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Publications

International Journals

[1] Hiren J. Modha, Ashish M. Kothari (2020). Systematic approach for economic use of natural resources by means of machine learning. Our heritage journal nal, (ISSN: 0474-9030), http://ourheritagejournals.com/images/short_pdf /1580279548_517.pdf

[2] Hiren J. Modha, Ashish M. Kothari (2021). Crop diseases severity identification by deep learning approach, ADBU Journal of Engineering Technology, (ISSN: 2348-7305, Volume10, Issue 1, June 2021, 0100101808(11PP).

[3] Hiren J. Modha, Ashish M. Kothari (2022). Soil Moisture Prediction using Deep Neural Network Approach. Neuroquantology (ISSN : 1303-5150), Volume 20, No 8 (2022) , DOI: 10.14704/nq.2022.20.8.NQ44456.

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Systematic Approach For Economic Use of Natural Resources By Means of Machine Learning

Hiren J. Modha[1]

Ashish M. Kothari[2]

[1]Assistant Professor, Electronics and Communication Dept. SVIT VASAD

[2]Associate Professor and Head, Electronics and Communication Dept.Atmiya University,

Abstract:

Machine Learning has the potential to offer superior way for saving resources like water, electricity. It also enhances the flexibility and throughput of system with use of precision algorithm and other logical operations. ThisPaper elucidates how it can help in different field to improve throughput by applying intelligence with use of electronic sensors and mathematical algorithms. The logical programs help to make the decision or it supports the system for particular task. Now days machine learning become asignificant part in Agriculture, irrigation, garbage monitoring, Traffic in a city, Industries and other survival matters. With the help of IoT any function can be carried out by effective means of cost and effective utilization of resources. Also it can help to make process fast flexible and cheaper. It helps people to access and deploy the assetsremote. This paper shows how soil moisture and nutrients can be monitored continuously and the prediction based analysis so that we can make our decision support system so strong.

Key words:Data Processing System, Sensor Data Integration, IoT, Farming Data

I. INTRODUCTION

Intelligence is deployed for smart farming with use of precision algorithm, image comparison, and other software based logical operations. Here different machine learning based systematic approach is analyzed and from the results it discuss how it helps to reduce the cost as well as resources whichfurther improve eco system and make it healthy. In smart cities the major problem is deal with traffic garbage and environment. With suitable technique it eliminates the critical problems and prevent from troubles. It also used for financial analysis and other cost related issues. It uses the real time data and developed mathematical model. After it apply appropriate logic for prediction, [1][2]

comparison, etc. Then with use of decision support system for the next phase of the operation, it potentially gives high throughput , high accuracy and better solution.Fertilization irrigation and other management process can be improved by using wireless protocols, such as Zigbee, Wi-fi and others. The real time monitoring of any physical quantity can be maintained by use of A.I.

Crop Diseases Severity Identification by Deep Learning Approach

Hiren J. Modha[1], Ashish M. Kotharir[2],

[1]Research Scholar, Electronics & Communication,
Atmiya University, Rajkot, Gujarat- India
Email: hiren_modha2001@yahoo.com

[2]Associate Professor, Electronics & Communication,
Atmiya University, Rajkot, Gujarat- India
Email: amkothari.ec@gmail.com

Abstract*: Improving yield and maintaining crop strength with optimization in use of resources are the major requirements in smart farming. To build a smart decision support system for improving production with flexibility, it requires Remote Sensing Systems. Now days with effective use of machine learning and deep learning techniques, it is possible to make the system flexible and cost effective. The deep learning based system has enormous potential, so that it can process a large number of input data and it can also control nonlinear functions. Here it should be discussed that from continuous monitoring of crop leaves images shall ensures the diseases identification. The research concludes that the quick advances in deep learning methodology will provide gainful and complete classification of crop with 98.7% to 99.9% accuracy. In this research, different crop diseases are classified based on image processing and Convolutional neural network method. For classification of maize crop diseases, different models have been developed, compared, and finally best one is found out. Also the finest model has been tested for different crop diseases to check its consistency.

