Evaluation of Deep Learning Approaches for Classification of Drought Stages Using Satellite Imagery for Tharparker

Muhammad Owais Raza¹, Tarique Ahmed Khuhro², Sania Bhatti¹, and Mohsin Memon¹

¹Deepartment of Software Engineering, Mehran University of Engineering and Technology, Jamshoro, Sindh, Pakistan ²Department of City and Regional Planning, Mehran University of Engineering and Technology, Jamshoro, Sindh, Pakistan

Correspondence Author: Muhammad Owais Raza (owais.leghari@hotmail.com)

Received February 15, 2022; Revised November 11, 2022; Accepted November 11, 2022

Abstract

Droughts have grown increasingly common, severe, and widespread in recent decades due to climate change, aggravating their harmful repercussions. Drought prediction is very effective for providing early warning and protecting the most susceptible areas from the dangers of drought. This study looks at the feasibility of applying Deep Neural Networks to create drought stage classification models for the Tharpakar District of Pakistan. A collection of satellite pictures of Tharpakar at various degrees of drought were employed in this investigation. The unique dataset utilized in this study was gathered utilizing the time-lapse function of Google Earth Pro. The drought stages in this study are 'Before Drought,' 'Drought,' 'After Drought,' and 'No Drought.' DenseNet, ResNet, InceptionV3, Xception, and VGG19 deep learning architectures are utilized for training the models. F1 Score, Precision Accuracy, Recall, and ROC curves are used to evaluate all models. According to the experimental results, DenseNet and ResNet were the best-performing models with an accuracy of 70%, while VGG19 is the lowest-performing model with an accuracy of 60%.

Index Terms: Classification Models, Computer Vision, Deep Learning, Drought Stage, Satellite Images.

I. INTRODUCTION

Drought is a natural phenomenon induced by various variables such as high temperatures, low precipitation, groundwater depletion, high evaporation, and water resource mismanagement. Drought is a natural element of the climate and may occur nearly anywhere on the planet [1]. It frequently happens in locations with less than usual rainfall over an extended amount of time, typically months or years [2]. The evaluation, tracking, and detecting of the beginning and conclusion of droughts and their progression is a challenging and complex undertaking. To address these issues, many indices have been developed in recent decades. Rainfall and other meteorological data are commonly used to create these indices [3]. Drought can occur when a region gets chronically below-average precipitation. It can considerably impact the environment and agribusiness of the affected area [4]. Drought has serious repercussions, such as increasing poverty, economic difficulties for farmers, food shortages, increased expenses, job loss, and many others. Drought has a detrimental effect on Pakistan, which is among the most drought-prone regions because of its agricultural reliance. Agro-economy employs over 43 percent of the country's labor force and generates approximately 21% of Pakistan's Gross Domestic Product (GDP) [5], and [6].

The growth of technology has been incredible in recent years, especially in machine learning and its applications.

Machine Learning (ML) is being employed to manage potential future situations better. ML can analyze and interpret data to extract useful information that humans would not be able to detect. The applications of ML are very vast. ML in environmental and science meteorology ranges from rainfall prediction systems to climate modeling. Deep neural networks are one of the most common approaches to today's climate modeling tasks due to the vast data availability.

This study applies deep learning to predict the drought stage using satellite imagery. Various pre-trained neural network architectures are fine-tuned to predict drought stages. The region selected for this study is Tharpakar which is among the most drought-affected region.

Contributions of this study are as follows:

- 1. Curation of a novel satellite image dataset for drought stage prediction. To the best of our knowledge, this is the only dataset that has drought stages.
- 2. Creation and evaluation of deep learning model for drought stage prediction using satellite imagery for the Tharparkar Region. To the best of our knowledge, this is the only study that uses satellite images for drought stage prediction.



3. Based on the evaluation we were able to achieve 70% accuracy in drought stage prediction using satellite images.

The content of this research study is organized in the following manner:

The literature review for this study is done in Section II. In Section III Research methodology employed in this study is comprehensively discussed. In Section IV, the Experimental result of this study are discussed, and in Section V conclusion for this study is drawn, and its limitation and future work are discussed.

