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A Coordinated Yield Suggestion System for Effective Cultivation

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Abstract: India has 159.7 million hectares of agriculture land and second largest agriculture land in world. According to the FAO 70 percent of its rural households still depend primarily on agriculture for their livelihood, with 82 percent of farmers being small and marginal. So the meliorate of economic status of rural area is important factor for development of our country. Enhance the agriculture productivity is depends of various resources such as water, land and soil, agro advisory network and so on. So here our concern is effective utilization of agriculture land and train the farmers with the help of agriculture and forest department guidance and support. It's a challenge to the agriculture department to identify agriculture area and give some statistics or giving suggestions to the farmers about different food production strategies, for that finding agriculture land is very important. Remote sensing is the science and technology by which the characteristics of object of interest can be identified, measured or analysed the characteristics without direct contact.

Keywords: FAO, Meliorate and Remote sensing.

I. INTRODUCTION

Indian economy is depending on agriculture also the agriculture is important for world to produce huge amount of food for fulfilling's the demand of it. to increase the agriculture production by train the farmers to utilize the land efficiently. In our country more formers are not educated because of poverty and depends on cultivation. Many technologies are introduce but they are not fully reached real-time goals so the train the agriculturists with the help of agriculture and forest departments, before that identify the land for agriculture by Satellite imagery. Here we using remote sensing technic(satellite imagery) to identify the land ,classification of land and its location ,time period of land unused, along with the help of computer science technologies(machine learning technics). In India Farmers have to face the issue of lesser rainfall due to improper irrigation, and hard to achieve sustained progress in irrigation. Because of the farmers suffer from infrastructural and economic problems in their routine life. This is mainly due to the lack of education and technical resources. Farmers are not acquainted with advanced agricultural practices. This holds them back from utilizing the proper technical resources in farming and other practices. In order to reduce their problems, farmers should be educated about utilization of technologies and scientific facts about soil and crops. If they get familiar with the mechanism of technical devices, farmers can eliminate several problems faced by them. Remote Sensing is the science of obtaining information about objects or areas from a distance, typically from aircraft or satellites. Remote sensors collect data by detecting the energy that is reflected from Earth. These sensors can be on satellites or mounted on aircraft. Remote sensors can be either passive or active. Passive sensors respond to external stimuli. They record natural energy that is reflected or emitted from the Earth's surface. The most common source of radiation detected by passive sensors is reflected sunlight. In contrast, active sensors use internal stimuli to collect data about Earth. For example, a laser-beam remote sensing system papers a laser onto the surface of Earth and measures the time that it takes for the laser to reflect back to its sensor.

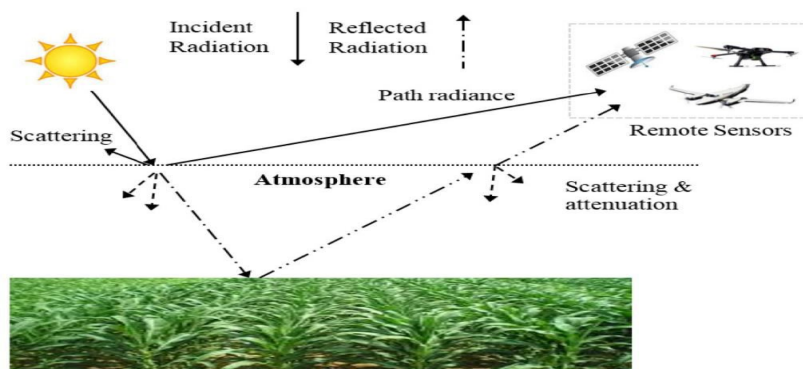


Fig.1 Atmospheric effect on radiation measured by remote sensors.

