

A potential way to effectively and economically handle growing computational and storage needs is through cloud computing. Unfortunately, current optimization techniques frequently mischaracterize the complex and intermittent nature of cloud workloads, resulting in inefficient use of power and resource allocation. To ensure that close this gap, we suggest a fractal model that makes use of ideas from fractional calculus. This model effectively represents the fluid character of cloud workloads and makes resources more efficient provisioning and energy conservation. Even though our fractal model outperforms conventional non-fractal models in predicting bursty workload scenarios, implementation and parameter estimation may call for additional computing power and knowledge [8].

Drawback: Implementing the fractal model expertise, potentially increasing the complexity could necessitate more computer power and of cloud optimization systems.

The research suggests eight different versions of the cloud burst index, or I_{cb} [10], which is predicated on the weighted combinations of different tropospheric signs that are required for producing deep moist convection. These indicators, which have I_{cb} values ranging from 0 to 1, include vertical integrated water vapor and convective inhibition. At certain thresholds, these indicators abruptly change from low to high values. According to case studies, areas with high I_{cb} values (0.8 to 1) were associated with cloud burst observations, indicating the index's potential to identify high-risk areas. The inherent unpredictability of cloud bursts is partially responsible for the relatively elevated false alarm rate indicated by the existence of high I_{cb} locations without documented cloud bursts.

Drawback: Despite its ability to identify high-risk areas, the cloud burst index may result in a quite high probability false alarms as a result of the unpredictable nature of cloud bursts.

4. Proposed Method

Cloud burst prediction is an effective technique that analyzes historical weather data to forecast the occurrence of cloud bursts. This system makes use of a significant machine learning technique known as Bi-LSTM. It is a Bi-Directional Long Short-Term Memory that extracts and analyzes critical data features required for the prediction. The proposed system, the Bidirectional long short-term memory to develop a framework for predicting cloudbursts. the weather conditions are efficiently found by using both forward and backward hidden sequences. It shows the difficulties

caused by climatic conditions and significantly measures the critical feature data collected from various gathering historical weather data, which typically includes information such as temperature, humidity, wind speed, air pressure, and precipitation records.

3.1 Methodology

In order to predict the cloudbusters, we will be using a dataset called DS as input. Firstly, we need to pre-process the data and then apply min-max feature scaling normalization. The dataset is then split into two sets, DS train and DS test. After this step, the data is sent to the proposed system architecture, which consists of the Dense layer and the embedded layer. Subsequently, it is sent to the BILSTM mechanism for further classification, and the output layer releases the expected data. Finally, the predicted expected data is displayed in Figure 1 by the Model Accuracy Indicator.

The framework for a weather prediction model involves several crucial stages, as shown in Figure 1. These stages include data acquisition, data pre-processing, model selection and training, model evaluation, and visualization of results. With the advancements in technology like the Internet of Things, Wireless Sensor Networks, and Cloud Computing, weather data is now available in various formats and large volumes. However, this data often contains both valuable and extraneous information and is typically unstructured. After gathering the data, the next step involves pre-processing it to eliminate irrelevant and missing values, ensuring clean data. Data pre-processing involves tasks such as data cleaning, integration, reduction, and transformation, all aimed at enhancing the quality of input data. Quality input data is crucial for producing accurate outputs during the training phase. Data cleaning involves removing noise, handling missing values, and rectifying inconsistencies commonly found in real-world data. One common issue in real-world data is missing values, which often requires imputation using methods like mean value substitution. Data integration merges data from diverse sources into a coherent data repository, while data reduction techniques minimize data size through aggregation, feature elimination, or clustering. Data transformation involves normalizing or standardizing the data for processing, thereby improving accuracy, efficiency, and reducing training time for models. These pre-processing techniques are often employed together rather than individually. Once pre-processing is complete, the appropriate forecasting model is selected, trained, and tested using the prepared datasets. Knowledge of various forecasting models assists researchers in choosing the most suitable one for a given application domain. The selected model is trained using the training datasets, and its performance is evaluated using statistical error indicators such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-squared (R²). Subsequently, the results are visualized using appropriate plots, such as scatter plots, line plots, and semilog plots. These visualizations facilitate the graphical analysis of the variance between actual and predicted values, with semilog plots offering a more precise depiction of this variance.

