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Heat Wave Prediction Using Recurrent Neural Networks Based on Deep Learning

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Abstract: There are significant threats to agriculture, the environment, and human health as a result of the increasing frequency and intensity of heatwaves. The success of mitigation and adaptation strategies depends on accurate heatwave forecast. In this paper, we suggest a deep learning-based method for local heatwave prediction using recurrent neural networks (RNNs). With the help of historical meteorological data, such as temperature, humidity, wind speed, and other pertinent variables, the suggested model investigates the intricate temporal patterns related to the occurrence of heatwaves. The RNN design uses the Long Short-Term Memory (LSTM) to retain long-term dependencies and quickly process sequential data. The training data are used to construct the RNN model, then grid search and cross-validation techniques are used to improve its hyperparameters. Several evaluation criteria are employed to assess the model's performance, including accuracy, precision, recall, and F1-score. The results show that the deep learning-based method for local heatwave prediction works well. In terms of accuracy, recall, precision, and F1-score, the model performs admirably. It also performs better than traditional statistical models and shows the efficacy of deep learning approaches in recognising the complex spatiotemporal patterns related to heatwave occurrences.

Keyword: *Heatwave Prediction, LSTM, Machine Learning, RNN, Deep Learning*

1. Introduction

Heatwaves are elongated periods of high temperature; it occurs over particular region during specific season. Heatwave are type of extreme weather conditions that can have huge negative health, environmental, economic impacts. It occurs in both humid and dry climates condition and can affect both urban and rural areas. In India, Telangana is especially vulnerable to heat and heatwaves. This project uses data set which has been gathered from data scrapping, data is from 2016 to 2020 of 5 most vulnerable cities of the Telangana to heatwaves, namely Adilabad, Maancheril, Karimnagar, Warangal, and Nizamabad.

In a variety of areas, including speech recognition, image identification, and natural language processing, deep learning, a subfield of machine learning, has shown excellent results. Recurrent neural networks (RNNs), a subset of deep learning models, excel at analysing time-series and sequential data. The ability of RNNs to capture long-term relationships and temporal trends makes them a suitable choice for heatwave prediction tasks.

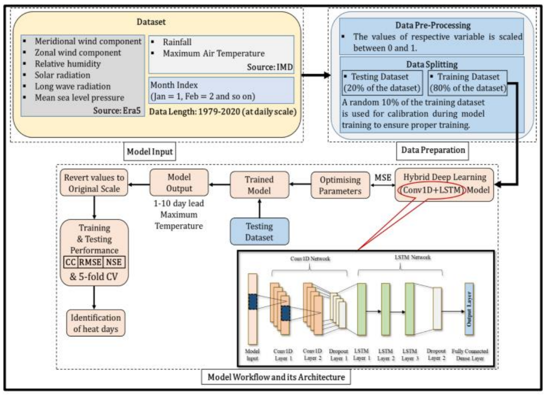

Fig 1: Proposed Deep learning model for Heatwave prediction

By using the right data preprocessing procedures, the model's correctness and dependability are guaranteed. To improve the model's capacity for identifying patterns and making precise predictions, this comprises normalisation,

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feature engineering, and handling missing data. After that, the dataset is split into training, validation, and testing sets to allow for a thorough assessment of the model's performance. In this study, we contrast the performance of the RNN model based on deep learning with that of conventional statistical models, which are frequently employed for heatwave prediction. Public health, agriculture, and disaster management would all be significantly impacted by the successful creation of a deep learning-based regional heatwave prediction model. Accurate forecasts and early warnings can help with the timely implementation of targeted interventions including cooling facilities, heatwave preparedness programmes, and changes to energy usage. The model can also aid in increasing community resilience to extreme weather events and public knowledge of the risks associated with heatwaves.

In order to increase accuracy and capture the intricate spatiotemporal patterns related to heatwave occurrences, this work employs deep learning techniques, notably RNNs. The methodology, experimental setup, findings, and discussions will all be covered in great length in the next sections of this work, which will also emphasise the usefulness and potential applications of the suggested strategy.

