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INTEGRATING REMOTE SENSING AND DEEP LEARNING FOR AGRICULTURAL DROUGHT MONITORING

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Abstract
An understanding of agricultural drought is critical in the management of agricultural lands especially in times of drought stress, which has adverse effects on agriculture. Management of drought, especially in its early stages, relies heavily on indices that are typically derived from onsite observations; thus coordination is often disadvantaged owing to the numerous factors that lead to drought. This study aims to improve the accuracy of monitoring drought conditions via deep learning techniques assisted by remote sensing data. A custom dataset of 544 JPG images (150x150 pixels) was compiled, consisting of 335 images representing drought conditions and 209 images without drought. Different deep learning architecture were executed employing varied layer and activation function configurations. It was observed that where models were developed employing multiple layers and using ReLU and Sigmoid activation functions, the accuracy obtained was as high as 97%. Emphasizing the gradual but progressive applicability of deep learning models for more efficient and forward-looking agricultural drought relying on satellite images. This mode of drought management is on the increase and enhances the overall effectiveness and viability of the agricultural drought monitoring systems.

INTRODUCTION

Agricultural drought is one of the most pressing problems globally since it hampers food production, disrupts economic development, and jeopardizes the environment. Because climate change keeps on exaggerating the consistency of weather patterns, it is imperative that effective observations and management of drought occurrences be integrated. Most of the conventional agricultural drought monitoring practices that are based on actual ground measurements and historical evidence tend to limit themselves in the geographical and temporal distribution of the drought incident, which is very common especially in large agro-rangelands [1]. ADOS and related technologies have been a boon in such conditions in assessing agricultural drought and other related impacts. For example, NASA's Moderate Resolution Imaging Spectrum (MODIS) satellite missions and Sentinel-2 launched by the European Space Agency provide high-definition images that can be used to evaluate vegetation, soil moisture content, and other vitals stressed by drought. These technologies help in real-time monitoring of large extents of area which is essential for making timely decisions in agricultural management with relevant information [2]. Distant sensing with the integration of deep learning techniques has elevated the art of drought assessment and monitoring. Deep learning allows the features extraction from huge amounts of data to be performed in an automatic as well as very complex way, particularly by means of Convolutional Neural Networks, Long Short-Term Memory networks, and more recently, Transformer models [3]. For example, [2] showed that by using a model based on the

Transformer it was possible to improve drought prediction by involving many data sources and understanding the relationships between climatic fields and drought symptoms. These pursued are yet showing great efficiency utilizing deep learning. [3] adopted such an approach, obtaining better drought forecasts employing a hybrid LSTM-CNN which exploits time-series multispectral satellite images. Moreover, this ability to merge vital information from different data sources is considered a step forward than the normal methods which are effective on assessing impacts of droughts on agriculture [4]. However, quite a few obstacles remain such as data availability, model interpretability, and real-time processing requirements [5]. How such challenges are addressed will be vital in reaping maximum benefits from both deep learning as well as remote sensing technologies towards effective agricultural drought monitoring. Deep learning is a machine learning paradigm that has become popular in the last few years owing to its considerable transformation across many applications such as computer vision, natural language processing, and healthcare. Simply put, deep learning applies the use of Artificial Neural Networks as functions which model multiple processed feature vectors through many layers in large datasets. The ability of such structures to learn embedded images has helped them greatly, which in turn has made them most useful in tasks requiring high complexity in terms of power and data [6]. One such evolution of deep learning is Convolutional Neural Networks (CNN) model, where image processing capabilities have improved to immense possessor. CNNs efficiently recognize edges, shapes, and textures in an image, thus making them successful in tasks such as image classification [7]. The ImageNet competition, for example, has illustrated that CNNs can deliver better results compared to previous planar classifications, with impressive shot advances, and new standards for image retrieval have been laid. Yet one more notable progress in deep learning research has been the development of Transformer models, which have revolutionized the field of natural languages processing. This model is based on self-attentive mechanisms and is very useful for such applications as processes, translates, analyses sentiments and even generates text [8]. The emergence of the models such as BERT and GPT has proven the effectiveness of the Transformers in understanding relationships between textual subjects therefore performing better on various tasks [9]. The application of deep learning has expanded from the area of image and language processing to other disciplines like health care, financial services, and agriculture. For instance, deep learning technologies are becoming more popular in diagnosing diseases, assessing the risks and in forecasting situations and events [10]. In the agricultural field, deep learning is utilized to assess the health status of plants, forecast their output and investigate their illnesses with the aid of remote sensing information incorporated into the decision-making process [2]. Nonetheless, despite that success, deep learning still experiences several obstacles including the need of large amounts of labeled data, high computation cost, and issues on prospects of understanding models. These issues are being researched by the use of methods such as transfer learning, data augmentation and model pruning which the researchers seek to augment the accessibility and efficiency of deep learning techniques [11]