***Keywords*: machine learning, deep learning, Probabilistic Neural Network, Convolutional neural network.**

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I. INTRODUCTION

In agriculture field, plant disease is the precarious and unavoidable trouble as it decreases the yield. Plant disease severity is a key measurable factor to determine infirmity stage and hence it can be used to guess yield along with advocate action. Maize crop leaves have lots of disease and the high level of damage. The quick, truthful verdict of illness extremity will assist to increase the production. Conventionally, botanist scientist and experts examined plant disease severity by continuous monitoring of plant tissue. This process is very costly and less effective. Manual assessment of plant crop diseases is obstructing the fast growth of modern agriculture [1].Now days, the disease diagnosis for crop is become fully automatic with use of digital cameras and commuter vision by preparing smart deep neural network models with different techniques. So the aim of the research is to classify plant diseases fully automatic and quickly with flexible manner.

Maize is a significant food and most occupied crop. Its whole yield is the biggest in the globe apart from for rice and wheat [2]. First we developed a deep neural network model in favour of classifying maize crop leaves in different class by monitoring the images of leaves so that we can conclude that the crop is healthy or it has some disease. To discover finest network architecture, initially we trained the general models with different depth from scratch and then we prepared high tech models by using pre-trained weight. The finest model achieved an accuracy of 98.7% of correct prediction for rest of test data set. Also the same model is used for different crop images to verify its performance. The comparison for different objects with same model is shown. Our results are better than previous work as mentioned in paper.

Part wise summary of the whole manuscript is given here. Part II indicates the related work in this field. Part III indicates the deep learning scheme. Part IV explains the tactic. Part V shows the algorithm for model preparation. Part VI shows result analysis for maize crop. Part VII shows the testing of same model with different dataset to check its consistency. Part VIII shows the results and associated discussions, and at last conclusion is presented.

II. RELETED WORKS

So many researchers have found that, it can be possible to achieve improved accuracy and excellent results through the image based assessments approaches, as compare to manual assessments for crop disease identification. Xihai Zhang et al. prepared models using GoogLeNet and

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Soil Moisture Prediction using Deep Neural Network Approach.

Hiren J. Modha[1], Ashish M. Kothari[2]
[1]Research Scholar, Electronics & Communication,
Atmiya University, Rajkot, Gujarat- India
Email: hiren_modha2001@yahoo.com
[2]Associate Professor, Electronics & Communication,
Atmiya University, Rajkot, Gujarat- India
Email: amkothari.ec@gmail.com

Abstract

Soil moisture content is the most significant element in fit farming output and circulation of water, and its accurate forecast is critical regarding water resource management. Mostly soil moisture is complicated through structural features in addition to climatic complications. It's tough to come up with an optimal mathematical model for soil moisture since there are so many variables for calculation. Presented forecasting models have issues with prediction accuracy, generality, plus other factors like Prediction performance, as well as multi-feature processing capabilities etc. considering all these factors taking Gallipoli, Turkey as a reference site for developing a deep neural network model to forecast moisture with good accuracy and minimum error. The dataset contains entities since 2008 to 2021. Doing quite a bit of mathematical analysis and establishing the correlation between selected features with the spearman coefficient, the appropriate weather data is able to give proper weight to forecast soil moisture. The output of the proposed method proves that the deep learning approach is realistic as well as efficient for the prediction of moisture. Also, deep learning technique is able to make model generalizations with excellent accuracy and minimum errors which is used to save irrigation water with controlling drought.

Keywords: Deep Neural Network, Machine Learning, Multilayer Layer Perceptron (MLP), Support Vector Machine (SVM), Rectified Linear Activation Function (ReLU).

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Introduction

Water is the most important asset for the existence as well as the growth of all living things on the planet. Soil moisture is not only necessary for plant growth, but it is also an important thing to water a farm with a system that has a correlation among soil-plant-atmosphere systems [1-3]. Groundwater resources, on the other hand, decrease in water quality when human activities increase and the quantity of excavation is greatly surpassed. Groundwater levels continue to fall, causing a drop-in water level on farm and a reduction in the soil's ability to store the water [4-5]. The absence of precipitation, especially in arid locations, creates drought on farm and there is no refilling of water at a particular time, which has a detrimental impact on crop development [6]. It is very critical in this scenario to create a suitable irrigation system at the proper time [7, 12]. Water consumption and crop growth are directly influenced by the increase and regression of soil moisture. Dryness of farmland, flood management plus the determination of proper watering of the farm is all key indicators in agricultural production. To