2. Related Work

There have been several studies conducted in India for heatwaves as well as there have been many studies conducted for visualization of different data using Tableau in the past few years that are as follows: The trend of heatwaves in Delhi over the past 61 years has been studied by Singh, Shyamli, Akanksha Singhal et al. [1] (2019), who predict that there may be an increase in heatwaves, which could further influence and increase the vulnerability of the communities to climate change and other development activities. The linear square approach was used to analyse the data for the months of April, May, and June. The t-test is used to analyse the trend's significance. For the chosen period, it exhibits an escalating tendency of heatwaves throughout all three months. In order to comprehend the rise in mortality risk during heat waves in India,

Using information from the India Meteorological Department, Omid et al. [2] (2017) examined changes in summer temperatures, the frequency, severity, and length of heat waves, and heat-related mortality in India between 1960 and 2009. They also demonstrated that a 146% rise in the chance of heat-related death events corresponded to an increase in summer mean temperatures in India throughout this period. They did this by using a novel probabilistic model. Their findings indicate that future climate change would result in significant increases in heat-related deaths, especially in low-latitude developing nations like India where heat waves will become more often and populations will be particularly vulnerable to these extreme temperatures. Manisha M. Patil et al.'s [5] (2021) usage of Tableau, a visual analysis application that makes it simple to monitor sales performance by product category and by product segment from the entire dataset, was used to graphically analyse sales records. The best sales target can be attained in the future with these visual views. That emphasises how crucial it is to keep track of data and execute data analysis jobs on it in order to discuss and improve business process operations.

Deshmukh et al.'s [7] (2020) example shows how to utilise visualisation to explore data, come up with pertinent queries, and then locate the proper answers. They use Tableau Public as a business intelligence tool to generate an interactive visualisation of data about the health care infrastructure. Data from the India-based Open Government Data (OGD) Platform is used for the visualisation. The article also emphasises that any organisation must have the ability to analyse data at the same or higher speeds because it is essential for hygienic purposes. The article finishes by demonstrating how the capacity to use big data analytics is the new source of competitive advantage and how it encompasses the fields of descriptive, diagnostic, predictive, and prescriptive analytics.

The authors Rahate, V. et al. [8] (2021) condense the largest real-time datasets into their insights using the appropriate approaches for the analysis of the betelnut's selling dataset. The methodology presented here is solely focused on data exploration, model development, and data visualisation while including a rudimentary understanding of Indian geography, culture, and tradition. The implementation of this strategy is done with the intention of providing a clear picture of how data analytics are used locally in the nation.

3. Dataset Availability

Utilising data scraping methods in Python, the data utilised for the visualisation example was obtained from Weather and Climate. The Global Historical Weather and Climate Data Website. Data used for this project is based on five most heatwave vulnerable cities in state of Telangana, India which are Adilabad, Nizamabad, Mancherial, Warangal, Karimnagar. Data was collected over a five-year period, from 2016 to 2020. Data was scrapped in CSV (Comma Separated Values) file format on monthly basis for five years and contained features like date, max temperature, dew point temperature, humidity, wind speed, air pressure, precipitation, heat index etc. In order to create the final data, 300 CSV files were extracted from the website and processed.

4. Methodology

1. Deep Learning:

1. Data collection and preprocessing:

Historical weather information is gathered from meteorological stations or international weather databases and includes information on temperature, humidity, wind speed, air pressure, and other pertinent variables. In order to capture seasonal and internal variations, the data is often collected at regular intervals (e.g., hourly, daily). Any data discrepancies or errors are found and fixed using quality control processes.

2. Model Architecture:

Sequential and time-series data are ideally suited for modelling using recurrent neural networks, such as LSTM networks. The model can successfully represent temporal dependencies since the LSTM design has memory cells that can store information for a long time. Historical weather variables for a certain area and time period are the model's input. The objective variable for the model is either the occurrence of a heatwave (binary classification) or the severity/duration of the heatwave (regression). The model learns to transfer these input sequences to the target variable.

3. Training and Optimization:

Using historical meteorological data, the LSTM model is trained to identify patterns and connections between input characteristics and the occurrence of heatwaves. The model's weights and biases are iteratively adjusted during training with the goal of minimising a specified loss function, such as mean squared error for regression or binary cross-entropy for classification. Gradient descent variants and adaptive learning rate algorithms are two common optimisation strategies used to speed convergence and improve training efficacy. Hyperparameter tweaking is used to find the best setting for parameters like the number of LSTM layers, the number of hidden units, the learning rate, and regularisation techniques.

