CNN-Based Terrain Mapping for Agriculture: Improving Land Use and Crop Management

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Abstract: Artificial intelligence has been keeping up with the fast-pacing world of agricultural innovations both conceptually and theoretically.In the more recent developments in AI, it has been noticed that artificial intelligence is presently dealing mostly with the discovery and not the distance mapping process concerning viable resources, and so, with a stronger functional perspective, the authors have made attempts towards AI-based systems that could potentially augment the meticulousness of the AI developmental aspect where fallow land needs dealing.Given a vertical mapping of ground data with the help of satellite images, land use can be identified adding onto this a horizontal mapping using RGB frames stands to improve model performance to determine if a given area of land is feasible for agricultural development. The paper proposes a CNN model that can interpret and categorize agricultural area based on GIS data. The primary application of this research is to facilitate farm land use cases to improve productivity and land viability.

Keywords: Convolutional Neural Network (CNN), Deep Learning, Agricultural Terrain Mapping, Satellite Imaging, RGB Frame, Image Processing.

1. Introduction

A broad area of computer science called artificial intelligence focuses on building intelligent machines that can carry out activities that usually call for human intelligence. Although artificial intelligence (AI) is an interdisciplinary subject with many different techniques, developments in machine learning, particularly deep learning, are drastically changing almost every area of the tech industry and now surprisingly the agriculture industry in recent years. Moving on to terrain mapping, it involves identifying distinctive features of an area so as to facilitate classification. When

applied on maps and landforms the interpretations of terrain mapping help determine the types, properties, hazards, physical conditions of soil and rock material.
Agriculture not only as a practice but also as a sector is believed to be conventional and traditional to a segregated number of individuals, that are as such only assigned the role of handling the build and drop of personal or borrowed land spaces. With reference to land space, the first idea to pop up is land type, now, terrain has generally been mapped based on five criteria: soil, sand, bricks, cement and flat [1]. This gives easy groupings to work with, imbibing it further into the soil land categorization leads to subdivision for land space use. Automating this based on visual data it makes sense that a convolutional neural network can be employed to automatically extract a hierarchic feature representation from the data, based on which the target recognition and terrain classification can be conducted [2].
Convolutional Networks is the image processing algorithm as a subset of deep learning. It is that part of the AI study that attempts to replicate the human ability of sight and visual perception. The task itself without a doubt is challenging due to the number of colours that can be interpreted by the human eye. CNN assists this very factor by using the major scales in digital pictorial framing, namely RGB color space, HSL color space and CMYK color space. In this paper, the authors have dealt with the RGB color space. Further, it is necessary to note that CNN can be modified and made more effective based on the improvement of different aspects such as layer design, activation function, the loss functions, regularization, optimization of model built and the speed of processing [3].
To understand more on RGB Frames it can be concluded that the color space works both on 2-D and 3-D images. The work is done using the concept of drown out, the procedure taking place depends on the amount of light falling on a picture which rationally brings out the hidden colours. The primary colours are red, green and blue the shades combine in different intensities to give rise to another secondary color. If all three are raised to the highest possible intensity i.e. (255, 255, 255) the color produced is white and antithetically the color reflected is black. This serves as a good ranging factor for interpreting image colors in case of CNN image processing.
The next stage is to read into the satellite images for a parallel mapping to the landform. The research in satellite image classification is by no means new. The data is hard to get but effective in automated processing. It is a known fact that, one of the difficult issues at the intersection of computer vision, machine learning, and remote sensing is the classification of satellite images. The majority of existing object classification techniques are not appropriate for processing satellite datasets because of the significant degree of variability included in satellite data. The absence of a single labeled high-resolution dataset with various class labels has further impeded the advancement of satellite image analytics [4].So, the easy technique of working around available data fed into CNN is taken up.
Deriving from the sumptuous, predetermined explanation, the preface investigated and proven so far is a clear indication towards the plain belief that, advancing AI algorithms