Literature Review:

Lessons learned and subsequent innovations have stimulated widespread global interest and the broadening of the scope of Remote Sensing research. Such information is usually obtained from space-borne remote sensing satellites, whereby several programs such as MODIS of NASA and Sentinel of ESA have started to capture important vegetation, soil moisture, and climatic parameters. According to [12] normalized vegetation index NDVI, soil moisture index SMI derived from satellite images have some relevance in calculating drought impact and its potential risk to crop production. The application of deep learning has improved the process and quality of drought extraction from remote sensing images. Two types of Artificial Neural Networks (ANN)- Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) do well in high dimensional data. Research carried out by [13] used CNNs to classify drought conditions using MODIS images and accurately classified drought in different levels. Researchers have harnessed the use of deep learning models and combined it with the remote sensing data for better and advanced drought monitoring systems. One such example is the one described in [14] which performed the task of agriculture drought forecasting in China utilizing a hybrid deep learning network comprising CNN and Long Short-Term Memory LSTM modules. This method was able to successfully detect both spatial and temporal structures improving the overall accuracy of predictions. Many case studies have shown the real-world applications of these methods in different regions of the world. For example, [15] attempted to study the use of deep learning methods for the assessment of droughts in the USA. They emphasized how the augmentation of Drought Assessment and Control systems can be improved with the integration of numerous satellite images using advanced machine learning techniques. While these advancements hold promise, the use of these technologies in practice remains a challenge. Some of the problems were pointed out by [16] like data quality, the explain ability of the model, and inadequate real-time monitoring systems of the weeds. The authors point out the need for standard procedures and the use of ground-truth data for better model performance.

This study, on the contrary, timely observes agrarian drought using an appropriate framework on deep learnings and spatial data from South Asia. For the period of tropic events performed during the 2010 to 2021, moisture content is assessed and assists in addressing crop production and water resource availability challenges. The use of remote sensing complements the conventional assessment of drought impacts and places emphasis on the need for incorporation of remotely sensed variables. It finally encourages use of cross sectoral approaches in enhancing the drought resilience capabilities of agricultural systems and improving drought management. (17 Water Management). Prolonged periods of little or no rainfall that occur during the growing season resulting in insufficient soil moisture resources are referred to as agricultural droughts and hinder proper management of food resources and water systems. Inability to monitor land phenomena by ground observation systems led to the increase of the use of remote sensing systems. Enhanced thermal and optical remote sensing techniques especially different vegetation indices enable more sophisticated evaluation of plant spectral Liechtenstein and evaluate vegetation Extension and drought stress. (Arthur et al 20 2021). To assess agricultural drought across three phonological stages in this study, a Deep Feed Forward Neural Network (DFNN) was used along with other soil vegetation and precipitation data. This model was more effective than other traditional models like Random Forest and Support Vector Machine. Even within regional differences, the DFNN consistently revealed a strong prediction capability and stability of drought indices. To enhance the resilience of agrarian systems to drought and understand its complex nature the study suggests the amalgamation of deep learning with the remote sensing data to carry out drought assessment more successfully [18]. Most of the research work regarding droughts in Pakistan during the years 2020 to 2022 was undertaken by Southeast Asian countries, whose economies are severely affected by these natural calamities like the current study. He emphasizes the importance of using remote sensing for the assessment of drought indicators, such as soil moisture and vegetation condition, and spatial data science strategies for improving decision making and hence resource governance. The purpose of this research work is the enhancement of the knowledge on drought behavior and the improvement of resilience on water-related issues in a changing world through the application of multi-sensor data and the formulation of drought indices. [19]. Most of them evaluate particularly vegetation indices from multispectral optical remote sensing and this study advocates that the main data sources for drought monitoring are over such literature. However, the application of multi-sensor products and machine learning for big data measurements remains a challenge despite the increasing interest in drought studies. More efforts in the future towards reducing the impacts of drought in Southeast Asia will have to adapt policies focusing on the normalizing practices that integrate EO and socio-economic aspects and enhance data sharing in order to enhance resilience and adaptation strategies [20]. This study implements composite drought indices for Shandong Province North China using remote sensing data sourced from multivariable linear regression during the years 2013 to 2017. It emphasizes how efficiently the