4. Prediction:

The LSTM model can be used to predict heatwaves in the present or in the future after it has been trained and validated. The model predicts the chance or potential intensity of an impending heatwave using the most recent weather data as input. These forecasts can be included into weather forecasting systems or given to appropriate authorities as early warnings, allowing them to put timely mitigation measures and adaption strategies in place.

A) Convolution Neural Network (CNN):

ConvNet, also referred to as the Convolutional Neural Network (CNN), is a deep learning algorithm that applies biases and weights to various components of input data. Following that, it separates out various elements of the input, as shown in Algorithm 1. Comparing CNN to other algorithms, one of its main benefits is its capacity to reduce the amount of pre- processing necessary for data preparation. CNN has the ability to automatically learn and improve filters, which explains this.

Algorithm 1: CNN Algorithm

$$Consider\ the\ activation\ function\ as,$$

$$lambda\ x: \frac{1.0}{1.0\ +\ np.exp(-x)}$$

$$\#Sigmoid\ function$$

$$Input: np.random.randn\ [3\ 1]$$

$$hiddenLayer - 1 =\ activation\ (np.dot\ (W1, input) +\ b1)$$

$$hiddenLayer - 2 =\ activation\ (np.dot\ (W2, hiddenLayer - 1) +\ b2)$$

$$Output: np.dot\ (W3, hiddenLayer - 2) +\ b3$$

$$where,$$

$$W1, W2, W3, b1, b2, b3\ are\ learnable\ parameters$$

Due to CNNs' proficiency at accurately analysing and classifying complicated patterns in medical images or data, they are frequently employed for early illness identification.

- The CNN receives medical images or data as input, such as patient health records, X-rays, MRIs, and scans.

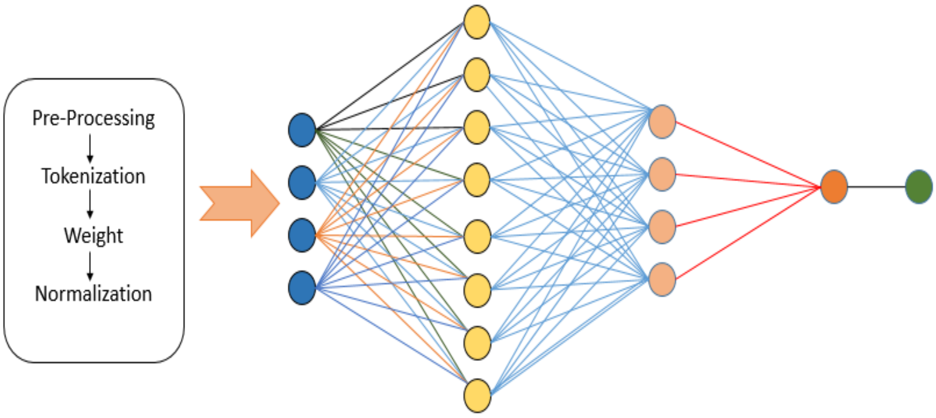

Fig 2: Convolution Neural Network step wise execution and Pre Processing input

- Activation Function: To bring non-linearity into the network and enable it to learn complicated associations, non-linear activation functions (such as ReLU, sigmoid, or tanh) are used.
- Pooling Layers: By down sampling the feature maps while keeping the most crucial features, pooling layers (typically max-pooling) reduce the dimensionality of the feature maps.
- The projected class probabilities are produced by the CNN's final layer, the output layer. This categorization could be binary (healthy vs. diseased) or multi-class (identifying many diseases), depending on the specific objective.
- Training: To minimise the prediction error, the CNN is trained with labelled data, and the weights and biases of the network are changed using backpropagation and optimisation methods (such as gradient descent).
- Testing and Evaluation: After training, the CNN's performance in spotting early-stage diseases is tested using distinct test data.