With increasing population across the world and the need for increased agricultural production there is a certain need for proper management of the world's agricultural resources. To make this happen it is first necessary to obtain reliable data on not only the types, but also the quality, quantity and location of these resources. Satellite imagery and GIS (Geographic Information Systems) will always continue to be a significant factor in the improvement of the present systems of acquiring and generating agricultural maps and resource data. Agriculture mapping and surveys are presently conducted throughout the world, in order to gather information and statistics on crops, range land, livestock and other related agricultural resources. Satellite Imagery for land cover, land use and its changes is a key to many diverse applications such as environment, forestry, hydrology, agriculture and geology. Natural resource management, planning and monitoring programs depend on accurate information about the land cover in a region. Methods for monitoring vegetation change range from intensive field sampling with plot inventories to extensive analysis of remotely sensed data which has proven to be more cost effective for large regions, small site assessment and analysis. Satellite Imaging Corporation (SIC) can provide automated satellite map datasets for vegetation and land cover use by updating papered area and incorporating a more recent image to determine the changes. Evaluation of the static attributes of land cover (types, amount, and arrangement) and the dynamic attributes (types and rates of change) on satellite image data may allow the types of change to be regionalized and the approximate sources of change to be identified or inferred. Satellite images with moderate to high resolution have facilitated scientific research activities at landscape and regional scales. Availability of satellite imagery can provide spatial resolutions of up to 30 centimetres for analysis of urban growth and transportation development for assessment and monitoring. Satellite image classification is a challenging problem that lies at the crossroads of remote sensing, computer vision, and machine learning. Due to the high variability inherent in satellite data, most of the current object classification approaches are not suitable for handling satellite datasets. The progress of satellite image analytics has also been inhibited by the lack of a single labelled high-resolution dataset with multiple class labels. We propose a classification framework that extracts features from an input image, normalizes them and feeds the normalized feature vectors to a Deep Belief Network for classification. Images were extracted from the National Agriculture Imagery Program (NAIP) dataset. The images consist of 4 bands – red, green, blue and Near Infrared (NIR). In order to maintain the high variance inherent in the entire NAIP dataset, we sample image patches from a multitude of scenes (a total of 1500 image tiles) covering different landscapes like rural areas, urban areas, densely forested, mountainous terrain, small to large water bodies, agricultural areas, etc.

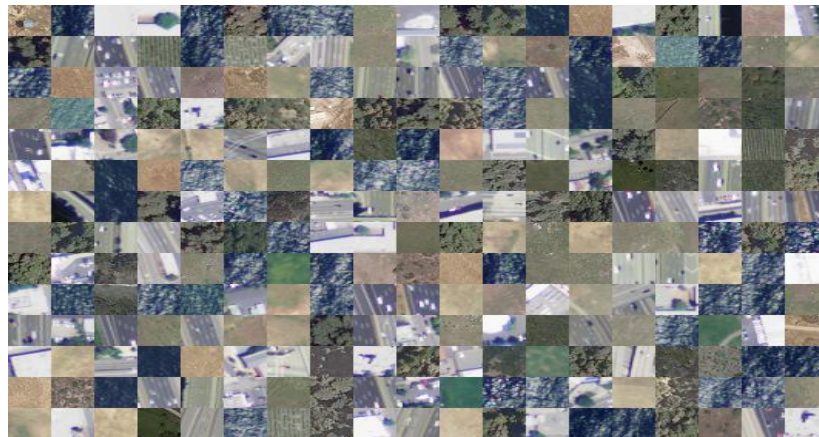


Fig. 2 Sample images from the SAT-4 and SAT-6 dataset

II. LITERATURE REVIEW

In this paper we refer various government agriculture plans and other technics to improve agriculture production and farmer interviews about their problems and type of technics used for crop produce. With the lack of proper knowledge about soil and crops, pesticides various challenges are faced such as land degradation, soil loss, land fragmentation and so on (St. A 2015) .

Remote sensing offers a potential solution for mapping irrigated land (Abernethy and Pearce, 1987). Some of the early remote sensing applications focused on mapping irrigated croplands (Huston and Titus, 1975; Draeger, 1977; Wall, 1979; Thiruvengadachari, 1981). In recent years, mapping has continued with enhanced techniques and capabilities for inventorying irrigated areas from different irrigation sources such as surface water, groundwater and irrigation tanks (Thiruvengadachari, 1983; Thiruvengadachari and Saktliivadivel, 1997). Remote sensing is used for assessing crop stress, discriminating crop types, and for monitoring temporal changes in irrigated areas by Azzall and Menethi, (1989); Rao and Mohan Kumar, (1994); Thiruvengadachari and Sakthivadivel, (1997).

Various technologies are introduced in agriculture but those are not fully utilize because lack of education and communication problems, those applications are Some initiatives in the public sector are Kissan Helpline (Farmer helpline), Mandi on Mobile Service by BSNL, Kissan Kerala, KVK (Virtual KrishiVigyan Kendra), and Mobile based Agro-Advisory System in North-East India(m4agriNEI).Private sector services include Fasal (crop), Awaaz de (voice it), Videokheti (video farming), Mandi Bhav (market price).

Arpit Narechania is introduced KisanVikas –Android Based ICT Solution in Indian Agriculture to Assist Farmers in 2015 to assist farmers via smart phone to achieve agriculture productivity. Nikesh Gondchawar, Dr R.S. Kawitkar, “IoT Based Smart Agriculture”, June 2016, It aims at making agriculture smart using automation and IoT technologies. The highlighting features are smart GPS based remote controlled robot to perform tasks like weeding, spraying, moisture sensing, human detection and keeping vigilance. Chetan Dwarkani M, Ganesh Ram R, Jagannathan S, R. Priyatharshini, “Smart Farming System Using Sensors for Agricultural Task Automation” in 2015 This idea proposes a novel methodology for smart farming by linking a smart sensing system and smart irrigator system through wireless communication technology.