Membrane Capacitive Dilution Index (MCDI) based upon the Standardized Precipitation Evapotranspiration Index (SPEI) correlates with meteorological droughts. Regarding the successful management of drought use, the authors cumulatively emphasize the need for incorporating satellite and field studies towards providing relevant information to the stakeholders and policymakers [21]. This study describes drought and climate change as very complicated relations and reveals the great impact which drought has on social and ecological sectors. To measure and analyze those characteristics of drought, it introduces the system of standard indices and including such indices as the Standardized Precipitation Index and the Standardized Terrestrial Water Storage Index. Also, with the intention of evaluating the efficacy of these indices the research uses the history of decade-long changes of vegetation and precipitation variability [22].

Methodology:

In this methodology, it is described how the architecture and the deployment of the Convolutional Neural Network (CNN) is done for the purpose of predicting various drought conditions with the use of multiple data inputs which includes soil meteorology and satellite images. In order to enable different formats like, CSV and GeoTIFF to be made use of, it requires starts with the process of data collecting. Data preprocessing includes normalization imputation for missing values, diversity enhancement through satellite image augmentation and labeling datasets according to the drought severity. The architecture of CNN is in such a way that there is ReLU activation to incorporate non linearity convolutional layers with different sized filters + several layers of inputs to accommodate different data types. Structural complexity is reduced using max pooling layers while the final layer can either be designed for regression or classification tasks. The learning process incorporates backpropagation while the model parameters were mainly optimized using grid or random search techniques. Using several performance metrics including accuracy, precision, and root mean square error, the developed model was then assessed using the test data set. The cloud based applications are launched after the training of the model for the application so that stakeholders can interact with the easy to use application. What is correct may highlight that, in order to ensure that the model learns and useful for the management of the agriculture and water resources in the long term, it is periodically updated through monitoring and retraining. It may also be the case that future improvements will be targeted at improving the explain ability of the models or incorporating additional data sources to enhance the prediction of the models.

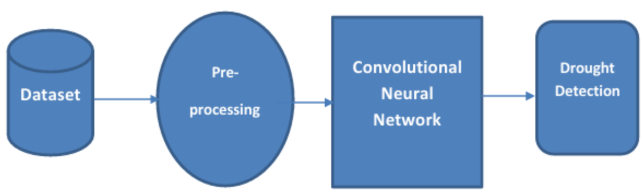


Figure 1: Process model for drought detection Description:

The first step involves collecting a relevant dataset that includes various drought characteristics such as soil moisture, precipitation and vegetative index in the proposed architecture wtih the illustration of figure 1. The dataset will then proceed to data preprocessing in order to prepare the dataset amnd quite ready for a Conv2D network. Contrary to classical CNNs, the architecture will comprise of a lot of layers, which are – several physically unconnected inputs related to different types of input data, which is followed by hidden layers which perform convolution operations in order to understand the spatial patterns and their features. To break the linearity of these hidden layers, activation functions such as ReLE will be employed. The network will finally end with one or more output layers, which according to the overall concept are meant for the prediction of weather conditions with regards to drought based on the processed data provided through the input layer. The model will be trained through the method of backpropagation where weights will be adjusted through training with a dataset that is labeled and shows levels of drought. Hyper-parameters such as the learning rate and batch size will also be played around to improve performance. The CNN will then be assessed on its predictive ability using a validation dataset, which was completely separate from the training data. Finally, it is possible to use the trained model for forecasting future droughts, which would come in handy in planning agricultural and water resources.

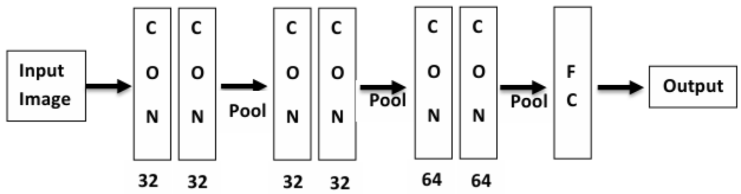


Figure 2. Architecture of a Convolutional Neural Network (CNN) for Image Classification.