where the ground level diagnosis ofthe state given an agricultural friendly land is not unattainable. Therefore, the primary goal of this work is to develop a method that can classify common fallow or harvestable land as either welcome land for mass agriculture or not. The author hereby disclaims that the diagnosis methods provided are outside of their purview and were developed through extensive research on the topic of satellite- and RGB-frame-based land maps, taking into account existing studies.Although AI is now used in the process of discovery rather than the distance mapping of resources that are viable, the authors have a more optimistic outlook and expect that AI-based expert systems will be able to improve the accuracy of the developmental aspect of fallow land.
As a brief understanding of the process, it is important to note that, CNN image mapping is characterized by the strong constraint of requiring that each neural connection implements the same local transformation at all spatial translations [5].Achieving the right kind of mapping is within reach as is the fine tuning of the CNN model. But a major challenge lies in the satellite images, to name a few would be the massive size of each figure, besides having been pulled from the farthest known distances these images though precise in their form are subject to external noise and even the environmental conditions. Thus, there is a need to preprocess the images so as to conform them to the same parameters that can be analyzed by researchers. Satellite images are widely used in many real time applications such as in agriculture land detection, navigation and in geographical information systems [6].
A majority of research efforts on the lines of terrain mapping have been devoted to solving the categorization difficulties differently and occasionally, by imposing many oversimplifications in framing the complete problem, due to the intricacy and plurality of challenges encountered in tackling each variation of land form.In this paper, the authors have concentrated on one particular land form, this subcategorization within terrain mapping immensely transform the use case and productivity of outcomes. Here, two core concepts take form, the vertical mapping of an area i.e. satellite imaging and secondly horizontally mapping the same area to find the feasibility of agricultural development. Satellite imaging helps to map distances and land spread this, as mentioned earlier, can be extended to formulate distance mapping algorithms to locate developmental resources. The second approach helps to check the categorization of land. For instance, a garden can be interpreted by a satellite as a green piece of land that may support cultivation, introducing horizontal mapping now tells if the land is greenhouse fit or is it actually fit for agronomy.

2. Literature Review

Artificial Intelligence for geographic information sensing is a relatively innovative concept. AI has been used in the past for land-based mapping as the state of art GMap clearly depicts, moving forward from here, as mentioned in the beginning, AI for GIS can morph into a selected-few forms for proper produce. AI for GIS is beneficial not only for the common man, it can also assist the government to make proper judgement pertaining to land allocation. Terrain classification on the other hand is assistive to agricultural enthusiasts or other field enthusiasts where land forms and soil content is concerned. According to the authors of robotic terrain classification, visual perception of land poses multiple difficulties pertaining to surface reflectivity given that results are nonlinear in response to moisture variation and atmospheric content [1]. This persuades that topography cataloguing is not out of reach for artificial intelligence but also brings on the challenge of natural variation in the quality of land / soil. Given a developed system to handle this use case we can move further to map the terrestrial plain.

Considering visual perception, in their study Abadpour and Kasaeihave come up with clear relationships in the preliminary RGB image conversions to binary i.e. black and white or even gray scales with their performance on the recognition of images and its components.Their paper color image process using principal element analysis describes the color recognition involves comparison of every pixel within the metric and leads to the dominant color because the color of the given object is explained [7].Conversions of RGB frames aside, based on the color spaces the heatmaps based on lightings can be generated as well. Moreover, Joy and Kaur confer that with the amount of color on an image, based on color space distance mapping gives an approximate and close to accurate idea of its value and name, the concept of distance mapping now applies to identifying a match for grassland or garden or lush green areas [8].

Now on to the image processing part, in an effort to help agricultural researchers better comprehend CNNs, Torres and Mora present a useful theoretical framework that makes it simple to demonstrate how CNNs work and apply it to various scenarios [9].Furthermore, image convolution, used in convolutional neural networks is a process where we pass an image split into kernels and thus transform it using the outcome of filtered values. This kernel is originally a small matrix of numbers mapped to the pixel points to facilitate the building of the CNN. The process further generates a feature map according to:

$$G[m,n] = (f*h)[m,n] = \sum_j \sum_k h[j,k]f[m-j,n-k]^{(8)}$$

Here the source image is f, kernel h and the indexes of rows and columns of the resultant matrix m and n [10]. CNN image classification can be further fine-tuned to better suite the requirement of land or terrain or even topographical classification [11].On the other hand, the classification results are not topographic maps. For topographic maps, generalizations of the map content and cartographic quality are required. High standards should be reached by the geometric precision.