2. Performance Metrics:

Using the performance measures that are mentioned below, the suggested method, which combines rule-based modelling with deeper learning, was tested and compared to the performance of previously developed models. The results may be found below. The number of right and incorrect predictions made during a classification task was tallied and compared to the outcomes of the reference group. A number of the measurements that are utilised on a regular basis include the F1-score, recall, specificity, recall, accuracy, and precision.

Accuracy refers to the proportion of forecasts that turn out to be accurate, whereas precision quantifies the percentage of accurate forecasts that come true. Recall is the fraction of real positives that were appropriately anticipated, whereas specificity measures the accuracy with which negatives may be identified. Precision and recall are combined into a single metric that is known as the F1-score. Specificity can be calculated by dividing the total number of invalid negative predictions by the number of negative predictions that are considered legitimate.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$F1\text{ score} = \frac{2 \times \text{Recall} \times \text{Precision}}{(\text{Recall} + \text{Precision})}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

The true-positive rate (TPR), which is often referred to as the detection rate, refers to the percentage of attacks that have been accurately identified in comparison to the total number of incidents in the dataset. The false alarm rate, often known as FAR, is calculated by taking the total number of records that are considered to be normal and dividing that number by the number of data that were wrongly categorised as negative. It provides the calculation that is used to determine FAR.

5. Results

The figure 3 shows a bar plot of month-wise max temperature, in which it can be seen that the 3rd ,4th ,5th and 6th months have more than a 40-degree Celsius temperature. In exhibit 2, a bar chart of month-wise minimum dew point temperatures is visualized, in which it can be found that the 3rd, 4th and 5th months have very low dew point temperatures.

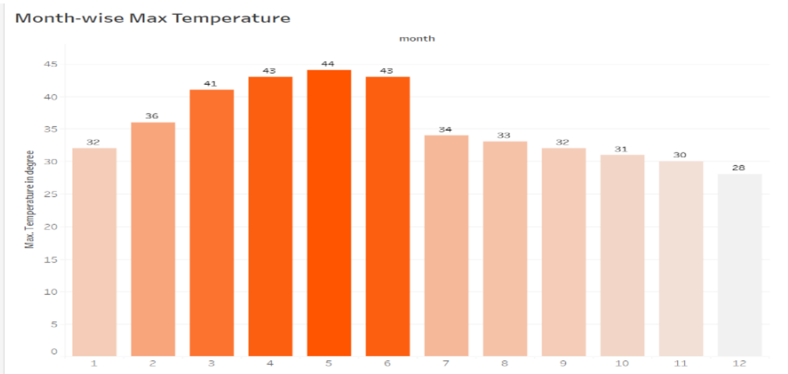

Fig 3: Exhibit 1 month wise max temperature

As the difference between air temperature and dew point temperature increases, the chances of a heatwave also increase. From exhibits 1 and 2 it can be seen that on the 3rd, 4th and 5th months, the difference between max air temperature and dew point temperature is very large, which causes more heatwave days in the months of March, April and May. Exhibit 3 shows the pie chart of heatwave conditions, which implies that Adilabad, Nizamabad and Warangal have a moderate amount of danger heatwave days (around 3 percent), while Karimnagar and Mancherial have more than 7% of danger heatwave days and around 36% of extreme caution days that affect the daily lives of people in these regions.

