2021 Asian Conference on Innovation in Technology (ASIANCON)
Pune, India. Aug 28-29, 2021

Performance Analysis of CNN, AlexNet and VGGNet Models for Drought Prediction using Satellite Images

Shilpa Chaudhari
Dept. of Computer Science and Engineering
M S Ramaiah Institute of Technology,
Bengaluru, India (Affiliated to VTU)
shilpasc29@msrit.edu

Vandana Sardar
Dept. of Computer Science and Engineering
M S Ramaiah Institute of Technology,
Bengaluru, India (Affiliated to VTU)
vandana.s@msrit.edu

D.S Rahul
Dept. of Computer Science and Engineering
M S Ramaiah Institute of Technology,
Bengaluru, India (Affiliated to VTU)
shilpasc29@msrit.edu

M Chandan
Dept. of Computer Science and Engineering
M S Ramaiah Institute of Technology,
Bengaluru, India (Affiliated to VTU)
chandanvirat10@gmail.com

Mahantesh Shivanand Shivakale
Dept. of Computer Science and Engineering
M S Ramaiah Institute of Technology,
Bengaluru, India (Affiliated to VTU)
mss891999@gmail.com

Harini K.R.
Dept. of Computer Science and Engineering
M S Ramaiah Institute of Technology,
Bengaluru, India (Affiliated to VTU)
harini5676@gmail.com

2021 Asian Conference on Innovation in Technology (ASIANCON) | 978-1-7281-8402-9/21/$31.00 ©2021 IEEE | DOI: 10.1109/ASIANCON51346.2021.9545068

***Abstract*—Drought is a naturally occurring event in particular geographical area. Droughts are classified as one of the major naturally occurring hazards causing severe impact on the entire environment as well as economy of the countries throughout the globe. Droughts are being aassociated with weather conditions that cannot be monitored only using weather data, strictly because these obtained data are likely to be incomplete, infrequent and ill-timed. Naturally predicting these kinds of events is not preferable and effective. Taking deep learning and artificial intelligence advancement into an account, we have analysed and compared the CNN, AlexNet and VGGNet using satellite images and indices calculated from those images of a particular geographical area and defined accuracy and performance of each models towards the data and for each type of drought indices like Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index(SAVI), Enhanced Vegetation Index(EVI) and Atmospherically Resistant Vegetation Index(ARVI), the models performance has been demonstrated in this paper .**

Keywords—Drought prediction, image processing, drought indices, neural networks.

I. Introduction

Drought is the non-appearance of the water over for a particular period of time. Drought is a part of climate cycle that naturally occurs. Drought can prosper in any region or a particular area and can last for a varying time length, usually from several weeks to decades. It can have a substantial impact on the livestock and ecosystem of the affected region. Droughts are among the most detrimental natural calamities as they cause severe conditions leading to a humanitarian crisis. Drought is mainly classified into four categories based on climatological community; Agricultural, Socio-Economic, Hydro-logical and Meteorological drought, Agricultural drought defined as a situation when soil moisture is not sufficient and leads to the scarcity of crop production and growth. Hydrological drought is caused by insufficient availability of groundwater and decreased river water discharge. Meteorological drought is caused by lack of rainfall. Socio-Economic drought defines as a time when there is a lack of availability of a certain goods or product. Though all these types of droughts have serious impacts on society, agricultural drought is a large threat to the economy sector, both to the producers and consumer of livestock.

Previously used methods for monitoringdrought were purely based only on rainfall data, which had numerous limitations like the climate data was insufficient and sometimes inaccurate in addition to the human errors and network of stations are limited, extensively it was difficult to obtain both spatial and temporal real time data. Taking all these into an account we can analyse the drought over a particular region using satellite images with the help of deep learning techniques. In order to obtain deep learning algorithmic predictions, algorithms have to be fed with some data but getting those data is a challenging task in the real world and those data are mostly not accurate as well. So using satellite images of a particular area we can calculate the indices values with the help of RGB and infrared bands using some formulas. By obtaining these calculated indices values we can train and test the deep learning models for the output predictions of the drought and by feeding satellite images to image processing algorithms in the deep learning along with the calculated indices values gives better drought predictions.

