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A Deep Learning Data Augmentation Experiment to Classify Agricultural Soil Moisture to Conserve Plants

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Abstract- Increasing water scarcity and frequent droughts pose a grave threat to agricultural production many areas. As a result, agrochemicals with potentially favourable effects on plants' ability to endure periods of low soil moisture are discovered. It's classified the soil moisture using a Generative Adversarial Networks Architecture based on deep learning. On the next step, its implemented the Grey Wolf Optimization (GWO) technique for hyperparameter tuning of Generative Adversarial Networks (GANs) classifier. In this experimental, its mostly employed raw-based datasets to create high-quality cameras for train and test process. To detect and identify agriculture soil moisture image capture system was developed to record lively in land. Its described the Data Augmentation as a regularization based method for preventing overfitting. Additionally, this was utilised to duplicate the photographs by flipping, cropping, and rotating them. The classifier model can classify illnesses with relative ease. In the prediction of soil moisture at dry condition, an alert message is kept in a cloud-based Wireless Sensor Network (WSN) storage system, and then the GSM model is used to transmit the disease-affected message to the farmer's mobile device.

***Keywords**: Agriculture, Agrochemicals, Plants, Soil and Water.*

1. Aims and Background

Effective water resource management is essential for achieving long-term success in agriculture and other social and economic domains. Agriculture is one of the leading causes of water quality degradation due to insufficient water management practises and ignorance of the soil-plant-atmosphere interaction.Therefore, great efficiency and even distribution of water will result from the use of well-designed procedures and the careful selection of irrigation systems[1]. Many different fields rely heavily on soil moisturefor a variety of reasons, including water resource management, irrigation scheduling, improved weather forecasting, natural hazards mitigation research, agricultural production predictions, crop insurance, environment predictions, ecological health & services, improved trafficability, groundwater recharge, water quality & quantity, and more. Despite its many potential effects, soil moisture is one of the variables that is underutilised in modelling, mainly because of its highly temporal and spatial behaviour in the natural environment and the difficulty of using point measurements or in-situ estimates to represent soil moisture on a large spatial scale [2-3]. Through a process known as carbon sequestration, soil acts as both a source and a sink for CO_2 in the atmosphere. If you're in the farming business, you know that soil moistureis your most valuable asset. Water scarcity caused by climate change is a worldwide issue for the agriculture sector. So, controlling the flow of irrigation water is the most important factor in ensuring agriculture's long-term success[4].

Water supply management from the irrigation system's origin to its final destination must be carefully and scientifically mapped out in order to address this issue. Alternate tillage methods, micro-irrigation (drip and sprinkler), mulch, and other forms of irrigation that take advantage of the soil moisture (SM) content can be employed effectively in dry and semi-arid regions. These methods of irrigation are becoming more commonplace since they reduce the amount of potable water used, the amount of human work required, the amount of energy expended, the amount of water lost to runoff and soil erosion, and the length of time between harvests[5]. When it comes to expanding and bettering agricultural production and water supplyhas been extensive study into the impact of moisture stress on crop output at a

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variety of scales and in response to a wide range of adaptations and farming methods[6]. These days, farmers routinely get crop insurance to protect their businesses from the financial fallout of disasters like drought, flood, or other unforeseen events. Field ponding increases with soil moistureand decreases with soil moisture. The exchange of water and energy between the ground surface and the atmosphere is controlled by soil moisture. As a critical variable in the water and energy exchanges that occur at the land-surface/atmosphere interface and conditions that regulate the evolution of weather and climate over continental regions, soil moisture plays a crucial role in Earth's water cycle. In other words, water flows between the atmosphere, the surface, and the subsurface are controlled by the state variable of the water cycle over land. Therefore, SM measurements on a global scale are desperately needed to provide light on the interconnections between the water, energy, and carbon cycles on Earth, as well as the processes and functioning of hydrological systems and ecosystems[7]. In addition to aiding in the characterization of the relationship between SM and the freeze/thaw state, SM also gives useful information for the science of the Earth's system by allowing for the brief exploration of land-atmosphere interactions. Surface soil moisture estimation using remote sensing techniques, notably microwave-based methods, has shown tremendous promise.The ECH2O sensor family (EC-5 and were tested for their ability to monitor soil moisture content (h), bulk electrical conductivity (ECb), and temperature (T) for sensor various soils at measuring frequencies ranging from 5 to 150 MHz. The sensitivity of capacitance readings to soil characteristics including texture, electrical conductivity, and temperature is largely determined by the measurement frequency[8]. Verification of the accuracy of the ECH2O EC and TE values. A single calibration curve was produced for a variety of mineral soils using a measuring frequency of 70 MHz, independent of soil salinity, suggesting there may not be a need for a soil specific calibration. There was little variation between individual probes, therefore the R2 values stayed high (R2 = 0.98 overall) when all data for each soil type was combined. Up to a soil solution EC of around 12 dS/m, the inaccuracy for h after laboratory calibration was approximately 2%. Our findings demonstrated that a common calibration curve applicable to all mineral soils examined was achievable regardless of soil salinity.