Given that convolutional networks suffice with RGB frames, Vozenilek mentioned that GIS is an influential technique and mapping AI over it works towards building the convergence of AI over information derived from sources other than RGB frames [12]. Femin and Biju in their research have explored the area of using CNN over satellite images to identify buildings. According to the authors, applications for the classification of remote sensing images include groundwater exploration, urban planning, environmental disaster assessment, land monitoring, and terrain feature classification. The creation of a precise building detection system using satellite photos is discussed in this work. Several techniques are developed in the proposed work to identify buildings in satellite photos. It is discovered that the suggested approach is effective in identifying different kinds of building footprints [13].

A wide range of artificial intelligence (AI) applications, particularly deep learning for geographic problem solving, have been sparked by the recent interest in geospatial artificial intelligence (GeoAI). Nonetheless, there are still several important obstacles that prevent a thorough integration of AI with geospatial research, including a dearth of training data and a lack of understanding of spatial principles and spatial impacts in AI model building as mentioned by Wenwen [14].

Song brings to light that classifying land cover using satellite photography can yield important data for a variety of uses, such as surface analysis, environmental monitoring, building reconstruction, etc. Traditionally, unmixing-based, shallow, and deep learning approaches have been used to classify land cover. However, unmixing-based approaches have stability problems because of the compositeinherentdata parameters, while approaching DL algorithmically, such as a two dimensional base CNN, require massive sizes of labeled training sets that are frequently found unavailable for satellite images specifically, and so spatial discontinuities get founded on the small ground truth gathering, making 2D CNN approaches unfeasible. In order to improve categorization, we first present in this research a simple single dimensional convolution neural network-based framework that can not only virtually but programmatically be applied to every pixel subset matric in the virtual domain. From there, we extract descriptive local features [15].

Authors of Satellite Image Classification for Detecting Unused Landscape using CNN proposed the idea of classifying used and unused land using CNN on satellite images. The usage of vacant land is growing as a result of daily landscape changes. vacant land can be put to many uses, including improving municipal infrastructure, farming, and more. This paper contributes to the automation of the land-use detection procedure. This article proposes a system for processing satellite images that can identify underutilized land. In this case, pre-processing steps include converting the image to a greyscale format, compressing it, and removing noise from it. In order to divide the area into used and undeveloped lands, segmentation is done [16].

Taking the idea further, the concept of running two simultaneous approaches, namely RGB frame as horizontal mapping and Satellite Image as vertical mapping assists in further classifying productivity of land based on area and land space. This paper proposes a novel system of classifying agricultural land in real time relying on the two-step process of terrain classification and land use objectifying. Zujevs and Pudzs have defined the dynamic vision sensing to work with data in RGB frames [17]. Earth cache as well offers on demand satellite data as in the past [18].

3. Methodology

As a facile approach to understanding the intertwining of AI, DL, CNN with ATM, GIS, in order to accomplish the aforementioned goals, the design flow divides the overall concept into modules of milestones. It facilitates and streamlines the process of following through. The dataset had to be developed, imported, and made suitable for usage, as shown in the picture below. Subsequently, each model is constructed and trained, and at last, a fresh data piece is classified for model success and verification.