Tharparkar is a district of the province Sindh in Pakistan centered in Mithi. It has the lowest Human Development Index (HDI) ranking of all the districts in Sindh. Tharparkar lies between 69° 3' 35" East and 71° 7' 47" East longitudes and between 24° 9' 35" North and 25° 43' 6" North latitudes. Drought devastated Tharparkar in 2014, causing widespread destruction. One hundred eighty-two children under the age of five were reported deceased, as well as 149 adults (91 men and 58 females) [7]. Tharparkar is one of the most drought-stricken areas. Due to the substantial adverse effects of drought on Tharparkar, it is selected for this research study, see figure I.



Figure I: Study Area Map for Tharparkar District based on Talukas

II. RELATED WORK

The forecast of drought plays a significant role in minimizing the adverse impacts of drought. As a result, several drought prediction methodologies, such as stochastic processes, mixed statistical and dynamic models, categorical prediction, machine learning techniques, and hybrid models, have been assessed regularly [8]. The Researchers used three cutting-edge Machine Learning methodologies to evaluate the feasibility of constructing drought prediction models for Pakistan: ANN, SVM, and KNN [9]. Using the Standardized Precipitation Evaporation

Index, 3 types of droughts were considered: modest, hefty, and extreme for the two main cropping seasons of Rabi and Kharif (SPEI). Several techniques were used in studies to predict drought using ML, such as Effective Drought Index (EDI) at thirteen stations in the CANFIS, MLPNN, and the Multi-Linear Regression (MLR) process are all developed in the Indian state of Uttarakhand [10]. Researchers used the Random Forest (RF) technique to integrate the drought characteristic f(x). Previous droughts' Soil Moisture Index (SMI) anticipated severe drought areas. The RF method helps investigate large datasets and is suited for satellite image analysis. Support Vector Machine (SVM), a statistical machine learning tool, was used to approximate seasonal changes in the Standardized Precipitation Index (SPI) in four reservoir basins [11]. The use of Artificial Neural Networks (ANN) as a technique for forecasting droughts in Sri Lanka is presented by researchers. The SPI, a drought monitoring gauge, was used to create prediction models. Over an extended period, monthly rainfall data from 13 climatological stations encompassing both the wet and dry zones were used to train and test the neural networks [12].

As a result of the recurrence of drought concerns, humans are currently dealing with many environmental issues. To anticipate drought, researchers employed an MLPNN method. The MLPNN techniques were tested utilizing monthly time-series data from the Standardized Precipitation Evapotranspiration Index (SPEI) for 17 meteorological locations in the Northern Area and KPK (Pakistan). The MLPNN algorithm was evaluated using monthly time-series data from the SPEI for seventeen climatological locales in the KPK and Northern Area (Pakistan) [13]. A researcher emphasizes that drought forecasting accuracy is an essential first step in assisting policymakers in formulating drought hazard management plans. The SPI was used to forecast long-term and shortterm droughts in Tabriz, Iran, using ANN models at several time periods, including 3, 6, 12, 24, and 48 months. To that purpose, several combinations of estimated SPI and timeseries of other meteorological variables like wind velocity, precipitation, sunshine hours, and relative humidity were employed to train the ANN models from 1992 to 2010 [14]. Researchers developed seven ANN forecasting models between 1986 and 2015 that included meteorological attributes to forecast SPEI for 7 stations in Ethiopia's Blue Nile basin. The main purpose was to compare expected and observed outcomes to figure out how sensitive and predictive drought-trigger input factors were [15]. To predict drought situations, researchers used ten vegetation and precipitation variables that were delayed over one, two, and three months [16].

Besides the typical greedy search among utmost predictive variables, the General Additive Model (GAM) approach is utilized in the model space examination for the most accurate ANN model. To reduce the cardinality of the model space, we combine this with a set of assumptions. Despite the creation of 102 GAMs, only 21 had an R2 larger than 0.7 and were thus submitted to an ANN technique. A brute-force method is used in the ANN process. The training data is automatically partitioned into ten sub-samples, in which ANN models are built and their performance is evaluated using a variety of metrics [16].