The technological gadgets called "soil moisture sensors" are the quickest and most accurate way to determine the amount of water present in the ground. Maintaining optimal irrigation conditions calls for constant measurement of soil moisture levels in the irrigated areas. Because different soil moisture sensors come with their own set of benefits and drawbacks, using the right probe to measure soil moisture is crucial[9]. The Sensors measuring soil moisture can help with water usage planning. Unfortunately, the cost of commercial sensors prevents them from being used by most farmers at present. The sensor's accuracy and repeatability were measured after being calibrated in leaf disease.[10-12].

2. Material and Methods

The soil moisture using a Generative Adversarial Networks Architecture based on deep learning. On the next step, its implemented GWO technique for hyperparameter tuning of GAN classifier. In this experimental most of the employed in raw-based datasets to create highquality cameras for train and test process.

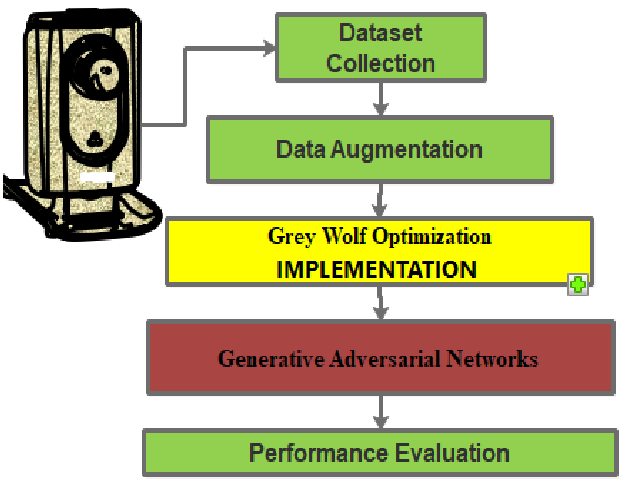

Fig.1 Proposed architecture for proposed methodology

To detect and identify agriculture soil moisture image capture system was developed to record lively in land. The Data Augmentation as a regularization-based method for preventing overfitting. Additionally, this was utilised to duplicate the photographs by flipping, cropping, and rotating them. The classifier model can classify illnesses with relative ease. In the prediction of soil moisture at dry condition, an alert message is kept in a cloud-based Wireless Sensor Network (WSN) storage system, and then the GSM model is used to transmit the disease-affected message to the farmer's mobile device.

Data Augmentation: Its examine and contrasts several methods used to address the problem of data augmentation in image classification. Simple data augmentation procedures, such as cropping, rotating, and flipping input photographs, have proven effective in earlier research. We compare several data augmentation methods using an intentionally reduced subset of the Image Net dataset. Here are the five most common methods currently in use for enhancing images through manipulation. The other four common techniques for altering images are inversion, enhancement, rotation, and scaling. These techniques of enhancement allow for the collection of at least one thousand photos per class. The equalised image augmentation dataset included 76,000 images with just the most basic adjustments done to them. A total of 32073 pictures were used to create this approach; these photos were altered in various ways, including scale, rotation, the addition of colour using principal component analysis, and the addition of noise. Information on the sizes of each class was decreased from more than 2,000 images to just over 2,000. Data augmentation trials that improved classification accuracy were shown to be successful. There is no denying the efficacy of traditional augmentation on its own.

The term "optimisation" is commonly used to describe a set of techniques for improving the performance of technological systems. An optimisation algorithm is a programme that iteratively evaluates a number of potential answers, narrowing the field down to the most optimal one. Many of the current systems use time-tested techniques to extract texture data. To get the best-matched photos to a particular query image, computational complexity need not be taken into account when the repository size is modest. Only when the search space explodes exponentially do we need to consider the computational complexity. The provision of an efficient means of retrieving photographs from the vast libraries of images utilised in many applications is now a need. The energy fitness function is the most important metric to determine while trying to pair together photos. The energy fitness function can only converge to a minimal value in a reasonable amount of time using optimisation procedures.