Nowadays, advancing technologies and Human thinking in the field of machine learning and deep learning techniques can improve drought monitoring, handling, precautionary measures towards this field. And also, it is very helpful to farmers in the agricultural sectors.

II. RELATED WORKS

Satellite Images for Drought Monitoring (SIDM)[1] helps in real-time drought monitoring in Ethiopia country. That develops a new unique way to extract information from satellite images. Using the concept of local minima and local maxima and deviation values(NDVI) the drought objects are extracted here. The maximum deviation value that is recorded in this region is -0.552, which is negative, here positive deviations show the healthy vegetation growth in the region while the negative NDVI deviations depicts the current drought in the region. Geo-spatial analysis gives the result of about 37% of the complete area had less than 40% of VCI, which nearly indicates the occurrence of a drought.

Agricultural drought and soil moisture analysis using satellite image based indices (ADUS) [2] examines the SPI as the count of total standard deviations with respect to cumulative rainfall that is recorded at a particular time scale of 1,3,6 months and VHI based on satellite image for drought intensity classification and soil moisture assessment. The drought regions with less than 40 VHI value are categorized as extreme (<10) drought, severe (10-20) drought, moderate (20-30) drought and mild (30-40) drought regions.

Deep Belief Networks for Short-Term Prediction of Drought Index(DBN)[3] discusses design of deep belief network to forecast drought index using SPI. The forecasting methods used are non-homogeneous Markov chain, Grey-time series combined method (GTCM), chaotic Bayesian method, vegetation temperature condition index (VTCI), ARIMA models, Back Propagation Network.

Monitoring of Drought using Satellite Data (MDS)[4] recognizes the high correlation between ground rainfall stations record and NDVI obtained from satellite sources. This also emphasized on use of remote sensing and Geographic Information System(GIS). The endeavor has been made to extract and identify drought risk regions encountering meteorological drought and agricultural drought by making use of NDVI. Therefore, it is culminated those temporal variations of NDVI are convincingly associated with precipitation.

Artificial intelligence models for forecasting meteorological drought using SPI (AIM)[5] explores prediction of short term (SPI-3) and long-term (SPI12) drought conditions using Artificial Neural Networks (ANN), regression vector systems (SVR), adaptive neuro-fuzzy inference system (ANFIS) and Fuzzy Logic(FL).The prediction results of ANN models has been improved by using wavelet analysis. ANN model's relative error(RE) was reduced to 88% when a WN model was used.

Deep learning-based approach for long-term drought prediction(DLP) [6] utilizes seasonal drought prediction model to describe hydrological drought across the Gunnison River Basin based on a Bayesian framework and they have used standardized stream-flow index (SSI) for analysis. Autoregressive integrated moving average (ARIMA), direct multistep neural network (DMSNN) and recursive multistep neural network (RMSNN) to forecast drought in the Kansabati River Basin, India and used a wavelet linear genetic programming (WLGP) model for long lead-time drought analysis. To predict long-term drought conditions using lagged SSI values as inputs, they used deep belief networks with two restricted Boltzmann machine models. Compared to MLP, Deep Belief Network model was found to provide better prediction results, recording lower prediction errors and therefore can be more efficient and reliable for long-term drought monitoring.

Satellite-based hybrid drought monitoring (SBDM)[7] develops satellite based prediction model called VegOut Ethiopia uses regression tree method at a monthly interval in the growing season in eastern Africa and predicts the vegetation outlook(vegetation condition).The attributes used for this model are Standardized deviation of NDVI, Soil water holding capacity, Digital elevation model, Pacific decadal oscillation, three month standardized precipitation index, Atlantic multidecadal oscillation index, North Atlantic oscillation, Pacific North American index, Multivariate ENSO index.

Severe Drought Area using Satellite Image and Topography Data(SDSI) [8] develops short-term drought called SDAP model without using meteorological data. The output predictions of this model give forecasting results of serious drought regions assuming non-rainfall, not a probability prediction of drought occurrence. New remote sensing drought index called Difference Drought Index (DDI) is used. The one developed by Palmer which is calculated from precipitation, temperature and soil moisture content data, is the so-called Palmer Drought Sensitivity Index (PDSI) that has been used in Hungarian study areas.