The DL technique, which is based on a 1D CNN, was used to extract information from hydro-meteorological precursors in this study. To demonstrate its ability to assess basin-scale meteorological droughts, as evidenced by various performance metrics and skill scores [17]. This work employs ANN to anticipate the development of drought in two distinct European areas, Lisbon and Munich, within a one-month time. The 28 soil and atmospheric variables from a single-model large ensemble are used as input parameters for this approach [18].

This study presents a novel method of drought stage prediction using deep neural networks on a novel satellite image dataset. The studies discussed above either use some index or remote sensing for prediction, but this study uses raw satellite images which create ease of use. The preliminary results of this study are presented, using machine learning and ensemble machine learning technique [19].



Figure II: Research Methodology Flowchart Diagram

III. METHODOLOGY

Figure II depicts the research approach used in this study. The methodology consists of 5 stages Data Gathering or Collection, Data Labeling, Data Preprocessing, Data Splitting, and Data Modeling and Evaluation. In this section, each stage of methodology is described comprehensively.

Experiments run on 'Google Collab'. All the experiments are performed using python, TensorFlow, and Keras. GPU-enabled runtime is used for training the models.

A. Data Collection

In this research, satellite images were acquired using 'Google Earth Pro's' time-lapse feature. A total of 1119 images were gathered into different time periods using Google Earth Pro. These satellite images are precisely used to classify changes in a given area over a period concerning the drought stage in that region. The satellite images sample shelters all talukas of the district Tharpakar. The images collected are very high resolution with 96 dpi, both horizontal and vertical. The images have 24-bit depth. The dimensions of the images are 4800 x 2718. Each of the images is saved with its time stamp for labeling purposes.

B. Data Labeling

After the collection of images next step is to perform annotation on these images. Each image has its timestamp. In the process of labeling, the time stamp of each image is checked with the drought stage of that region at that time, and based on that; those images are labeled. There are four labels used in this study; 'Drought', 'No Drought', 'Before Drought', and 'After Drought'. For example, if the image's timestamp is June 25, 2004, it is checked that at that time in that region, what were drought stages from the four classes used in this study and based on that image is annotated. The difference between no drought, before drought, and after drought is the 'Before Drought' label is the representation of drought is about to come and its labeling is done based on, 6 months before the drought. After drought shows that drought has ended but conditions haven't been restored to normal so images in the range of 6 months after ending drought are labeled as 'After Drought'.

C. Data Preprocessing

In Data Preprocessing phase, raw satellite images are preprocessed for better performance. Raw images are provided to 'Gaussian Filter' that removes any noise in the image and makes it smooth later 'Sharpening Filter' is applied for edge finding. The image is resized from 4800 x 2718 to 200 x 200px for efficient computation without affecting performance. The goal of this step is to make images ready for classification. See figure III.



Figure III: Step-by-Step Image Preprocessing Flow

D. Data Splitting

To train and evaluate, two separate subsets of this dataset are required. The stratified split is employed in this study to split the dataset into testing and training sets. This approach divides a single dataset into two subgroups based on the fraction of the image dataset utilized for testing and training. The 50-50 split refers to a split in which 50% of the dataset is utilized for training and 50% for testing. Using additional data for training is the best approach. According to the literature, 80-20% provides superior results, hence in this study, 80% of the data is utilized for training purposes and 20% for evaluation.

E. Data Modeling and Evaluation

The dataset has been split and is now available for training and testing by the algorithm. A deep neural network model is trained using transfer learning. In this study, five commonly used deep-learning microarchitectures are used. Let us discuss each architecture:

a) InceptionV3:

For the 'ImageNet' data, InceptionV3 is a popular Image Recognition (IR) architecture that has been shown to reach more than 78.1% accuracy. This model represents the culmination of numerous theories given by diverse researchers over time. By changing earlier Inception architectures, InceptionV3 is primarily focused on utilizing less computing power. InceptionV3 has been confirmed to be more processing efficient than other microarchitectures, both from the perspective of a number of parameters and the financial cost incurred.