Batch Normalization:

In the context of cloudburst prediction, the utilization of batch normalization plays a crucial role in ensuring the stability and convergence of the training process. Given the irregular and fluctuating nature of rainfall data collected batch by batch, it becomes imperative to address the variability in distributions encountered during training. Batch normalization provides a mechanism to

reparameterize the network by standardizing the mean (α_{DS}) and variance (α_{DS}^2) of each batch of training data. This normalization process ensures that the data aligns with a zero mean and unity variance, thereby facilitating smoother convergence of the network parameters throughout the training cycles.

$$\alpha_{DS} = \frac{1}{N} \sum_{j=1}^n a_j \quad (1)$$

$$\alpha_{DS}^2 = \frac{1}{n} \sum_{ij=1}^n (a_{ij} - \alpha_{DS})^2 \quad (2)$$

$$\hat{a}_{ij} = \frac{a_{ij} - \alpha_{DS}}{\sqrt{\alpha_{DS}^2 + F}} \quad (3)$$

$$b_{ij} = \gamma \hat{a}_{ij} + \beta \quad (4)$$

In the contemporary landscape of problem-solving, the Bidirectional Long Short-Term Memory (BiLSTM) has emerged as a cornerstone in various neural network models. Its application extends to diverse realms, including the prediction of flight delays, where its memory-centric capabilities prove highly effective. The efficiency of the BiLSTM approach stems from its adeptness at handling both past and future information, a feature facilitated by its hidden layer architecture. Within this layer, crucial values are stored and utilized in both forward and backward computations, enabling a comprehensive analysis of sequential patterns. This adaptability and versatility make BiLSTM a valuable asset in addressing modern challenges, such as predicting cloudbursts. By leveraging its capabilities, we can enhance our understanding and forecasting of extreme weather events, ultimately contributing to more effective decision-making in fields like hydrology and meteorology.

By incorporating batch normalization into the training pipeline, we can enhance the robustness of cloudburst prediction models, enabling more reliable forecasts by mitigating the effects of fluctuating data distributions encountered during training. This contributes to improved accuracy and effectiveness in forecasting extreme weather events such as cloudbursts, ultimately aiding in better preparedness and response strategies.

Design of Bidirectional Long Short-Term Memory:

The X_{t-1} input layer of a Bi-LSTM network is responsible for receiving sequential input data. In the case of predicting cloud cover, this inputs data usually consists of historical weather observations, such as temperature, humidity, air pressure, wind speed, and previous cloud cover measurements. The core of the Bi-LSTM network consists of two LSTM layers, each processing the input sequence in a different direction. One-layer processes the input sequence in the forward direction, while the other processes it in the backward direction.

$$f_m = \sigma(w[T_m, h_{m-1}, P_{m-1}] + n_u)$$

In this equation, x_m represents the sequence of inputs, h_{m-1} signifies the output of the previous block, and C_{m-1} denotes the block memory from the preceding LSTM. Additionally, the bias vector is denoted as nu , and each input has its own individual vector represented by w . The logistic sigmoid activation function is symbolized by σ .

Each LSTM layer contains memory cells that maintain state information over time and gates that control the flow of information into and out of the cells. Both LSTM layers process the input sequence step by step, updating their internal state and producing an output at each time step. The outputs from both directions are merged at each time step. This merging operation combines information from both directions, allowing the network to capture bidirectional dependencies in the input sequence.

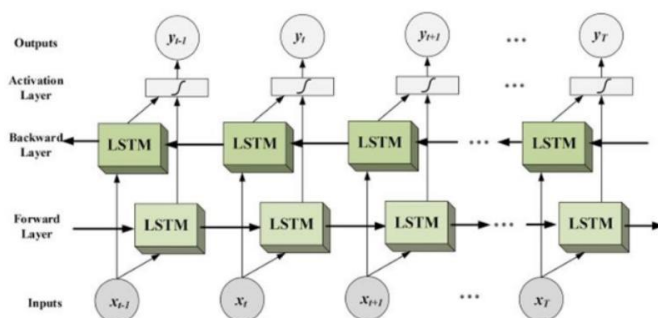


Figure 1 Architecture of Bidirectional Long Short Term Memory

The y_{t-1} output layer of the Bi-LSTM network processes the merged outputs from the LSTM layers to make predictions. When predicting cloud cover, the output layer may contain one or more neurons representing the predicted cloud cover values for future time steps. Activation functions such as SoftMax or Sigmoid may be applied to the output neurons to constrain the predictions within a specific range or to obtain probability distributions. The Bi-LSTM architecture effectively captures long-term dependencies in sequential data by leveraging the bidirectional processing capabilities of LSTM layers. By processing the input sequence in both forward and backward directions, the network can extract intricate patterns and relationships, making it well-suited for tasks like cloud cover prediction where past observations influence future outcomes.