Satellite image processing for precision agriculture and agroindustry (SIPF)[9] shows that Genetic Algorithm (GA) and convolutional neural network (CNN) can produce an optimum solution in a short time. Satellite image is processed using CNN then obtained data is modeled in a grid structure form, then this grid form model is evaluated. The optimization process is done GA and the process is referred as Recombination. It is a method to store all the individuals which are best in a multi-objective GA generation process making, a size of population two times larger by combining off spring and parents. After the combination each and every individual is given a crowding distance value and rank, after that the population will be reduced to half, taking this into consideration of a crowding distance value. By cutting the last individuals, next population carries the ones with higher values.

Monitoring of agricultural drought in Poland (MAPD)[10] uses satellite data to recognize and monitor drought. To calculate its impact towards the production of crops. Satellite images from NOAA/ AVHRR 14,16, 18,19, SPOT5/Vegetation2, SPOT-4/Vegetation 1 and Terra/Modis were used for the analysis. The images by Terra satellite were used to determine the agricultural production area. Images taken by NOAA and SPOT was used to determine vegetation indices such as NDVI, VCI and also Temperature Condition Index (TCI) from NOAA/AVHRR. By using this drought forecasting and drought monitoring using satellite images was done.

Enhanced Bag of Features using AlexNet and improved biogeography-based optimization for Histopathological Image Analysis(EABO) [11] is an efficacious method for image classification. It is an open-ended research problem because, it is applicable only on Histopathological images. This paper presents a huge bag of features based on Histopathological image classification. This method mainly involves three steps: (i) Feature extraction using AlexNet, (ii) Optimal visual vocabulary generation using improved biogeography-based optimization, and (iii) Classification done using support vector machine. The experiments are conducted on standard histopathological image dataset for the evaluation.

Utilizing AlexNet Deep Transfer Learning for Ear Recognition (ADLE)[12] provides an easy way of solving classification problem using very little amount of data. In this paper for a well-known AlexNet Convolution Neural Network (AlexNet CNN) they had applied transfer learning method, for recognizing humans using ear images. They had fine-tuned and backed this AlexNet CNN suitable for their problem domain.

A New Deep Learning Method Based on AlexNet Model and SSD Model for Tennis Ball Recognition (DAST)[13] demonstrates to accurately find the position of tennis ball. They have used deep learning methods in-order to improve the accuracy and speed of recognition. They divided this process into two parts to check the presence of the tennis ball using AlexNet network. If a tennis ball is present in that image, then to find the location of a tennis ball. Single Shot multibox Detector (SSD) model is used. If the ball is not present it will continue to check next images using AlexNet.

Deep Learning for Satellite Image Classification (DLSI)[14] focuses mainly on assessing common different techniques used for classification of satellite images and handling public remote-sensing dataset that are easily available based on the features used. The existing remote sensing classification methods are classified into four categories supervised feature learning methods, manually feature-based methods, object based methods and unsupervised feature learning methods.Scene

Classification with Improved AlexNet Model(SCIA)[15]here based on design principle of CNN's improved model of AlexNet has been proposed. Decomposition of large kernel of convolution into a structure plunged by two small kernels of convolution with reduced step. Next to the first layer another convolutional layer is added to intensify the integration process of the spacial data or low level features. For the last three layers, this asymmetric convolution kernel is applied. The accuracy of the classification using two datasets of the improved AlexNet model is higher than those of ZFNet model and normal AlexNet model for scene classification of 23 categories.

In-vivo Skin Capacitive Image Classification Using AlexNet Convolution Neural Network (VSCA)[16] here a novel technique called Skin capacitive imaging, which is implemented for the skin solvent penetration measurements and skin hydration. This research uses AlexNet model to estimate the execution of deep learning method in In-vivo skin capacitive image.