Dr. Hafizur Rahman introduced A paper called Satellite Based Crop Monitoring and Estimation System for Food Security Application in Bangladesh, to be an effective tool to extract information regarding condition and growth of agricultural crops. Satellite imagery is revolutionizing agriculture and can help farmers and public authorities take land monitoring to a new level. Here imagery infrastructure takes care of all the complexity of handling a satellite imagery archive and makes it available for end-users via easy-to-integrate web services.

Using a time series of satellite imagery to detect land use and land cover changes in the Atlanta, Georgia metropolitan area by X. Yang & C. P. Lo in 2010, This paper describes a suite of techniques that have been used to develop an operational approach, which will ensure high accuracy and compatibility in image classification from the satellite images of different resolutions and varying quality. Satellite Image Processing for Land Use and Land Cover Mapping In this paper, urban growth of Bangalore region is analysed and discussed by using multi-temporal and multi-spectral Landsat satellite images. Urban growth analysis helps in understanding the change detection of Bangalore region.

Deep Learning has gained popularity over the last decade due to its ability to learn data representations in an unsupervised manner and generalize to unseen data samples using hierarchical representations. The most recent and best-known Deep learning model is the Deep Belief Network [7]. Over the last decade, numerous breakthroughs have been made in the field of Deep Learning; a notable one being[8], where a locally connected sparse auto encoder was used to detect objects in the Image Net dataset [9] producing state-of-the-art results. In [10], Deep Belief Networks have been used for modelling acoustic signals and have been shown to outperform traditional approaches using Gaussian Mixture Models for Automatic Speech Recognition (ASR). They have also been found useful in hybrid learning models for noisy handwritten digit classification [11]. Another closely related approach, which has gained much traction over the last decade, is the Convolutional Neural Network [12]. This has been shown to outperform Deep Belief Network in classical object recognition tasks like MNIST [13], and CIFAR [14]

III.SYSTEM DESIGN

A. Architecture Of Proposed System

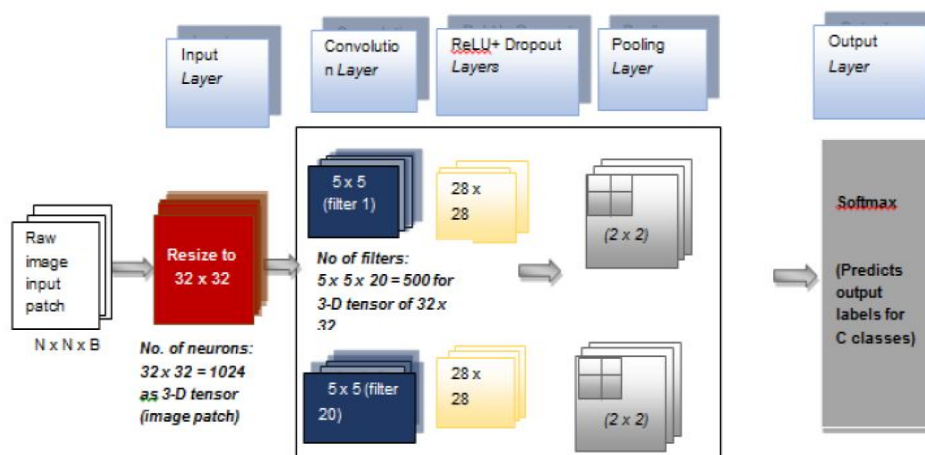


Fig. 3 Architecture of CNN for identification and classification of forest and agriculture land from satellite images

A large number of satellites capturing huge amount of images can be used for wide range of applications for land-use analysis, agriculture planning and rural & urban development. Visual world can be recognized better by using proper representation of objects. From an image, primitive features can be extracted followed by different parts of the object which leads to identification of the object. This is the key motivation behind deep learning, a branch of Machine Learning where neural networks are constructed with more than one hidden layer called as Deep Learning Networks. For image classification, deep learning methods using Convolutional Neural Networks (CNN) can be applied to develop generalized algorithms which can be used for solving problems of different domains. Figure 4.1 proposed a patch-based learning framework to design deep CNN (DCNN) models which can identify various land use and land covers present in a satellite image. The most important characteristic of CNN-based methods is that prior feature extraction is not required which leads to good generalization capabilities. CNNs have shown good performance in object recognition, object detection and remote image classification [1, 2, 3]. CNNs are inspired by the working of visual system of human beings where we do visual perception of things present around us using a layered architecture of neurons [4]. Hand-crafted feature extraction was the main method used for image classification, as reflected in most of the traditional image classification. CNN can learn suitable internal representations of the images. By using CNNs, learning models are able to obtain conceptual sensitivities by each layer. CNNs work as feature extractors and classifiers which are trainable as compared to traditional classifiers which makes use of hand-crafted features.