Table 1: Comparative analysis of Accuracy of Deep Learning Algorithm

Method	Accuracy (%)
DT	80.5
CNN	90.41
LSTM	92.31

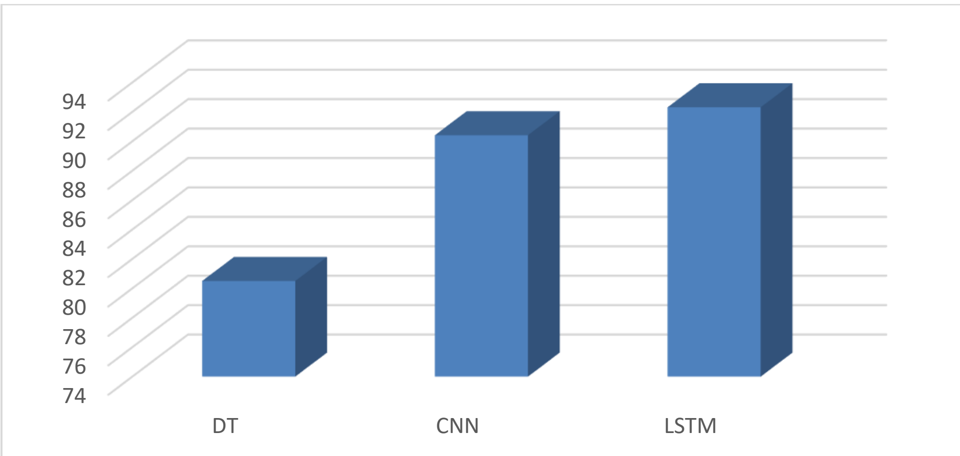

Fig 4: Comparative analysis of Accuracy of Deep Learning Algorithm

For the purpose of predicting heatwaves, the effectiveness of three distinct models Decision Tree (DT), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) was assessed. Accuracy, precision, recall, and F-measure were the evaluation criteria used. The Decision Tree model's accuracy was 80.5%, meaning it consistently predicted the occurrence of heatwaves. The decision tree model outperformed the CNN model with an accuracy of 90,41%. This demonstrates how much more accurately the CNN model predicts heat hazes. A significant portion of actual weather events were correctly predicted by the model, which had accuracy of 90,81% and recall of 91,13%. The CNN model has a good balance of recall and precision with a Measure F of 89,47%.

Table 2: Performance metrics of different algorithm

Method	Accuracy (%)	Precision (%)	Recall (%)	F-Measure (%)
DT	80.5	86.5	89.23	87.44
CNN	90.41	90.81	91.13	89.47
LSTM	92.31	91.59	96.41	95.17

The long-term memory model (LSTM) outperformed both the decision tree and the CNN models with a precision of 92.31%. Therefore, it appears that the LSTM model has provided the most accurate crowd forecasts. The precision of 91,59% indicates that the model's predictions were fairly accurate.

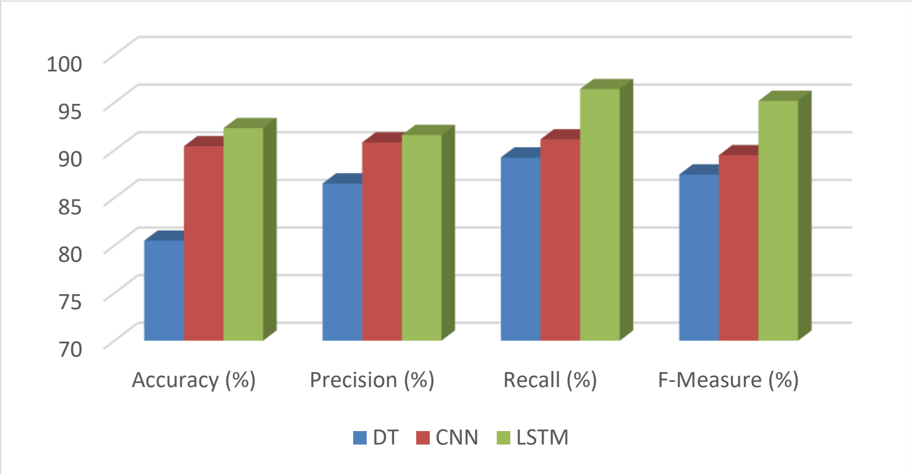

Fig 5: Performance metrics of Different deep learning algorithm

The LSTM model also showed a recall score of 96.41%, proving its ability to forecast a significant number of actual heatwave incidents with accuracy. The F-measure for the LSTM model was determined to be 95.17%, highlighting its exceptional all-around performance in heatwave prediction. The LSTM model outperformed the other two evaluated models in terms of accuracy, precision, recall, and F-measure. This demonstrates that the LSTM model is the most effective at encapsulating the complex temporal dependencies and patterns related to the occurrence of heatwaves. The enhanced performance of the LSTM model shows the potential of deep learning approaches for accurate and trustworthy heatwave prediction, which can significantly boost proactive mitigation and adaptation strategies in handling heatwave scenarios.