Sequence-dropout Block for Reducing Overfitting Problem in Image Classification (SBRO) [17] in this paper, to reduce the problem of over-fitting. Sequence-dropout(SD) method is implemented. When training the networks, the SD method works as from the network dropping out the units (features channels) in a sequence by replacing the old method of random omitting advanced strategies of aggregation are used to obtain global information of feature channels. Using gating mechanism, channel wise weights are produced. Medical Image Classification:

A Comparison of Deep Pre-trained Neural Networks(MCDP)[18] demonstrates the productiveness of utilizing Domain transferred neural networks(DCNNs) for medical X-ray images classification. Theyhave used two dissimilar CNN architectural models. AlexNet pre-trained on ImageNet and VGGNet-16 for the task of classification.1.2 million scenery non-medical image dataset was used in this research.

Classifying high resolution remote sensing images by fine-tuned VGG deep networks (CRFV)[19]. Here based on deep neural networks a transfer learning algorithm is implemented to knock the problem of lacking labeled RS samples, in especially on the circumstances of pre-trained deep convolutional networks that is VGGNet. The labled multimedia images given by "ImageNet Large Scale Visual Recognition Challenge" (ILSVRC) are used to train the VGGNet.

Facial expression recognition based on VGGNet convolutional neural network (FEVC)[20] here based on deep CNN VGGNet, it implements a facial expression recognition model. The recognition rate is significantly improved with a 2*2 small pool kernels and 3*3 small convolution kernels and with deeper network architecture and the number of parameters are slightly larger compared to shallow layer. Only the fully-connected first layer is preserved from the original network to further reduce the number of parameters.

Pre-trained VGGNet Architecture for Remote-Sensing Image Scene Classification (PVRC)[21] here based on canonical correlation analysis it implements a simple and powerful framework. Using SVM classifier having 4-layers. To extract mid-level and deep features for remote sensing scene images, initially trained VGGNet is employed.

III. METHODOLOGY

Implementing, comparing and analysing the CNN, AlexNet and VGGNet we followed step by step procedure. (1) Step 1: Calculate the required indices using the satellite image data. (2) Step 2: Implementation of CNN. I.e CNN combined with ANN. (3) Step 3: Implementation of AlexNet. I.e AlexNet combined with ANN. (4) Step 4: Implementation of VGGNet. I.eVGGNet Combined with ANN. (5) Step 5: CNN, AlexNet and VGGNet for training the images and ANN is for training indices data. (6) Step 6: Train these CNN, AlexNet, VGGNet with each index along with the satellite images to obtain the results. (7) Step 7: Obtaining results and graphs in the form of accuracy.

A brief description on each model is given in this section separately.

CNN Model for drought prediction: we used CNN is for training the images and ANN for training the indices data as shown in the Figure 1.

For this model, we have used a Convolutional Neural Network, which is described as a CNN model consists of Conv2D layer. Each Conv2D layers has a filter of size 3X3 which moves on the image from top left corner to the bottom right of that particular image. Using a convolution operation, a value is estimated based on filter. For each point on the image, a feature map is produced for each filter. After the images are passed through the filters, these are later carried through an activation function, which determines, in a image if some certain number of features is present at a particular location on the feature maps. In order to select the highest values, we have used pooling layers and we have used these as inputs to succeeding layers. In pooling layers any different kind of operations can be done in theory, but practically only max-pooling layers are used in order to determine the outliers. This can be seen when our network encounters the features.

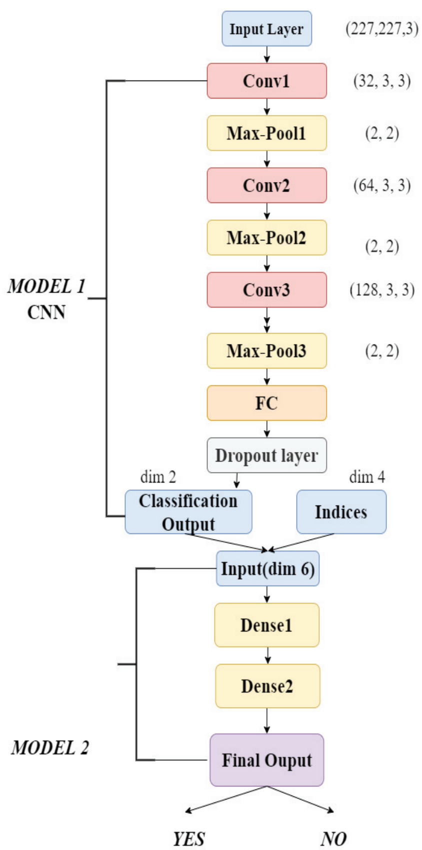

Fig. 1. CNN + ANN Model.