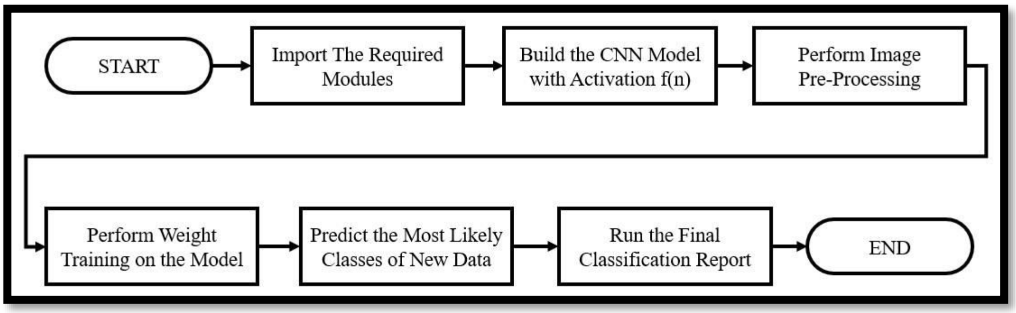

Fig 1. Design Flow of the Proposed System

The major developments in the given process are the building of the model, finding the right parameters for image processing and the weight training which consumes a tremendous amount of GPU. Thus, the functioningof the CNN divisive system can be categorized in the following two phases. The first phase caters to the GIS part where we apply deep learning on satellite-based images for referring land parameters consisting of individual model building for the major divisions of land imaging. The phase then following leaves us to build the CNN model around implicit relevance to RGB frames. Initially, here is a look into the constrained dimensions of the sparse-set used with the aim to train the models under each phase. The authors once again bring to light the industry accepted standard for training a CNN model i.e a minimum of 100s to 1000s images for each of the classifications. We are dealing with binary classification for each of the specifications. Given below is a tabular summary of the data referring to the total entries in the desired folders the model trains for and is subsequently validated on.

Table 1. Dataset Size for each Model Built

Specification	**Dataset Dimension**	**Dataset Classes**
RGB Frames	(4200, 2)	Training: 47.6 % (2000) Validation: 28.6 % (1200) Testing: 23.8% (1000)
Satellite Images	(1000, 2)	Training: 50% (500) Validation: 30 % (300) Testing: 20 % (200)

The math working within land classification has been discussed in the literature review. Further we see that there is a binary form, to our problem needing the output in terms of whether a land can be used for agriculture or not. Given that we are dealing with binary classification a Sigmoid activation function is use in the final layer of the neural network. On drafting the sigmoid equation we have:

$$S(x) = \frac{1}{1+e^{-x}} \quad (19)$$

This particular binary classified activation function works the same as any binary set. In the Sigmoid curve the values tending to positive are transformed to binary one and the negatively tended are transformed to binary zeroes, generally there is less need of transformation since the values are most usually the binary values themselves. Therefore, values not conforming to binary are plotted in between 0 and 1, without leaving the specific interval. The curve is sketched out as:

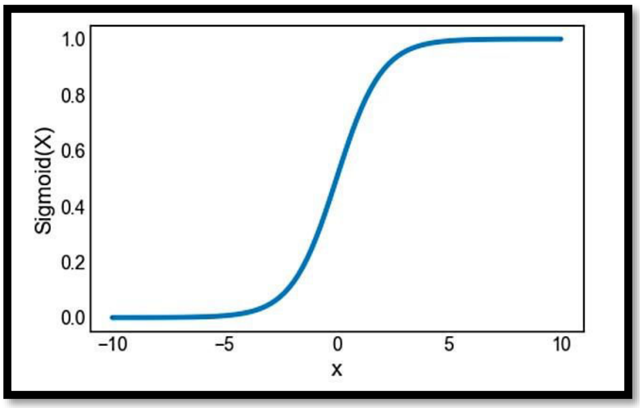

Fig 2. Sigmoid Graph (Binary Activation Function)

Consequently so far, in this paper a simple mechanical exercise on the machine over a training algorithm was built with the aim to understand whether a land image can be interpreted in terms of fruitful or fallow based on visual dynamics. The end of the network is achieved with a single unit (a dense layer of size 1) and a sigmoid activation, as previously discussed, because the authors of this research are addressing a binary classification problem.

By virtue of the sigmoid, we have understood that all tendency values are converted to absolute or discrete values as 0.0 and 1.0,to make it clear all values much smaller than 0.0 are converted to 0.0 the same for all values that are around one.For the sake of neural networks, till and even through the early 1990s, Sigmoid had been the primary activation function that had been implemented on neural networks by default. To overcome some of its limitationthe ReLU was introduced hence explaining why we have used two different activation functions in the same model [20]. The ReLU graph has been given below.