B. Flowchart

Below figure 4 flowchart explain the steps involving to achieve this paper completely successful.it include collecting the data from the satellite and classify those data and make proper report and send it to the respective department to train the farmers and utilization land.

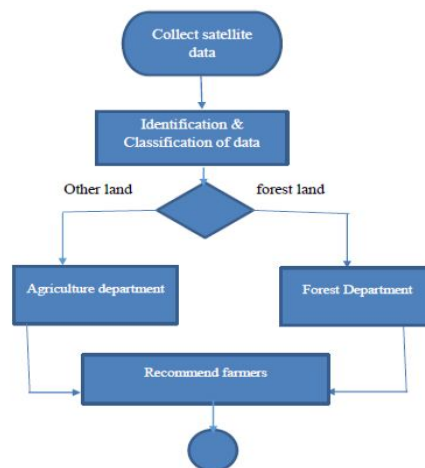


Fig. 4 Flowchart of proposed system

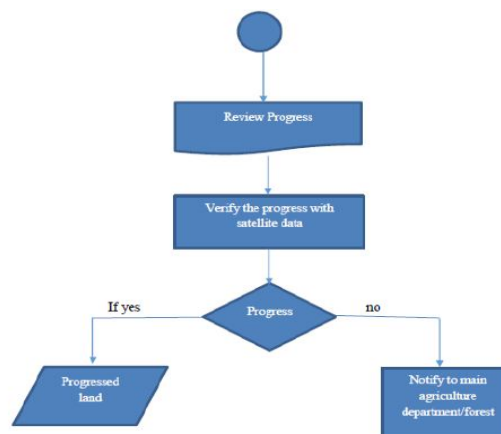


Fig. 5 Flowchart of proposed system

C. Dataflow Diagram

Data flow diagram also referred as bubble graph. This diagram is useful for representing the system for all degree of constructions. The figure is differentiated into parts which show maximizing data path & practical aspect.

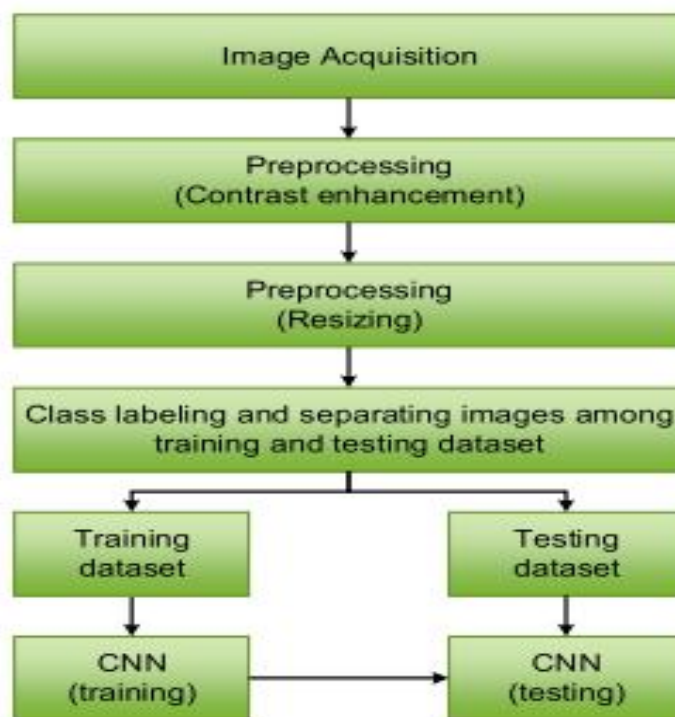


Fig. 6 Data Flow Diagram

IV. IMPLEMENTATION

A. Deep convolutional neural networks (DCNN)

Profound convolutional neural systems have indicated awesome execution in tests led on far off detecting pictures for arrangement or item discovery purposes. Building a DCNN requires significant advances: making the convolutional neural system engineering, getting ready preparing and test information and introducing boundaries for preparing measure. In CNNs/DCNNs, the properties identified with the structure of layers, number of neurons, number and size of channel, responsive field (R), cushioning (P), the information volume measurements (Width x Height x Depth, or $N \times N \times B$) and step length (S) are called hyper-boundaries [14, 15]. Interfacing all the neurons with all potential territories of the info volume is a troublesome assignment and prompts huge number of loads to prepare. This outcomes in an exceptionally high computational multifaceted nature. In this way, rather than associating every neuron to every conceivable pixel, a 2-dimensional district, say of size 5×5 pixels is characterized and it reaches out to the profundity of the info, making responsive field size to be $5 \times 5 \times 3$ (for 3 band input picture). Calculations are completed for these open fields creating the enactment map.