Figure IV represents the inceptionV3 microarchitecture [20].



Figure IV: InceptionV3 Architecture [20]

b) Xception:

The Xception refers to the most extreme kind of inception. The Xception microarchitecture is made up of a linear pile of 'Depthwise Separate Convolutional Layers' with skip (residual) connections. This simplifies the process of defining and altering the architecture. It is devised by 'Google'. A pre-trained version of this model is trained on 'Google's ImageNet' database. Figure V shows the architecture's entry, middle, and exit flow. This is a layer diagram to represent the Xception Neural Network microarchitecture.

• ResNet50V2:

Resnet50V2 is a vast architecture. A modern Convolution Neural Network (CNN) uses residual blocks in the architecture to solve vanishing gradient difficulties. Many skip connection blocks (residual blocks) are slanted on top of each other inside a residual network. Each residual block is constructed by connections from one or more layers.



Figure V: Xception Architecture [21]

r(64, 7X7) Conv Lays 224X224 sized image Block 1 Max Pool (3X3) Conv Layer 1(64, 1X1) Block 2 Conv Layer 2 (64, 3X3) X3 Conv Layer 3(256, v Layer 1(128. Layer 2 (128 X4 Block 3 Laver 3/512. ayer 1(256 Block 4 X1) onv Layer 2 (256, X6 Average Pool2D Flatten nse FC Layer Classifier v Layer 1(512, Block 5 v Layer 2 (512, Dropout Output Layer X3 er 3/2048

Figure VI: ReSNeT50 Architecture [22]

Resnet50V2 has weight layers that are pre-activated. On the datasets, ResNet50V2 makes accurate predictions.

In later years, it was adapted from Resnet50 for better performance than preceding systems such as Resnet101. The layered representation of ResNet50V2 is shown in the figure, i.e., figure VI.

• VGG19:

The VGG model belongs to a family of models that includes the VGG11, VGG16, and others. VGG19 has 19 layers (Convolutional layers, MaxPool layers, Dense layers) and 19.6 billion FLOPs. A 224 x 224 grayscale image is fed into the VGG-based convNet.

The preprocessing layer uses a grayscale image with pixel values ranging from 0 to 255. But in this case, the input is modified to take a 200 x 200 grayscale image. VGG19 is depicted in figure VII.

• DenseNet201:

DenseNet201 is a convolutional neural network with 201 layers. According to a recent study, convolutional networks with fewer connections between layers near the output and those near the input can be trained to be considerably deeper, more correct, and more efficient. DenseNet joins everyone layer to all other layers in a feedforward method. Unlike standard N-layer convolutional networks, which have N connections – one between all layers and the layer after it – the DenseNet network has N(N+1)/2 direct connections.



Figure VII: VGG19 Architecture [23]

The feature maps of all previous layers are utilized as input into each layer, and their feature maps are castoff as input into all future levels. DenseNet has a plethora of enticing features: It solves the problem of vanishing gradient, boosts feature propagation, stimulates feature reuse, and drastically reduces the no of parameters. The layered depiction of DenseNet201 is shown in figure VIII.



Figure VIII: DenseNet Architecture [24]

Table I shows the training parameter used in this study. The image's shape is kept at 200×200 with three channels for RGB, the number of epochs utilized for training is 30, and the learning rate is kept constant at 0.001 for all the models. Although the number of layers varies from architecture to architecture, DenseNet has the highest number of layers, 201, which is the reason for its performance. The model

with the smallest number of layers is VGG19. It has only 19 layers.

After creating the deep learning models, each of the models is evaluated. The evaluation parameters used in this study are Accuracy, Precisions, Recall, F1-Score, and Roc Curve. Each of these metrics is discussed as follows:

• Accuracy:

Accuracy is the degree to which the experimental value corresponds to the actual amount of the substance in the matrix. eq. (1) is used to represent it. TN denotes True Negative, FP denotes False Positive, TP denotes True Positive, and FN denotes False Negative.