Natural Process of the GWO Algorithm: The grey wolf's hierarchical society and strategic hunting style serve as inspiration for GWO. Grey wolves are typically the top predators in their natural habitats. Most of the time, grey wolves will congregate in packs of five to twelve. Particularly among grey wolves, a clear social order exists. The male and female wolves in a pack of grey wolves take turns acting as alpha, making decisions about the pack's whereabouts, prey, and wake-up times. The members of the pack generally have to follow the lead of the alpha. But there are signs of democracy in the grey wolf pack (alpha may follow other individuals of the pack). People in a group show their agreement with the alpha's choice by lowering their tails. It's also intriguing to learn that the pack's alpha doesn't have to be the strongest member.

Identification and Classification: For targeted and land-specific treatments, a dependable land identification and classification system that instructs agricultural robots where and when to trigger their actuators to execute the appropriate action is essential. For instance, weeds demonstrate rapid growth and compete parasitically with legitimate crops for nutrients and space, although possessing little nutritional or medicinal benefit. Classification, weed identification, and plant seedlings are currently the topic of intensive research because inefficient methods, such as manual weeding, have resulted in substantial losses and rising costs due to physical labour.As a result, precision farming techniques can more successfully manage weeds by altering herbicide dosage based on the density of the weed infestation.

3.Experimental

3.1 GAN Designs - Fully Connected GANs

Both the generator and the discriminator in the earliest GAN designs were fully linked neural networks. The MNIST (handwritten digits), CIFAR-10 (normal pictures), and Toronto Face Dataset (faces) were some of the simpler image datasets used to test this architecture (TFD).

Convolutional GANs: Given that CNNs are particularly well-suited to picture data, it is a natural progression from fully-connected to convolutional neural networks. It was found in early tests on CIFAR-10 that CNNs with the same capacity and representative capability as those used for supervised learning made it more challenging to train generator and discriminator networks. One approach to resolving this issue is the Laplacian pyramid of adversarial networks (LAP-GAN), which does so by breaking down the generation process at multiple levels: first, a ground truth image is broken down into a Laplacian pyramid, and then a provisional, GAN is trained to produce each layer of the pyramid given the one above it.

The development of novel uses for adversarial training of deep networks is a hotspot for academic investigation. In this article, we take a look at some of the computer vision programmes that have been published and improved upon after their first publication. These examples do not capture the whole scope of the potential uses for GANs; rather, they are meant to showcase some of the many ways in which these representations might be put to work in picture modification, analysis, and characterisation.

Wireless Sensor Network based authentication: WSN is a network of distributed wireless sensor nodes which senses physical parameters, process, and communicate the collected data to a sink node for storage and further analysis and decision making. In WSN, Localization is categorized as range-based and range-free localization approaches. In this thesis, only the range-based localization methods are taken in to consideration. The reason to select the range-based localization approach is the range-free localization algorithms, despite their valuable contributions in low power consumption and minimum cost of the total network, these methods depend on unrealistic assumptions such as the circular signal propagation of sensor nodes To monitor agricultural land for the onset of illness, a network of sensor nodes can be set up. Those nodes can be geared up with the equipment they need to develop the illnesses that wreak havoc on plants. Wireless sensor networks will allow the fire department to know when a disease has started and how it is spreading based on the location of the sensor nodes, and the data will be kept in the cloud after the GSM module sends an alert message to the farmer or other authority persons.

4.Results and Discussion

TensorFlow and Kera’s is used to implement both proposed and existing models.The models are built using the Real time dataset. For implementing the models used 3.4GHz Intel Core i7 processor, 32 GB-RAM and 4 GBGraphic cards.

Performance Analysis: The Loss and accuracy of the proposed Inception model is presented in thefigure. The accuracy and loss analysis of the proposed Inception perfect andcompetitive modelshas discussed. The Inception model achieves higher accuracy and less loss ascompared to the competitive models.

Classification Accuracy: To evaluate the efficacy of a classification model, we look at how many test pictures were correctly categorised in relation to the total number of test photos. Accuracy in classifying data might range from zero to one hundred percent.

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

Precision: When evaluating a model's performance, accuracy is calculated as the ratio of correct identifications and rejections to all predictions. The optimal percentage of correct labels may be determined using accuracy. A value between zero and one is considered acceptable for accuracy. The superiority of the classification systems used to create the predictions is reflected in the accuracy levels at their peak. The following formula may be used to compare the efficacy of different categorization strategies:.