Initial step is to pick channel/bit of proper size to convolve over the info picture. The primary objective of this progression is to distinguish key highlights in the picture. This convolution tasks produces initiation maps. Initiation maps speak to „activated“ neurons/districts, for example zone where highlights explicit to the portion have been found in the info fix. Introduction of weight esteems to channel is done arbitrarily here and afterward these qualities are refreshed with each learning emphasis over the preparation set, as a major aspect of back proliferation. Convolution tasks find noteworthy highlights like edges, lines and power, when fitting channels are convolved over the picture fix. Determination of appropriate size of the channels is significant advance to distinguish the noteworthy highlights. Thusly it's critical to locate the fitting size of the portion/channel. In our structure of DCNN, part size utilized are 5×5 , 3×3 and 1×1 relying on the info size of fix for that convolution layer. The keys focuses in planning a DCNN model are setting nearby associations and pooling. The fundamental objective of pooling layer is to lessen the dimensionality of information, likewise called as down-examining. In the case of pooling is taken out, the dimensionality of the difficult increments definitely prompting enormous preparing time. While choosing stride factor for pooling, care must be taken that it doesn't bring about loss of data.

Any crude picture of any size can be given as contribution to the calculation structured which is first resized to the ideal picture fix size of 32x32. Resized picture fix (multispectral picture) is taken care of as contribution to DCNN. Picture fix is spoken to as a 3D tensor of measurements $N \times N \times B$, where N speaks to length and width of the picture and B is number of groups/channels. Hence, all the elements examined above assume a noteworthy part in making profound systems get prepared. Engineering building squares of DCNN models are appeared in Figure 5.1. In the models structured by us, for pooling layer, a step factor of 2 is utilized. This layer is generally positioned after convolution layer. Despite the fact that pooling brings about some measure of data misfortune, it despite everything is discovered valuable for the system as decrease in size prompts less computational overhead for the up and coming layers of the system and it likewise neutralize over-fitting.

A significant part in the preparation cycle is the decision of enactment work, the manner in which loads are introduced, and how learning is actualized. Actuation capacities are personality or direct capacity, sigmoid or strategic capacity, hyperbolic digression and Rectified Liner Unit (ReLU). Significant job is played by the decision of enactment work, most broadly utilized is ReLU [16]. The yield layer is the softmax layer which creates a lot of yield actuations speaking to anticipated probabilities which consistently total to 1. The capacity of the Softmax layer is to change over any vector of genuine numbers into a vector of probabilities, accordingly relating to the probabilities that an info picture is an individual from a specific class. Cluster standardization conceivably helps in two different ways: quicker learning and higher generally speaking precision. It is performed on the smaller than expected cluster size determined in the boundaries. For standardization purposes, we isolate the determined estimation of the initiation grid by the aggregate of qualities in the channel framework. Since there is an extremely enormous number of patches in our dataset we utilize stochastic angle plunge with small clumps for enhancing learning.

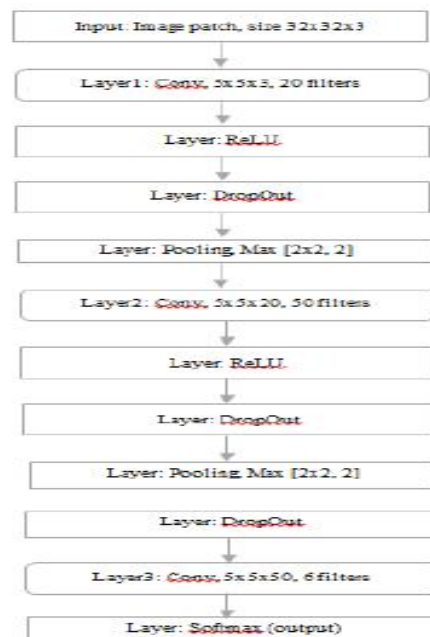


Fig. 7 Deep Convolutional Neural Network Model 1

B. Creation of Training and test Labelled Dataset

CNNs require enormous number of pictures for preparing for learning task. The picture goals, size and size of articles impacts the preparation cycle, as errand significant data changes with spatial goal. How an item is recorded in picture relies upon article's area, edge of catch and its size. This is to be considered for information growth. CNNs can manage change in area as loads are partaken in convolutional layers. Greater part of the analysts have utilized hand-named dataset made for both preparing and testing and since naming pictures is a very tedious cycle, the datasets have been little in both aeronautical picture applications and general picture marking work.