CNN model is mainly composed of layers and these layers are not completely connected to each other, these layers have filters that are cube-shaped sets of weights that are applied throughout the image. Here in the filters, each 2D slice is referred as kernels. These filters instigate parameter sharing and translation invariance. Padding basically makes the feature maps made by the filter kernels constant size because the original image. this is often terribly helpful for deep CNN's as we tend to don't need the output to be reduced in order that we tend to solely have a 2x2 region left at the tip of the network upon that to predict our result. Pooling layers square measure kind of like convolutional layers, however they perform a particular functions like soap pooling, that takes the most amount value in a particular filter region, or average pooling, that takes the common amount value in a particular filter region.

To reduce the dimensionality of the network these are normally used before the classification output of the CNN model. Fully connected layers are placed and before the classification, these are used to flatten the output results. To reduce over-fitting of the model we have a dropout layer before the last layer. Last layer of the network is output layer which consist 2 output classes as defined in the dataset. The output of this model is appended with the other indices calculated from the image such as NDVI, SAVI, ARVI, and EVI. The input for the final model consists of 6-dimension data including the output data from the previous model of 2 dimensions. Then the data is normalized as to reduce dependency of model on certain features. Then the model is trained with the above data.

AlexNet Model for drought prediction: We use AlexNet for training the images and ANN for training the indices data as shown in the figure 2. It is implemented similar to the CNN model, here we have replaced the CNN model with the popular AlexNet algorithm, and everything else is kept the same. In AlexNet algorithm the sequence of the Conv2D and Max-pool layers changes compared to CNN.

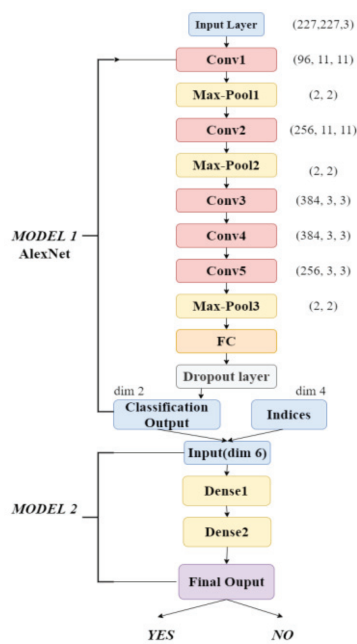

Fig. 2. AlexNet + ANN Model

VGGNet Model for drought prediction: We use VGGNet for training the images and ANN for training the indices data. It is almost similar to that of mentioned two model's Figure 1 and Figure 2. In this model, we have replaced the VGGNet with the popular CNN and AlexNet algorithms, and everything else is kept the same. In VGGNet algorithm, the sequence of the Conv2D and Max-pool layers changes compared to CNN and AlexNet.

IV. RESULT ANALYSIS

In our research, we have created three models for the prediction of drought over a particular area using satellite images and indices data. Each model has performed very well with the best training limits. The accuracy of these models for each index is obtained as given in the Table 1. CNN accuracy is around 94% for NDVI index. VGGNet accuracy is more for ARVI index, both CNN and VGGNet gives same accuracy for SAVI index and VGGNet performed well for EVI index in our implementation.

TABLE I. MODEL ACCURACY COMPARISON FOR DIFFERENT INDICES

Model	NDVI	SAVI	EVI	ARVI	All Indices
AlexNet	0.76	0.67	0.73	0.67	0.79
CNN	0.94	0.91	0.88	0.88	0.89
VGGNet	0.91	0.91	0.94	0.97	0.94

A. *Image data and indices with AlexNet Model*

While training the model, we got small amount fluctuations initially as shown in Figure 3, then for later epochs, we got constant and consistent accuracy. While for testing, we got rise in accuracy then with constant accuracy after certain number of epochs of training. Here we got very less model loss as shown in Figure 4, while testing the model than while training.