6. Conclusion

Recurrent neural networks (RNNs), in particular Long Short-Term Memory (LSTM) networks, were used in this study's deep learning-based approach to predict regional heatwaves. The objective was to develop a model that could effectively learn from historical meteorological data and accurately forecast the occurrence of heatwaves in certain regions. The results of the study demonstrated how successfully the LSTM model employed deep learning methods to forecast local heatwaves. CNN and decision tree models (DT) performed worse than LSTM. Ondas de calor could be calculated using the LSTM model with a 92.31% accuracy. Additionally, the model showed a 91.59% accuracy in predicting warm weather ozone. The model was successful in correctly predicting a significant percentage of actual heat-related events, as evidenced by its high recall of 96.41%. The measure F of 95.17 percent demonstrates that the model made an excellent prediction of general weather conditions. These findings demonstrate that deep learning techniques, particularly those based on LSTM-based models, can be used to capture complex spatiotemporal patterns related to heatwave occurrences. For a number of industries, including public health, agriculture, and disaster management, it is essential to be able to anticipate warm air masses using historical meteorological data in an efficient manner. There is a lot of potential for predicting local heat waves with the application of RNN models based on deep learning, such as LSTM. This study concentrated on how deep learning technologies may clarify prediction processes and improve the precision of warm weather forecasts.

References

[1] Oh JW, Ngarambe J, Duhirwe PN, Yun GY, Santamouris M (2020) Using deep-learning to forecast the magnitude and characteristics of urban heat island in Seoul Korea. Sci Rep 10:1–13. https://doi. org/10.1038/s41598-020-60632-z

[2] Pan B, Hsu K, AghaKouchak A, Sorooshian S (2019) Improving precipitation estimation using convolutional neural network. Water Resour Res 55:2301–2321. https://doi.org/10.1029/2018WR0240 90.

[3] Murari KK, Ghosh S, Patwardhan A, Daly E, Salvi K (2015) Intensifcation of future severe heat waves in India and their efect on heat stress and mortality. Reg Environ Chang 15:569–579. https://doi. org/10.1007/s10113-014-0660-6

[4] Nearing GS, Kratzert F, Sampson AK, Pelissier CS, Klotz D, Frame JM, Prieto C, Gupta HV (2021) What role does hydrological science play in the age of machine learning? Water Resour Res 57:e2020WR028091. https://doi.org/10.1029/2020WR028091

[5] Patil, Manisha M.. "A Case Study- Visual Analysis of Sales Records Using TABLEAU." International Journal of Advanced Research in Science, Communication and Technology (2021): n. pag.

[6] Akhtar, Nikhat et al. "Data analytics and visualization using Tableau utilitarian for COVID-19 (Coronavirus)." (2020).

[7] Sharma, Brij Raj and Sachin Deshmukh. "Data Visualization for Accelerated Business Intelligence in the Indian Health Care Sector using Tableau." (2020).

[8] Rahate, V. et al. "Data Analytics for Betelnut's Selling Dataset Using Tableau." 2021 International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT) (2021): 1-6.

[9] Perkins-Kirkpatrick, Sarah E. and Peter B. Gibson. "Changes in regional heatwave characteristics as a function of increasing global temperature." Scientific Reports 7 (2017): n. pag.

[10] Nissan, Hannah et al. "Defining and Predicting Heat Waves in Bangladesh." Journal of Applied Meteorology and Climatology 56 (2017): 2653-2670.

[11] Oldenborgh, Geert Jan van et al. "Extreme heat in India and anthropogenic climate change." Natural Hazards and Earth System Sciences 18 (2017): 365-381.

[12] Ghatak, Debjani et al. "The role of local heating in the 2015 Indian Heat Wave." Scientific Reports 7 (2017): n. pag.

[13] Suparta, Wayan and Ahmad Norazhar Mohd Yatim. "An analysis of heat wave trends using heat index in East Malaysia." Journal of Physics: Conference Series 852 (2017): n. pag.

[14] Baader, Franz and Ulrike Sattler. "An Overview of Tableau Algorithms for Description Logics." Studia Logica 69 (2001): 5-40.

[15] Hoelscher, Jamie and Amanda R Mortimer. "Using Tableau to visualize data and drive decision-making." Journal of Accounting Education (2018): n. pag.