To develop the marked dataset for picture arrangement, satellite picture of IRS LISS-IV sensor, high goal symbolism from business satellite was obtained for the investigation district. It has pixel size of 5.8m and phantom range from 0.52 μm to 0.86 μm . The picture is shading Infrared picture for example groups are joined as NIR, Red and Green (CI Image). At that point preparing/test dataset is made as picture patches where locales of enthusiasm for each class are made independently.

These picture patches are additionally resized to wanted fix size of 32x32, which is given as contribution to CNN's first layer. Number of picture patches are changing because of level of essence of land covers present in the investigation scene. Picture patches are resized to 32x32 pixels size. This dataset is additionally expanded to 3000 pictures for each class utilizing information growth techniques like picture pivot, flipping, Gaussian separating for improving exactness and decreasing over-fitting. Information expansion is changing a picture that doesn't change the picture mark. There are numerous approaches to do it like pivot, scaling, flipping, editing (arbitrary), shading jittering and so on. Likewise RGB powers can be modified. Among the absolute pictures 80% are utilized for preparing and 20% for testing reason. Figure 4 shows test picture patches of the dataset made. The mean ghastly reflectance bend of every one of the six classes which is utilized to consider picture patches for incorporation into the dataset is recorded while picture patches were set up to be added to last dataset. Those picture fixes whose mean reflectance esteems strayed outside the ideal range were eliminated from the dataset, as they contained enormous number of blended pixels.

C. Experimental Setup with parameters set for Training Network

We have actualized DCNNs utilizing Tensor stream and keras. It is a python bundle for executing Convolutional Neural Networks (CNN). CNNs need a great deal of preparing information for learning measure and furthermore requires proficient executions. Tensor stream Package gives this as it has techniques for improvements and supporting calculations on GPUs. Building squares of CNNs, convolution, standardization and pooling can be handily consolidated and broadened assemble DCNN models.

Subsequent to making DCNN models, they are prepared by giving the made marked datasets independently. The base learning rate is 0.0001, boundaries to figure additions are: force = 0.9, and weight rot = 0.0005. The quantity of ages are shifted from 100 to 500 to check precision. DCNN models are prepared with various cluster sizes of 64, 128 and 256 where 128 is found to give best execution. Group sizes is number of tests stacked into memory for the preparation period of the DCNN. Models measures the total preparing dataset, by making additions characterized as cluster size. Cluster size is utilized for proficient calculations and is additionally subject to the equipment where CNN is prepared. During preparing the DCNN, information utilized from the preparation set will limit the mistake. The approval information is utilized to check the reaction of the CNN model on new and comparable pictures, which system hasn't seen before for example it isn't prepared on. Approval or test information passes just in forward go, as no blunder is determined in this pass. As the preparation and testing measure is finished, CNN model is spared and used to register disarray framework. Setting the estimation of learning rate is a significant advance as this qualities takes the system towards union, and choosing the fitting worth is an observational cycle. All through the preparation period of the CNN, the system produces three plots appearing, Top1 mistake, Top 5 blunder, and goal for each fruitful age. The top1 mistake portrays that, the class with the most elevated likelihood is the genuine right objective, for example organize found the objective class. The best 5 blunder delineates that, the genuine objective is one of the five top probabilities. The last layer, for example softmax is appended for conclusive characterization and it is completely associated. It has a channel profundity of C for example number of classes of the distant detected scene information base. In our CNN model, channels of size 3x3xC, 5x5xC have been utilized with arbitrary weight instatement, where C is number of groups. To improve precision of our structured model, we fused information expansion in the dataset planning measure.

V. RESULTS AND SCREENSHOTS

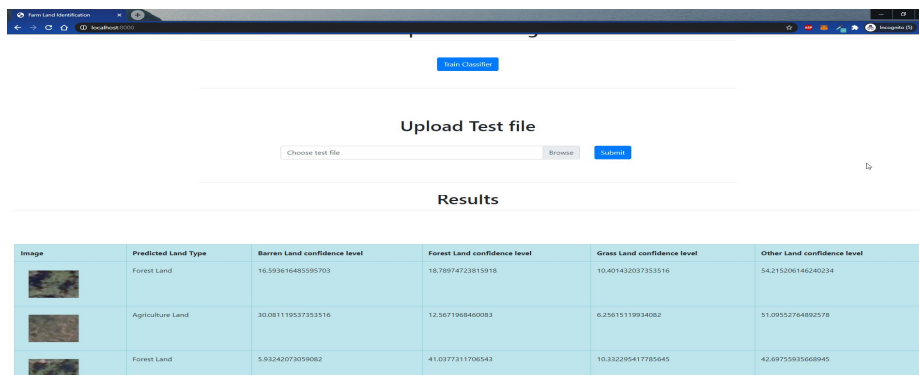





Image	Predicted Land Type	Barren Land confidence level	Forest Land confidence level	Grass Land confidence level	Other Land confidence level
	Forest Land	16.593616485595703	18.78974723815918	10.401432037353516	54.215206146240234
	Agriculture Land	30.081119537353516	12.5671968460083	6.25615119934082	51.0952764892378
	Forest Land	5.93242073059082	41.0372311706543	10.332295417785645	42.69755925660945

Fig. 8 Test data result predicted

Figure 8 shows the result of uploaded test image. It includes image uploaded, preferred type of land it is, barrel land confidence level, forest land confidence level, grass land confidence level and other land confidence level label values.