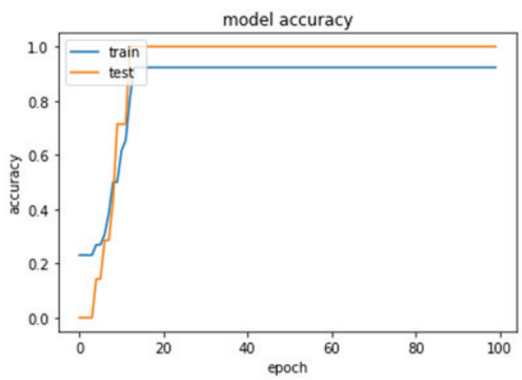

Fig. 3. AlexNet Model accuracy graph

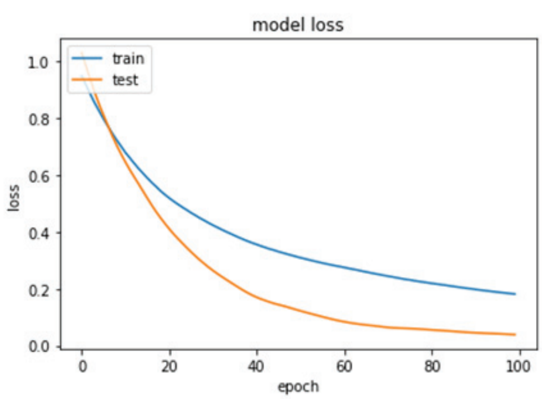

Fig. 4. AlexNet model loss graph

B. *Image data and indices with CNN Model*

In this model also, we got some fluctuations while training the model initially later we got constant accuracy as shown in Figure 5. In this model we have got loss of less than 10% while testing the model as shown in Figure 6.

C. *Image data and indices with VGGNet Model*

While training we got accuracy of less than 85%. But while testing we got almost 94% of accuracy for VGGNet model as shown in Figure 7. While training we got some higher loss upto some number of epochs but while testing the model we got very less loss and fully improved model as shown in Figure 8.

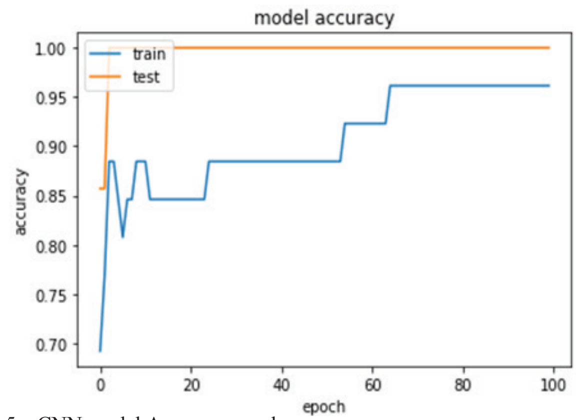

Fig. 5. CNN model Accuracy graph

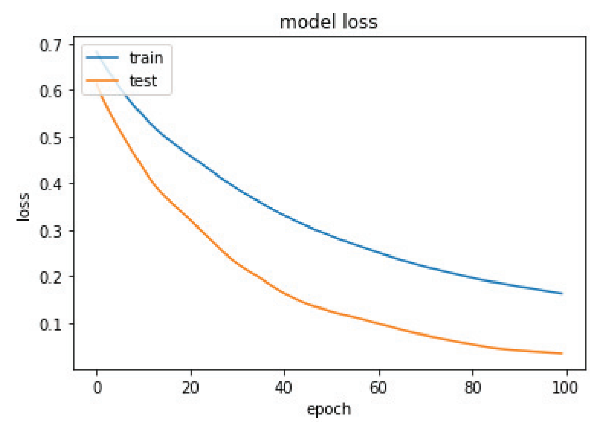

Fig. 6. CNN Model loss graph.