The One-way Long Short-Term Memory (LSTM) Network design is a kind of neural network used for processing input time series sequences. In this design, the encoder processes the input sequence and generates a vector containing hidden and cell states for each LSTM cell. Additionally, the decoder receives supplementary inputs that are used for making predictions. During the model's training phase, the decoder uses these inputs along with the target output sequence to train against. This process involves the decoder producing outputs that are compared to the expected results, allowing the model to be refined iteratively.

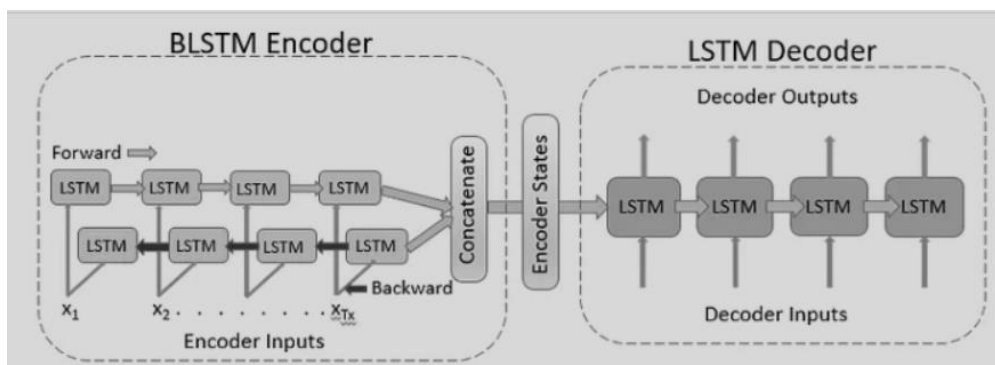


Figure 2 The One-way Long Short-Term Memory (LSTM) Network design

5. Experimental Results and Discussion:

This research highlights the significant impact of cloudburst on weather patterns, which poses considerable challenges for both hydrology and meteorology. The study proposes a solution to this issue by developing a predictive system based on Bidirectional Long Short-Term Memory (BiLSTM) using historical data. The prediction of cloudburst can be achieved through the use of Bi-Lstm and related machine learning techniques. It has been observed that cloudbursts are having a significant impact on weather patterns, leading to significant challenges in the fields of hydrology and meteorology. To address this issue, historical data is being used to build a predictive system based on Bidirectional Long Short-Term Memory (BiLSTM) and related Machine Learning techniques. The aim is to accurately predict cloudbursts and mitigate their effects. The Cloudburst prediction system uses the BiLSTM architecture, which allows it to process both historical and future data to improve its predictive capabilities. To achieve this, the system first reads Cloudburst data from historical datasets, followed by a data-cleaning phase to filter out weather patterns. The system then normalizes various weather metrics by the total number of cloudbursts to standardize the data. Finally, the system preprocesses and normalizes different types of humidity, precipitation, wind speed, wind bearing, and temperature, which are then analyzed further as shown in Figure 3.