Image	Lat	Long	View On Map
	14.1761176	76.3876615	Click to view on Map
	14.1761176	76.3871815	Click to view on Map
	14.1755922	76.3882433	Click to view on Map
	14.168607	76.390722	Click to view on Map
	14.1754982	76.3917733	Click to view on Map

Fig. 9 Forest department page

Figure 9 shows the forest department page where we get the details of the land which is identified as forest land along with the link to see that land in map.

Image	Lat	Long	View On Map
	14.765352	76.121836	Click to view on Map
	14.761217	76.141918	Click to view on Map
	14.757222	76.144014	Click to view on Map
	14.759828	76.124293	Click to view on Map
	14.787312	75.978082	Click to view on Map

Fig. 10 Agriculture department page

Figure 10 shows the agriculture department page where we get the details of the land which is identified as forest land along with the link to see that land in map.

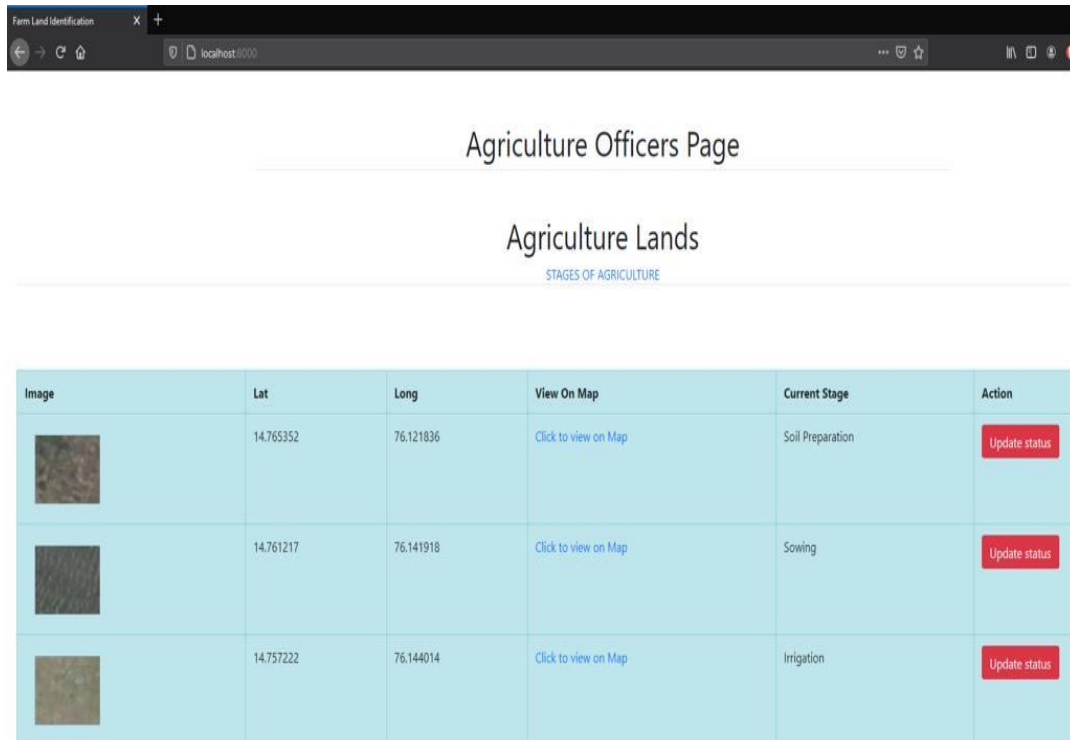


Fig. 11 shows the webpage where agriculture department take action towards the identified land.