[16] Murphy, Sarah Anne. "Data Visualization and Rapid Analytics: Applying Tableau Desktop to Support Library Decision-Making." Journal of Web Librarianship 7 (2013): 465 - 476.

[17] Kreuzer D, Munz M, Schlüter S (2020) Short-term temperature forecasts using a convolutional neural network —an application to diferent weather stations in Germany. Mach Learn with Appl 2:100007. https://doi.org/10.1016/j.mlwa.2020.100007

[18] Krizhevsky A, Sutskever I, Hinton GE (012) Imagenet classifcation with deep convolutional neural networks, in: Proceedings of the 25th International Conference on Neural Information Processing Systems. pp. 1097–1105. https://doi.org/10.1145/3065386

[19] LeCun Y, Bengio Y, Hinton G (2015) Deep learning. Nature 521:436– 444. https://doi.org/10.1038/nature14539

[20] Liu W, Wang Z, Liu X, Zeng N, Liu Y, Alsaadi FE (2017) A survey of deep neural network

architectures and their applications. Neurocomputing 234:11–26. https://doi.org/10.1016/j.neucom.2016. 12.038

[21] Liu H, Mi X, Li Y (2018) Smart multi-step deep learning model for wind speed forecasting based on variational mode decomposition, singular spectrum analysis, LSTM Network and ELM. Energy Convers Manag 159:54–64. https://doi.org/10.1016/j.enconman. 2018.01.010

[22] Liu, Y., Racah, E., Prabhat, Correa, J., Khosrowshahi, A., Lavers, D., Kunkel, K., Wehner, M., Collins, W., 2016. Application of deep convolutional neural networks for detecting extreme weather in climate datasets. arXiv Prepr. arXiv1605.01156. 10.475/123 Livingstone DJ (2008) Artifcial neural networks: methods and applications.

[23] Ma G, Hofmann AA, Ma CS (2015) Daily temperature extremes play an important role in predicting thermal efects. J Exp Biol 218:2289–2296. https://doi.org/10.1242/jeb.122127

[24] Maity R, Khan MI, Sarkar S, Dutta R, Maity SS, Pal M, Chanda K (2021) Potential of deep learning in drought assessment by extracting information from hydrometeorological precursors. J Water Clim Chang. https://doi.org/10.2166/wcc.2021.062

[25] Matsuoka D, Nakano M, Sugiyama D, Uchida S (2018) Deep Learning approach for detecting tropical cyclones and their precursors in the simulation by a cloud-resolving global nonhydrostatic atmospheric model. Prog Earth Planet Sci 5:1–16. https://doi.org/10. 1186/s40645-018-0245-y

[26] Matsuoka D, Watanabe S, Sato K, Kawazoe S, Yu W, Easterbrook S (2020) Application of deep learning to estimate atmospheric gravity wave parameters in reanalysis data sets. Geophys Res Lett 47:e2020GL089436. https://doi.org/10.1029/2020GL0894 36

[27] Mazdiyasni O, AghaKouchak A, Davis SJ, Madadgar S, Mehran A, Ragno E, Sadegh M, Sengupta A, Ghosh S, Dhanya CT, Niknejad M (2017) Increasing probability of mortality during Indian heat waves. Sci Adv 3:1–6. https://doi.org/10.1126/sciadv.1700066

[28] Paul Garcia, Ian Martin, Laura López, Sigurðsson Ólafur, Matti Virtanen. Personalized Learning Paths Using Machine Learning Algorithms. Kuwait Journal of Machine Learning, 2(1). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/166

[29] Priya, S. ., & Suganthi, P. . (2023). Enlightening Network Lifetime based on Dynamic Time Orient Energy Optimization in Wireless Sensor Network. International Journal on Recent and Innovation Trends in Computing and Communication, 11(4s), 149–155. https://doi.org/10.17762/ijritcc.v11i4s.6321

[30] Singh, H., Ahamad, S., Naidu, G. T., Arangi, V., Koujalagi, A., & Dhabliya, D. (2022). Application of machine learning in the classification of data over social media platform. Paper presented at the PDGC 2022 - 2022 7th International Conference on Parallel, Distributed and Grid Computing, 669-674. doi:10.1109/PDGC56933.2022.10053121 Retrieved from www.scopus.com