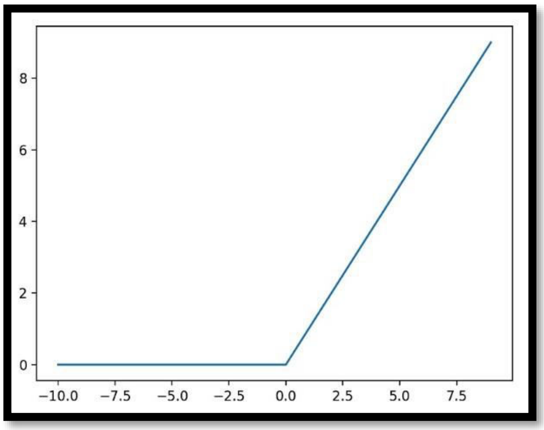

Fig 3.ReLU Activation Function Graph

The model summary given below encodes the likelihood that the neural network is essentially looking at one of the two classes. The sequential model is built of multiple layers with the primary aim to fine tune it so as to process the data given as input. Breaking it down, the CNN model is parameterized with convolutional and max pooling layer, this in essence refers to the data passage the same way as you would pass tea through a strainer. In essence the max pooling layer down-samples data input with respect to its dimensions in 2 D space. This makes sense when interpreted such that, an RGB frame actually captures a 3 D image in the 2-dimensional space. Further, convolutional layering maps the instantaneous values that are found in the overlapping samples which represent the two input signals. In this process one of signals is flipped, such that when multiplied and added together they accomplish convolution.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_1 (Conv2D)	(None, 72, 72, 64)	18496
max_pooling2d_1 (MaxPooling2	(None, 36, 36, 64)	0
conv2d_2 (Conv2D)	(None, 34, 34, 128)	73856
max_pooling2d_2 (MaxPooling2	(None, 17, 17, 128)	0
conv2d_3 (Conv2D)	(None, 15, 15, 128)	147584
max_pooling2d_3 (MaxPooling2	(None, 7, 7, 128)	0
flatten (Flatten)	(None, 6272)	0
dense (Dense)	(None, 512)	3211776
dense_1 (Dense)	(None, 1)	513

Total params: 3453121 (13.17 MB)
Trainable params: 3453121 (13.17 MB)
Non-trainable params: 0 (0.00 Byte)

Fig 4. CNN Model Summary

Once the model is built, the next is to set it over each data piece. Initially the input format needs to be converted into floating point tensors [21]. So the steps taken next rescale the pixel values (between 0 and 255) to the [0, 1] interval given that neural networks prefer to deal with small input values [22].

For this, Keras has functionalities to handle it automatically with the class ImageDataGeneratorthis is an image processing assistant tool, located at keras.preprocessing.image. In particular, it quickly sets up python generators that can instinctively turn image files on disk into batches of pre-processed tensors points. In the next step, using the generator, we fit the data onto the model. This process is done using a method that is a subset of the module model i.e. thefit method, the latest equivalent of fit_generatorthat Keras has introduced and this is for the data generators in the outcome of the previous step. It takes a Python generator as its initial argument, which will produce input batches and targets endlessly. The generator must determine, for example, how many samples to take from the generator before announcing the end of an epoch because the data generated is not discrete. The steps_per_epoch option serves this purpose: the fitting process moves on to the next epoch after drawing steps_per_epoch batches from the generator, or after running for steps_per_epoch gradient descent steps.Finally, the training accuracy can be plotted.

Furthermore, the processing of the satellite images is fairly simple with the singular aim of classifying land-based data by the color and depth of each image. In the figure below, the two major types of satellite imaging have been displayed. The “Nag” abbreviation stands for non-agrarian land space, “F” is forest which is again, not an agrarian land space. “Ag” represents strictly agricultural land space.