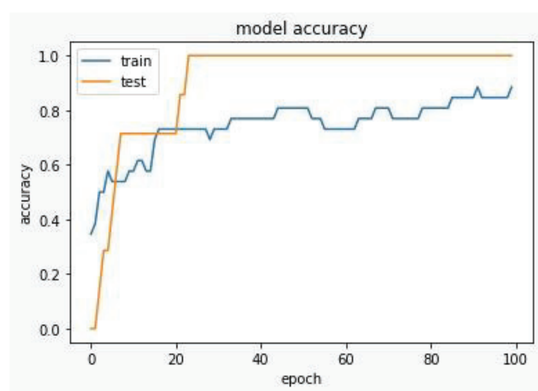

Fig. 7. CNN model Accuracy graph .

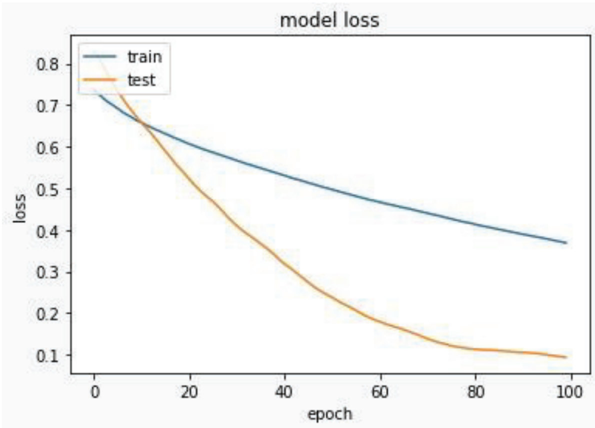

Fig. 8. CNN Model loss graph.

V. CONCLUSION and FUTUREWORK

Developments in satellite image analysis for drought monitoring for early warning are an ongoing research area. Most of the works are supported the classification of the image region in to drought and non- drought categories at pixel level. Prediction of the probable decrease in crop yield during harvesting is based on this classification results. Though there are certain patterns that drought occurrences could manifest, there were little considerations. The image-based analysis provides more profound information, especially for areas where ground monitoring using meteorological data is scarce.

In our research, we have modeled three deep learning techniques CNN, AlexNet and VGGNet. Analyzed and compared these techniques among few drought indices, we found CNN outperforms over other two models in NDVI index and also gives better accuracy for other indices as well. When compared to AlexNet and VGGNet. Next to CNN we found that VGGNet performs better than AlexNet in accuracy for these indices, VGGNet's performance is almost nearer to CNN model. Overall, we found that CNN is slightly better in handling the image data with little higher accuracy and very minimum loss than other two models.

Future works of this research continues with making use of some more drought indices for the model training, developing models which can take other image formats like JPEG,JPG etc. And we also are striving to combine these models with Bio-inspired techniques to obtain better accuracy and performances.

REFERENCES

[1] S.Sreekesh, Navneetkaur , Sreeramanaik S. R, Agricultural drought and soil moisture analysis using satellite, image based indices the international archives of the photogrammetry, remote sensing and spatial information sciences, volume xlii-3/w6, 2019 isprs-geoglam-isrs joint int.

[2] Akanbi, Adeyinka K., and Muthoni Masinde. "Towards the development of a rule-based drought early warning expert systems using indigenous knowledge." *2018 International Conference on Advances in Big Data, Computing and Data Communication Systems (icABCD)*. IEEE, 2018.

[3] Himanshu, S. K., Singh, G., & Kharola, N. (2015). Monitoring of drought using satellite data. *International Research Journal of Earth Sciences*, *3*(1), 66-72.

[4] Abdelhamid elibrahimi Abdennasserbaali, "Application of several artificial intelligence models for forecasting meteorological drought using the standardized precipitation index in the saïss plain (northern morocco)", doi: 10.22266/ijies2018.0228.28,international journal of intelligent engineering and systems, vol.11, no.1, 2018.

[5] Norbert a agana,, Abdollah Homaifar "Deep learning based approach for long-term drought prediction", Department of Electrical and Computer Engineering North Carolina A&T State University Greensboro, NC.

[6] Norbert A. Agana, Abdollah Homaifar, "A hybrid deep belief network for long term drought prediction", Computing by the National Science Foundation under Award Number: CCF-1029731 and DOT under UTC-60040605 and Air Force Research Laboratory and OSD under agreement number FA8750-15- 2-0116.