S. Architecture Input Epoch No. of La	earning
No Snape ¹ Layers	Rate
1. DenseNet201 (200,200,3) 30 201	0.001
2. ResNet50V2 (200,200,3) 30 50	0.001
3. InceptionV3 (200,200,3) 30 48	0.001
4. Xception (200,200,3) 30 71	0.001
5. VGG19 (200,200,3) 30 19	0.001

Table I: DNN Parameter used in Experiments

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$
(1)

Mathematically accuracy is the ratio sum of True Positive and True Negative to all the observations.

• Precision:

Precision simply indicates the number of correctly predicted data items among the predicted data elements. Mathematically it is represented by eq. (2).

$$Percision = \frac{TP}{TP + FP}$$
(2)

Precision shows how many correct positive observations are among all the positive observations.

• Recall:

It shows the number of correct data items predicted. Recall shows how many genuinely positive observations have been predicted by the algorithm. Mathematically it is represented by eq. (3).

$$Recall = \frac{TP}{TP + FN}$$
(3)

• F1-Score:

The F1-Score is a prominent measure chosen for classification performance evaluation as it considers both Precision and Recall. Due to the involvement of Precision and Recall, this metric is considered quite authentic for performance evaluation. Mathematically it is calculated by eq. (4). It is the harmonic mean of Recall and Precision.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$
(4)

ROC Curve:

This statistic is premeditated by means of the receiver operating characteristic curve, which shows the relationship between the TPR (also known as sensitivity) and the FPR (1- specificity). The ROC-AUC (Area Under the ROC) Curve is a binary classification statistic that reflects how effectively a classification model can differentiate between negative and positive goal classes.

A multiclass ROC is plotted in this study. In the ROC curve, FPR is depicted on the X-axis, while TPR is represented on the Y-axis.

IV. RESULT AND DISCUSSION

In this part, the empirical results of this research are discussed. The results are categorized as individual class evaluation, Overall and weighted metrics evaluation, and ROC evaluation.

This is a classification problem and the reason for choosing these parameters is because these are standard classification evaluation performance metrics.

A. Individual Class Evaluation:

The Accuracy, Precision, Recall, and F1-Score are the primary requirements for this unique study. Figure IX depicts the Recall, Precision, and F1-Score for all classes. The two best-performing algorithms, according to the results, are DenseNet and ResNet. The highest performance is obtained on the 'After Drought' class where DenseNet produced 0.93 precision, 0.66 Recall, and 0.77 F1-Score and Precision, Recall, and F1-Score for 'After Drought' produced by ResNet are 0.91, 0.8, 0.85. Figure IX gives a clear overview of the individual performance of each class in terms of Precision, F1-Score, and Recall. The least Performing classes are 'Drought' and 'No Drought'.



Figure IX: Precision, Recall, and F1 Score for Individual Classes

B. Overall Evaluation:

To better understand the performance, it is essential to evaluate the model as a whole. Table II displays the model's overall precision, weighted and macro average, 0020Precision, Recall, and the F1-Score. In terms of accuracy, DesnseNet and ResNet rank first with an accuracy of 0.7, followed by InceptionV3 with an accuracy of 0.68. The model with the lowest accuracy is VGG19, which has a score of 0.6.

Evaluation of Deep Learning Approaches for Classification of Drought Stages Using Satellite Imagery for Tharparker

In terms of Precision, Recall, and F1-Score, DenseNet exceeds all other models, with weighted average Precision, Recall, and F1-Scores of 0.74, 0.7, and 0.7, respectively, and macro Precision of 0.73, Recall of 0.7, and F1-Score of 0.7. The VGG19 macro average and weighted average Precision of 0.63, Recall of 0.61 and 0.6, and F1-Score of 0.6 are the poorest performing models.

C. ROC Curve:

Figure X shows the multiclass ROC for all the models. Each graph of the model plots the False Positive rate against the True Positive rate. Four classes are plotted on each of the graphs. A shallow ROC curve represents more AUC, and more AUC represents the better-performing class. It can be observed from figure X that the curve of 'After Drought' has the most area under the curve for all of the models. Hence it is another proof that it contributes more to the model's performance.