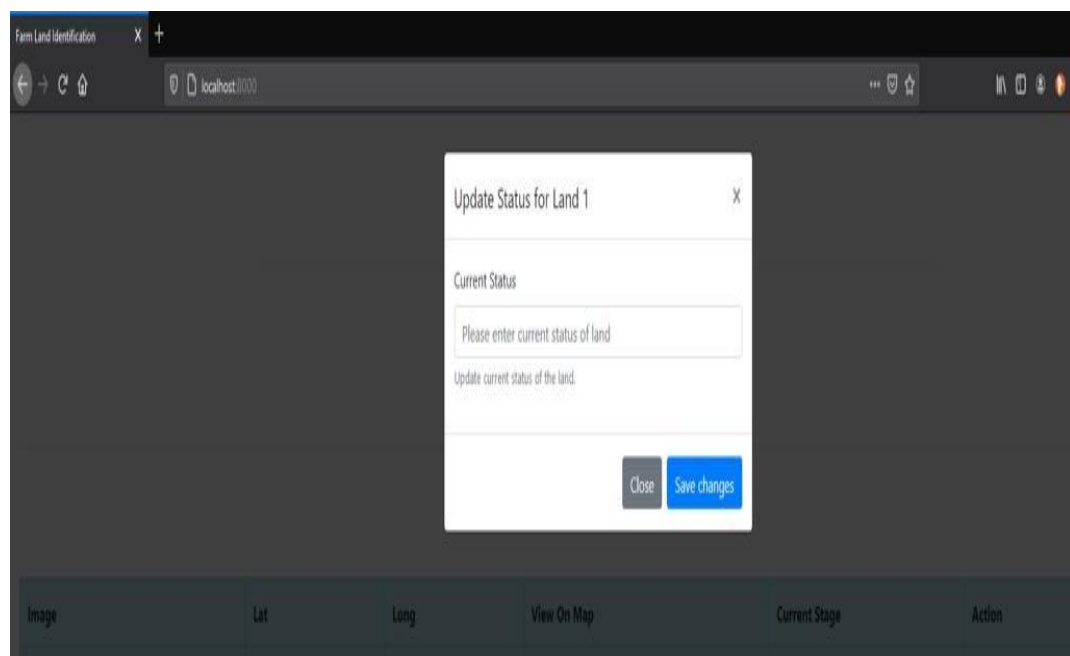


Fig. 12 updating progressing status of respective land.

VI. CONCLUSIONS

In this paper we tried to help agriculturist with the combined help of agriculture department, forest department and computer technologies so every plans and schemes of government could reach agriculturist to enhance their economic status and agriculture productivity. This work can be further extended in real time with the help of government, here we used dummy entities as a forest and agriculture department in real time paper we can use real entity and data to achieve an effective recommendation system for agriculturist.



REFERENCES

- [1] <https://www.satimagingcorp.com/>
- [2] State_of_Indian_Agriculture, 2015-16 report
- [3] Wikipedia
- [4] Atzberger, C. Advances in Remote Sensing of Agriculture: Context Description, Existing Operational Monitoring Systems and Major Information Needs. Remote. Sens. 2013
- [5] International Journal of Geo-Information Article-Sentinel-2 Based Temporal Detection of Agriculture Land Use Anomalies in Support of Common Agricultural Policy Monitoring.
- [6] A comparative study and analysis of searching and sorting algorithms w.sarada, International Journal of Advanced Research in Computer Engineering & Technology (IJARCET) Volume 5, Issue 5, May 2016.
- [7] G. E. Hinton and S. Osindero. A fast learning algorithm for deep belief nets Neural Computation, 18:2006, 2006.x
- [8] Q. V. Le, M. Ranzato, R. Monga, M. Devin, G. Corrado, K. Chen, J. Dean and A. Y. Ng. Building high-level features using large scale unsupervised learning. In ICML, 2012.
- [9] J. Deng, W. Dong, R. Socher, L. jia Li, K. Li, and L. Fei-fei. Imagenet: A large-scale hierarchical image database. In In CVPR, 2009.
- [10] A.-r. Mohamed, G. E. Dahl, and G. E. Hinton. Acoustic modeling using deep belief networks. IEEE Transactions on Audio, Speech & Language Processing, 20(1):14–22, 2012.
- [11] S. Basu, M. Karki, S. Ganguly, R. DiBiano, S. Mukhopadhyay, and R. Nemani. Learning sparse feature representations using probabilistic quadrees and deep belief nets. In Proceedings of the European Symposium on Artificial Neural Networks, ESANN, 2015.
- [12] Y. Lecun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. In Proceedings of the IEEE, pages 2278– 2324, 1998.
- [13] WWW1. MNIST. <http://yann.lecun.com/exdb/mnist/>.
- [14] A. Krizhevsky. Learning multiple layers of features from tiny images. Technical report, 2009.
- [15] DeepSat – A Learning framework for Satellite Imagery Saikat Basu¹, Sangram Ganguly², Supratik Mukhopadhyay¹, Robert DiBiano¹, Manohar Karki¹ and Ramakrishna Nemani³, September 14, 2015.
- [16] https://keras.io/guides/sequential_model/#when-to-use-a-sequential-model.
- [17] <http://csc.lsu.edu/~saikat/deepsat>.



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