Figure 2 shows architecture model which consists of three convolutional-pooling blocks with increasing filter sizes (32, 32, 64, 64), followed by a fully connected (FC) layer leading to the output. "C" denotes convolution, "O" denotes operation (activation), and "N" denotes normalization. The model's input layer corresponds to the point where the data is entered especially image data called array of picture pixels. Data is then sent into the first three convolutional layers which employ first learnable filters or kernels that are depicted in the image and are swept over via element-wise multiplication and the summing of all the images to fashion certain maps that can encapsulate edges, environments, and regular patterns. The number of filters determines the depth of particular feature map; for instance, in the first layer because there were 32 filters, 32 distinct feature maps were produced. Every convolution layer is followed by the inclusion of a Rectified Linear Unit (ReLU) ann activation so as to import non-linearity in which each negative valued pixel is set to 0 and the positive valued ones reserved to assist in the learning of intricate interactions from the data. Right after ReLU activation, the following max pooling layers serve to take the spatial size of the feature maps down but preserving important content by taking out the maxima in the separated segments. It is through this hierarchy of convolutional layers followed by releu activations and max pooling that allows the model to learn progressive manner features where the first features captured low levels and the last layers captured high levels supreme features. In the end, the feature maps after being flattened are directed to one or more fully connected layer(s) where the model perf

TensorFlow:

TensorFlow's strength lies in the interaction between the programming instruments of very high-level dataflow programming and low-level parameter server-based systems in that it allows to express the state and computations of an algorithm as a single dataflow graph. The graph vertices in TensorFlow are capable of representing computations with operands that have variable states which is not the case with other dataflow approach. Its network is limited but able to span barriers using tensors that are arrays of arbitrary dimensionality that move across the network's nodes via edges connecting them[24]. This is because both computations and state management are integrated in a single entity and under such circumstances, it is possible for the programmer to try different ways of decomposing problems in parallel such as offloading computations to servers that manage shared states thereby reducing the network overhead. [23]

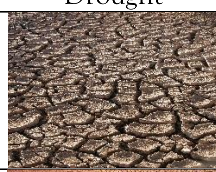
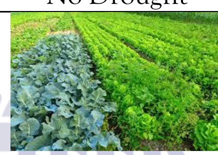
Rectified linear units (ReLU).

The application of neural network architectures is enhanced by replacing the standard hyperbolic tangent activation function with ReLU (Rectified Linear Unit) whose origins stem from biological processes as well. Values defined by (f(x) = max (0 x)) are sharpened point where f (x) is equal to or less than 0 and linear relief or input is called zero. The ReLU is the activation function for hidden layers while the softmax is the activation function for the output. In spite of that Softmax is frequently employed for classification in this investigation the softmax cross-entropy function shall be employed for regulating the network's weight parameters called theta whereas ReLU is taken over as predictive unit. Repetition of the above "No Go" explaining as objective during testing. To revise these parameters, the section of the gradient computed by the ReLU classifier is transferred backwards. [24].

Data augmentation for improving the model:
The given validation error and the given training error will always decrease in order to make useful Deep Learning models. If you want to achieve this, it is often the case that data augmentation is used for this purpose. Since the modified data will be able to cover a wider range, the dichotomy of the training and validation set and any subsequent testing set will be lower.

Dataset:
543 images were collected through a search on Google.com where 335 images are in drought conditions while 209 images are not. All images are in JPG format and of the size 150 x 150 pixels. The images present equal proportions of the drought affected and non-affected regions and hence a model for predicting drought would be easy to build, train, and test with this dataset. Some set of images showing the condition of drought and no drought is shown is provided in table-1. The same procedures have been adopted here as then so the same file formats and size will be used in future analysis.

Table 1: Set of images for Drought and without Drought condition

S.no	Drought	No-Drought	Format
01			JPG
02			JPG
03			JPG
04			JPG
05			JPG
06			JPG
07			JPG

08			JPG
09			JPG
10			JPG

Results and Discussion:

The evaluation of the CNN architecture for the prediction of droughts through the experiments showed different levels of success that were affected by the different configurations of layer types and activation functions presented in table-2 and figure 3. The first experiment implemented a simple architecture composed of one convolution layer (32 filters) and one max pooling layer and one fully connected layer with 64 neurons and ReLU activation. The structure was sufficient to produce an accuracy of 97%, proving that indeed the main aspects of drought conditions were captured shown in figure 4. The second experiment maintained this structure but included one more convolution layer and kept accuracy at the rate of 97%, showing that more features were being extracted but the model was still generalizing. On the other hand, in the 3rd experiment, the inclusion of the third convolution layer with 64 filters brought it down to about 85%, suggesting that the features were redundant in that the network started to pick signals from the noise. The sever shift to SELU and Tanh activations in the fourth experiment also resulted in a drop of accuracy to 83%. The effects of activation selection on performance were evidenced by this study. In the 5th experiment, SELU was applied across all the layers of the network and the accuracy rate dropped even lower to 72%, revealing that the activation function used was not suitable for the dataset. This trend followed and experiment 6 had an accuracy rate drop to 40% suggesting potential convergence problems perhaps due to wrong selection of activations. Conclusively, we observed that the experiment number 7, equally employed exceptions of Tanh across the convolutional layers returning modest improvement of 85% suggesting that there is growing importance of deep architectures using tanh but does not guarantee superiority to the deep architectures using Relu.

Table 2: Comprehensive results of all experiments conducted

Experiment No	No. of Epochs	Batch Size	Layers	Activation Functions	Accuracy
Experiment 1	100	64	2	relu, sigmoid	97%
Experiment 2	100	64	3	relu, relu, sigmoid	97%
Experiment 3	100	64	4	relu, relu, relu, sigmoid	85%
Experiment 4	100	64	4	relu, selu, tanh, sigmoid	83%
Experiment 5	100	64	4	selu, selu, tanh, sigmoid	72%
Experiment 6	100	64	4	selu, selu, selu, sigmoid	40%
Experiment 7	100	64	4	tanh, tanh, tanh, sigmoid	85%

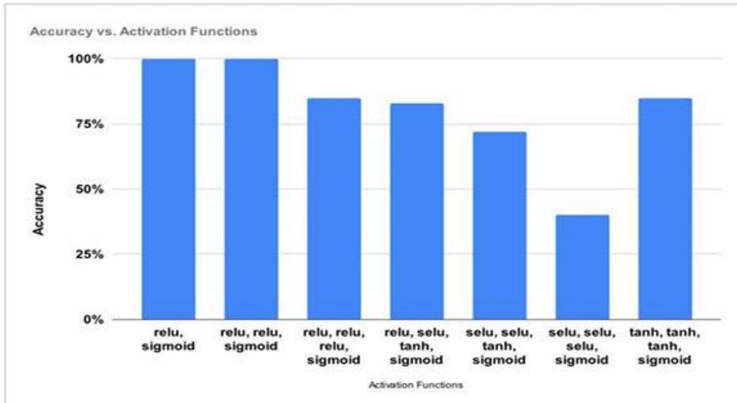


Figure 3. Graphical representations of experiments

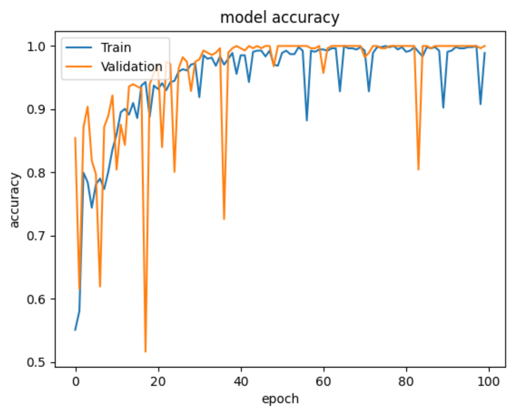


Figure 4: Model accuracy of train and validation of experiment

Conclusions

This paper focuses on drought assessment using Convolutional Neural Networks (CNN) and deep learning methods. The paper demonstrates that CNN models, which are based on custom datasets, can forecast drought conditions following image classification. This accuracy underwent several rounds of experiments where the first experiment was remarkably able to get 97 % accuracy and subsequent experiments ranged between 40% and 85%. These results demonstrate how far CNNs can go in learning and classification of drought situations while also emphasizing the importance of optimizing the multiple regularization strategies, activation functions, and models used to improve the validity of the predictions and also avoid overfitting. Finally, the next task would be improving the CNN architecture, trying new augmentations, and adding other parameters like temperature or soil moisture. There is also a need to evaluate the CNN models and the eventual application of the models in field settings to enhance such understanding across regions increasing the probability drought pronouncements would be reliable.

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