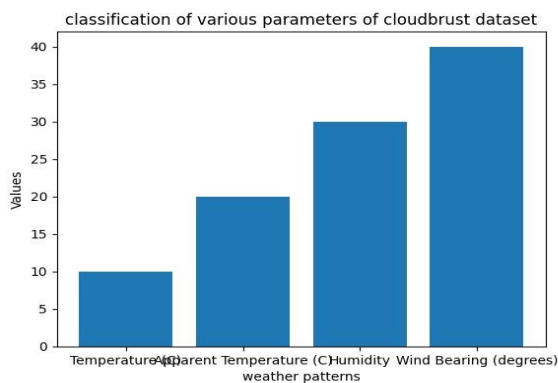


Figure 3 Classification of various weather patterns in cloudburst dataset

The Weather history dataset was pre-processed to filter out weather patterns. This step aimed to improve the accuracy of predictions in different scenarios. The dataset was then split into training and testing subsets, with a large portion reserved for testing. To avoid overfitting during training, an early stopping method was used. During the training process, the early stopping method was employed to avoid overfitting. The model was trained over 500 epochs with the Adam optimizer and binary cross-entropy loss function. Several metrics were used to evaluate the model's performance. Figure 4 displays various weather patterns, such as temperature, wind speed, wind bearing, and perception, along with loss and accuracy metrics. However, Figure 5 is not mentioned in the text.

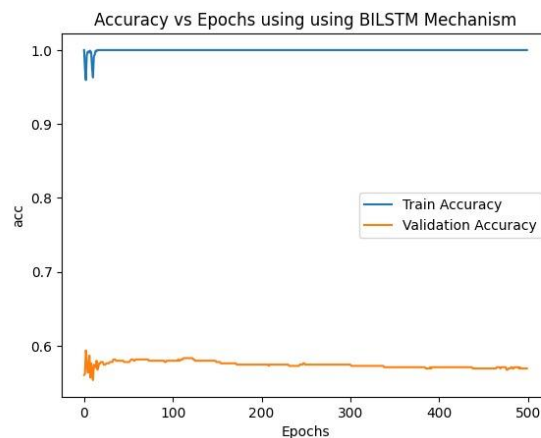


Figure 4 Bi-LSTM archives high accuracy

The loss curve is an important metric that indicates how well the system can accurately categorize cloudburst. To evaluate the model's ability to generalize, we used both the training and validation datasets. After reviewing the results, we found that the algorithm was effective in predicting cloudburst. The gradual decrease in loss across epochs suggests that the model was able to learn successfully.

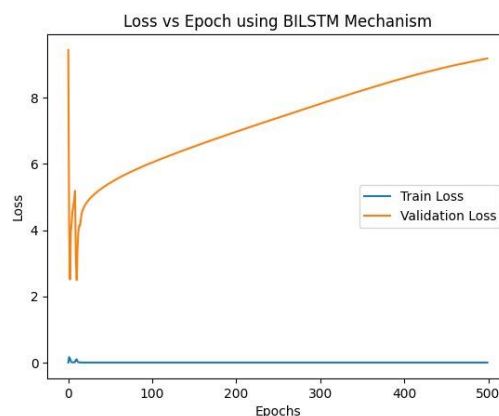


Figure 5 the BiLSTM architecture archives Loss

The system's ability to classify weather patterns was demonstrated by the steady rise of the accuracy curve. The curve's constant ascent was noteworthy, reaching its peak at the 150th epoch for both the training and validation datasets. The system achieved a final accuracy of 96.55% on the validation set, indicating that it correctly classified 96.55% of the weather patterns in the test dataset.

6. Conclusion:

In conclusion, as technology continues to advance, the challenges posed by unpredictable weather patterns persist, demanding innovative solutions in fields such as hydrology and meteorology. The development of a cloudburst prediction system emerges as a critical need, offering invaluable support to stakeholders ranging from farmers to emergency responders in mitigating the impacts of extreme weather events. Among the array of techniques available for rainfall prediction, the application of machine learning models, specifically Bi-LSTM (Bidirectional Long Short-Term Memory), proves particularly promising. Leveraging its adeptness in sequence modeling tasks, the

Bi-LSTM model exhibits remarkable accuracy in forecasting rainfall values when trained on historical data. The comparison with the LSTM model, a widely used architecture in sequence prediction tasks, highlights the superior performance of the Bi-LSTM approach, achieving an accuracy of 96.55% compared to LSTM's 94.36%. This disparity underscores the efficacy of Bi-LSTM in capturing intricate sequential patterns within rainfall data, thereby empowering decision-makers with enhanced predictive insights. As we embrace such advancements, it becomes evident that leveraging cutting-edge technologies like Bi-LSTM holds immense potential in revolutionizing our approach to weather prediction and management. By continuing to refine and implement such methodologies, we can fortify our resilience against the impacts of weather variability, fostering a more prepared and adaptive society.

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