The areas under the curve for different models are different as observed DensNet and ResNet have a higher AUC. VGG19 has the least AUC, i.e., VGG19 ROC curves are steeper.
 Table II: Macro, Weighted Precision, Recall, F1-Score, and Overall

Acculacy							
Architecture	Metric	Precision	Recall	F1-Score	Accuracy		
DenseNet	Macro Average	0.73	0.7	0.7	0.7		
	Weighted Average	0.74	0.7	0.7			
ResNet	Macro Average	0.71	0.7	0.69	0.7		
	Weighted Average	0.71	0.7	0.69			
InceptionV3	Macro Average	0.65	0.64	0.64	0.68		
	Weighted Average	0.65	0.65	0.65			
Xception	Macro Average	0.68	0.68	0.68	0.65		
	Weighted Average	0.69	0.68	0.69			
VGG19	Macro Average	0.63	0.61	0.6	0.6		
	Weighted Average	0.63	0.6	0.6			



Figure X: ROC Curve for each of the Model

V. CONCLUSION

Drought is an ongoing problem in Pakistan due to high toxic emissions, climate change, and variability. Drought has wreaked havoc on Tharparkar, which has 1.6 million people. As a result, drought stage estimation is the most effective method for an early warning system for preparing vulnerable areas to deal with the drought. DNN is a potent tool employed for classification and forecasting. In this research, Different DNN architectures are utilized to predict drought stages in the region of the Tharpakar district with help of satellite images of various time periods. The model built on the DenseNet and ResNet architecture outperformed all the other models with an accuracy of 0.7. This study will help in the early detection of drought stages and will allow inhabitants to take possible actions to fight these drastic effects of drought.

The limitation of this study includes a limited amount of data to be trained. Neural networks require a massive amount of data to train. Moreover, the dataset used in this study focuses on a single region, contributing to the lack of images.

In the future, more diverse regions will be covered, more amount of data will be gathered, and a multitude of Deep neural network architectures will be used. Nevertheless, this study paves the way toward drought stage prediction using satellite images and deep learning.

Acknowledgment

The authors would like to thank almighty Allah first and then the management of Mehran University of Engineering and Technology, Jamshoro, Sindh, Pakistan, for their support and their assistance throughout this study.

Authors Contributions

Each author has equally contributed to achieving the objectives of this research study.

Conflict of Interest

The authors declare no conflict of interest and confirm that this work is original and not plagiarized from any other source.

Data Availability Statement

The testing data is available in this paper.

Funding

This research received no external funding.

References

- Siddiqui, S. and Safi, M. W. A. (2019). Assessing the Socio-Economic and Environmental Impacts of 2014 Drought in District Tharparkar, Sindh-Pakistan. *International Journal of Economic and Environmental Geology:* 8-15.
- [2] Wilhite, D. A. (2005). Drought and water crises: science, technology, and management issues. Crc Press.
- [3] Le Page, M., & Zribi, M. (2019). Analysis and predictability of drought in Northwest Africa using optical and microwave satellite remote sensing products. *Scientific reports*, 9(1), 1-13.
- [4] Juana, J. S., Makepe, P. M., Mangadi, K. T., & Narayana, N. (2014). The socio-economic impact of drought in Botswana. *International journal of environment and development*, 11(1), 43-60.