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

Recall: Correctly recognised and incorrectly rejected results are added together and then divided by all applicable sample data to determine recall. Using recall rates, one may determine what proportions of true positives were correctly identified. Recall values for classifiers range from 0 to 1, inclusive. A classification method's predictive power is quantified by its maximum recall. The following equation may be used to compare the recall of different categorization methods:.

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

F1 Score: The F1 score is one of the most popular metrics used to evaluate the performance of machine learning algorithms. The F1 score represents a compromise between memory strength and memory capacity. The F1 score can range from 0 to 1. The F1 score provides a numeric representation of the predictive accuracy of the best classification methods. In order to compare the F1 scores of different classifiers, we may use the following formula..

$$F1\ score = \frac{2TP}{2TP+FP+FN}$$
(4)

Table 1: Inception with the competing models

Design (Model)	No of Parameter	f1-score	Recall	Precision	Validation Accuracy
MobileNet CNN model	Over-all params: 23,785,418 Trainable params: 200,706	0.97	0.96	0.95	95%
XceptionNet CNN model	Over-all params: 21,271,02 Trainable params: 419,602	0.96	0.95	0.97	91%
Proposed Inception model	Over-all params: 25,339,968 Trainable params: 17,7045704	0.98	0.99	0.98	98%

After Fine-Tuning with Epoch rate = 20. From the Figure 2 it is clear that the accuracy is improving further with increase in the number of Epochs. The testing accuracy reached 98.01% which is an improvement over the previous accuracy of 95.36% at Epoch rate = 10. Similar is the case for model.

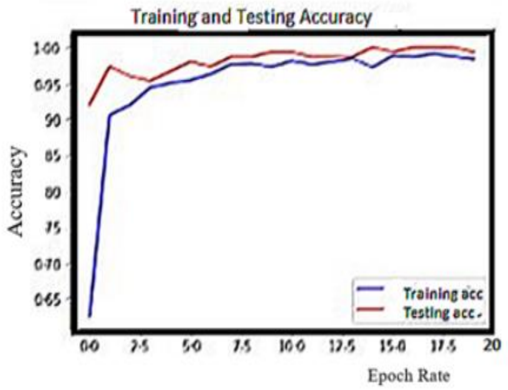

Fig.2 Training and Testing Accuracies of proposed model

Table 2 and Figure 3 above compare the outcomes of using several classifier models to access the data, and they show that the K-Nearest Neighbor model's initial accuracy of 95.27% is the highest. The impressive 94.87% accuracy was achieved with the help of a Recurrent Neural Network. In the end, the proposed model is tested, and the results show that it has an accuracy of 98.36%..

Table 2: Performance evaluation of proposed with other models.

Classifier models	Precision	Recall	Sensitivity	Accuracy
K-Nearest Neighbor	74.00	99.77	98.82	95.27
Recurrent neural network	94.78	98.88	98.91	94.85
Proposed GAN model	94.94	98.92	98.62	98.36

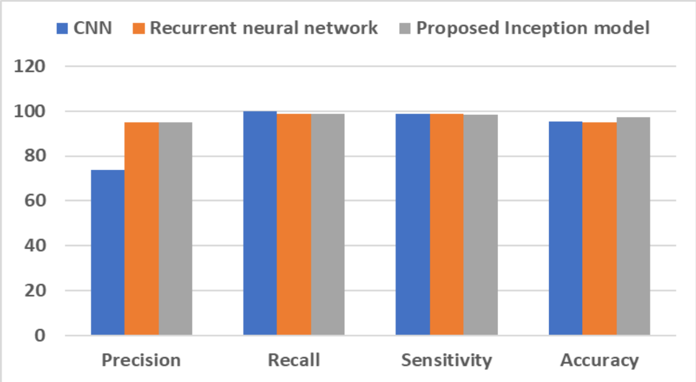

Fig.3: Performance evaluation of soil moisture prediction

4. Conclusion

The soil moisture by using a Generative Adversarial Networks Architecture based on deep learning. On the next step, its implemented on the GWO technique for hyperparameter tuning of GAN classifier. In this experimental, it's mostly employed raw-based datasets to create high-quality cameras for train and test process. To detect and identify agriculture soil moisture image capture system was developed to record lively in land. Its described Data Augmentation as a regularization-based method for preventing overfitting. Additionally, this was used to flip, crop, and rotate the images in order to duplicate them. With relative ease, the classifier model can classify ailments. In the prediction of soil moisture in a dry environment, an alert message is stored in a cloud-based Wireless Sensor Network (WSN) storage system. The GSM model is then utilised to convey the disease-affected message to the farmer's mobile device.

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