[7] J Wu1,3 and Y F Chen2,, "Research of using RF model to drought forecast on Huaihe River", Water Resources Department of Hebei Province, Shijiazhuang 050000, China, College of Hydrological and Water Resource, Hohai University, Nanjing 210098,China.

[8] Gulácsi, A., &Kovács, F. (2015),"Drought monitoring with spectral indices calculated from MODIS satellite images". Hungary. *Journal of Environmental Geography*, *8*(3-4), 11-20.

[9] Arkeman, Y., Buono, A., &Hermadi, I. (2017). Satellite image processing for precision agriculture and agro-industry using convolutional neural network and genetic algorithm. In *IOP Conference Series: Earth and Environmental Science* (Vol. 54, No. 1, p. 012102). IOP Publishing.

[10] Dąbrowska-Zielińska, K., Ciołkosz, A., Malińska, A., & Bartold, M. (2011). Monitoring of agricultural drought in Poland using data derived from environmental satellite images. *Geoinformation Issues*, *3*(1), 87-97.

[11] Pal, R., & Saraswat, M. (2018, August), "Enhanced bag of features using Alexnet and improved biogeography-based optimization for histopathological image analysis" *2018 eleventh international conference on contemporary computing (IC3)* (pp. 1-6). IEEE.

[12] Abd Almisreb, A., Jamil, N., & Din, N. M. (2018, March). Utilizing AlexNet deep transfer learning for ear recognition. In *2018 Fourth International Conference on Information Retrieval and Knowledge Management (CAMP)* (pp. 1-5). IEEE.

[13] Gu, S., Ding, L., Yang, Y., & Chen, X. (2017, November). A new deep learning method based on AlexNet model and SSD model for tennis ball recognition. In *2017 IEEE 10th International Workshop on Computational Intelligence and Applications (IWCIA)* (pp. 159-164). IEEE.

[14] Shafaey, M. A., Salem, M. A. M., Ebied, H. M., Al-Berry, M. N., &Tolba, M. F. (2018, September). Deep learning for satellite image classification. In *International Conference on Advanced Intelligent Systems and Informatics* (pp. 383-391). Springer, Cham.

[15] Xiao, L., Yan, Q., & Deng, S. (2017, November). Scene classification with improved AlexNet model. In *2017 12th International Conference on Intelligent Systems and Knowledge Engineering (ISKE)* (pp. 1-6). IEEE.

[16] Zhang, X., Pan, W., & Xiao, P. (2018, June). In-vivo Skin Capacitive Image Classification Using AlexNet Convolution Neural Network. In *2018 IEEE 3rd International Conference on Image, Vision and Computing (ICIVC)* (pp. 439-443). IEEE.

[17] Qian, L., Hu, L., Zhao, L., Wang, T., & Jiang, R. (2020). Sequence-Dropout Block for Reducing Overfitting Problem in Image Classification. *IEEE Access*, *8*, 62830-62840.

[18] Alebiosu, D. O., & Muhammad, F. P. (2019, October). Medical Image Classification: A Comparison of Deep Pre-trained Neural Networks. In *2019 IEEE Student Conference on Research and Development (SCOReD)* (pp. 306-310). IEEE.

[19] Liu, X., Chi, M., Zhang, Y., & Qin, Y. (2018, July). Classifying high resolution remote sensing images by fine-tuned VGG deep networks. In *IGARSS 2018-2018 IEEE International Geoscience and Remote Sensing Symposium* (pp. 7137-7140). IEEE.

[20] Jun, H., Shuai, L., Jinming, S., Yue, L., Jingwei, W., & Peng, J. (2018, November). Facial expression recognition based on VGGNet convolutional neural network. In *2018 Chinese Automation Congress (CAC)* (pp. 4146-4151). IEEE.

[21] Muhammad, U., Wang, W., Chattha, S. P., & Ali, S. (2018, August). Pre-trained VGGNet architecture for remote-sensing image scene classification. In *2018 24th International Conference on Pattern Recognition (ICPR)* (pp. 1622-1627). IEEE.