- [5] Brohi, S., Khuhro, T. A., Kalwar, S., Brohi, A. A., Brohi, Y. K., & Rajput, A. A. (2020). Assessment of agriculture sector using SWOT analysis: A case study of Mirpur Khas, Sindh. *Sindh University Research Journal-SURJ (Science Series)*, 52(04), 369-374.
- [6] Khan, M. A., Tahir, A., Khurshid, N., Husnain, M. I. U., Ahmed, M., & Boughanmi, H. (2020). Economic effects of climate change-induced loss of agricultural production by 2050: A case study of Pakistan. *Sustainability*, *12*(3), 1216.
- [7] reliefweb.int. (2019). Pakistan: Drought Response Plan (Jan Dec 2019). Retrieved From: https://reliefweb.int/report/pakistan/pakistandrought-response-plan-jan-dec-2019
- [8] Park, H., Kim, K., & Lee, D. K. (2019). Prediction of severe drought area based on random forest: Using satellite image and topography data. *Water*, 11(4), 705.
- [9] Khan, N., Sachindra, D. A., Shahid, S., Ahmed, K., Shiru, M. S., & Nawaz, N. (2020). Prediction of droughts over Pakistan using machine learning algorithms. *Advances in Water Resources*, 139, 103562.
- [10] Malik, A., & Kumar, A. (2020). Meteorological drought prediction using heuristic approaches based on effective drought index: a case study in Uttarakhand. *Arabian Journal of Geosciences*, 13(6), 1-17.
- [11] Shahbazi, A. R. N., Zahraie, B., Sedghi, H., Manshouri, M., & Nasseri, M. (2011). Seasonal meteorological drought prediction using support vector machine. *World Applied Sciences Journal*, 13(6), 1387-1397.
- [12] Illeperuma, G., & Sonnadara, U. (2009). Forecasting droughts using artificial neural networks. *Promoting Knowledge Transfer to Strengthen Disaster Risk Reduction & Climate Change Adaptation*, 100.
- [13] Ali, Z., Hussain, I., Faisal, M., Nazir, H. M., Hussain, T., Shad, M. Y., ... & Hussain Gani, S. (2017). Forecasting drought using multilayer perceptron artificial neural network model. *Advances in Meteorology*, 2017.
- [14] Hassanzadeh, Y., Ghazvinian, M., Abdi, A., Baharvand, S., & Jozaghi, A. (2020). Prediction of short and long-term droughts using artificial neural networks and hydro-meteorological variables. arXiv preprint arXiv:2006.02581.
- [15] Mulualem, G. M., & Liou, Y. A. (2020). Application of artificial neural networks in forecasting a standardized precipitation evapotranspiration index for the Upper Blue Nile basin. *Water*, 12(3), 643.
- [16] Adede, C., Oboko, R., Wagacha, P., & Atzberger, C. (2019). A mixed model approach to drought prediction using artificial neural networks: Case of an operational drought monitoring environment. arXiv preprint arXiv:1901.04927.
- [17] Maity, R., Khan, M. I., Sarkar, S., Dutta, R., Maity, S. S., Pal, M., & Chanda, K. (2021). Potential of Deep Learning in drought assessment by extracting information from hydrometeorological precursors. *Journal of Water and Climate Change*, 12(6), 2774-2796.
- [18] Felsche, E., & Ludwig, R. (2021). Applying machine learning for drought prediction in a perfect model framework using data from a large ensemble of climate simulations. *Natural Hazards and Earth System Sciences*, 21(12), 3679-3691.
- [19] Raza, O., Memon, M., Bhatti, S., & Pathan, N. (2021). Drought Prediction with Raw Satellite Imagery and Ensemble Supervised Machine Learning. *Review of Environment and Earth Sciences*, 8(1), 1-7.
- [20] Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 2818-2826).
- [21] Chollet, F. (2017). Xception: deep learning with depthwise separable convolutions In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR).
- [22] Das, A. K., Ghosh, S., Thunder, S., Dutta, R., Agarwal, S., & Chakrabarti, A. (2021). Automatic COVID-19 detection from X-ray images using ensemble learning with convolutional neural network. *Pattern Analysis and Applications*, 24(3), 1111-1124.
- [23] Zuppichini, F. S. (n.d.). Pytorch Module Storage: A easy to use API to store outputs from forward/backward hooks in Pytorch. Retrieved from: https://github.com/FrancescoSaverioZuppichini/PytorchModuleStorage
- [24] Jaiswal, A., Gianchandani, N., Singh, D., Kumar, V., & Kaur, M. (2021). Classification of the COVID-19 infected patients using DenseNet201 based deep transfer learning. *Journal of Biomolecular Structure and Dynamics*, 39(15), 5682-5689.