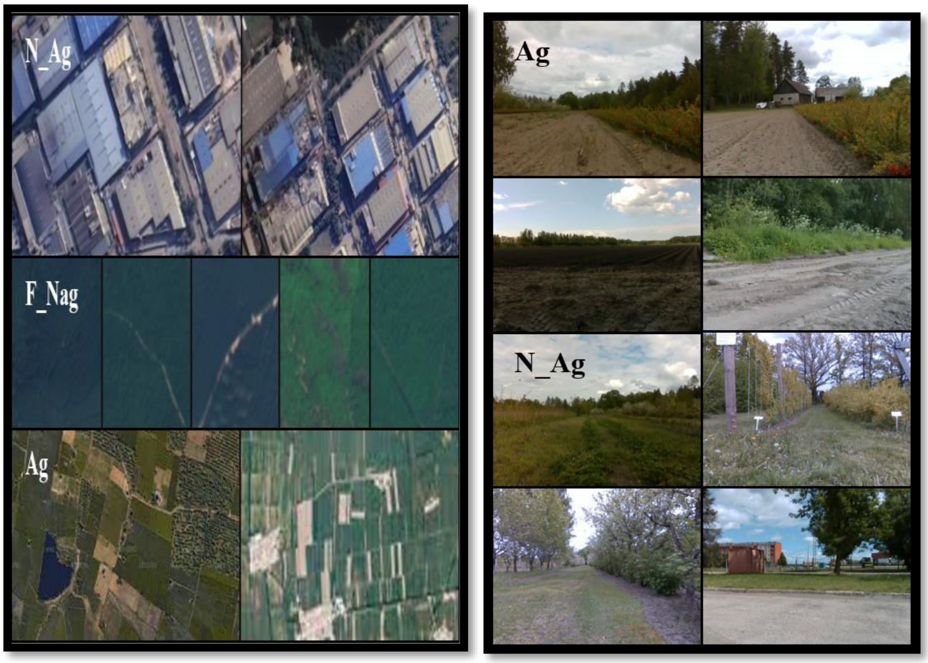

Fig 5. Satellite and RGB Image Descriptors

For the use case in application to the CNN model there have been only two defenders of identity, "Ag" for agrarian land space and "N_Ag" for non-agrarian terrain. The forest classification is to clarify a false positive outcome in the model output.

4. Experimental Result

In lieu of jargons that govern the complete experimental process, let us begin with the resultant insights gathered from the scoring matrices and statistical meanings. Reveling in the model performance with just the training and validation dataset the accuracy hits 0.96 for the RGB model where shot images were used to determine agrarian land and crediting to the dataset size in the model that was built for satellite imaging, the accuracy is brought down to 0.93, in either case all parameters used are tunable. The activation function, optimizer and test size also affect the accuracy. The model losses are calculated by the binary_crossentropy algorithm, again given that the problem statement leans towards binary classification. It computes the cross-entropy loss between true labels and predicted labels [23].

Since statistics requires veto, we use the test dataset to drill the model and so, the accuracy spread is received by means of the confusion matrix in both the specifications. A confusion matrix has four segments that potentially represent the following: True Positive (TP), False Negative (FN), True Negative (TN), False Positive (FP) [24]. The equation below depicts the accuracy calculation that gets derived from the confusion matrices. With the general aim to achieve more of TPs and TNs, given spread and sparse data, the accuracy can be interpreted in terms of model performance under data constraints.

Accuracy: $\frac{TP+TN}{TP+FN+TN+FP}$

The confusion matrix for RGB frames grades789TPs and 137TNs, meritorious to the model is the absence of major incorrect predictions amounting to 74, this so results in a peaking93% accuracy, this acknowledging the comfortable size of data fed into the CNN model which by virtue works best with a larger amount of data. Due to hardware constraints the data size is limited, the accuracy may be improved by a stronger GPU and a larger dataset.

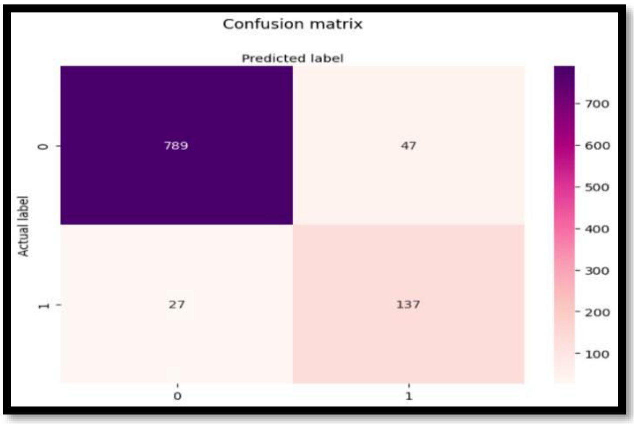

Fig 6. Confusion Matrix for RGB Framing

Moving ahead, the confusion matrix for satellite imagesgives 113TPs and 64 TNs, here the incorrect predictions are much lower referring to 23, this results the firmly sinking accuracy at89%. Here antithetical to the parallel RGB model the dissent of the score belongs to a vastly low amount of data being fed into a CNN model. A thousand pictures barely give a consolation to the model itself and the results are likely to improve given a machine learning algorithm. Image processing at a lower level with lesser amount of data though, will close in on the said validity of data.

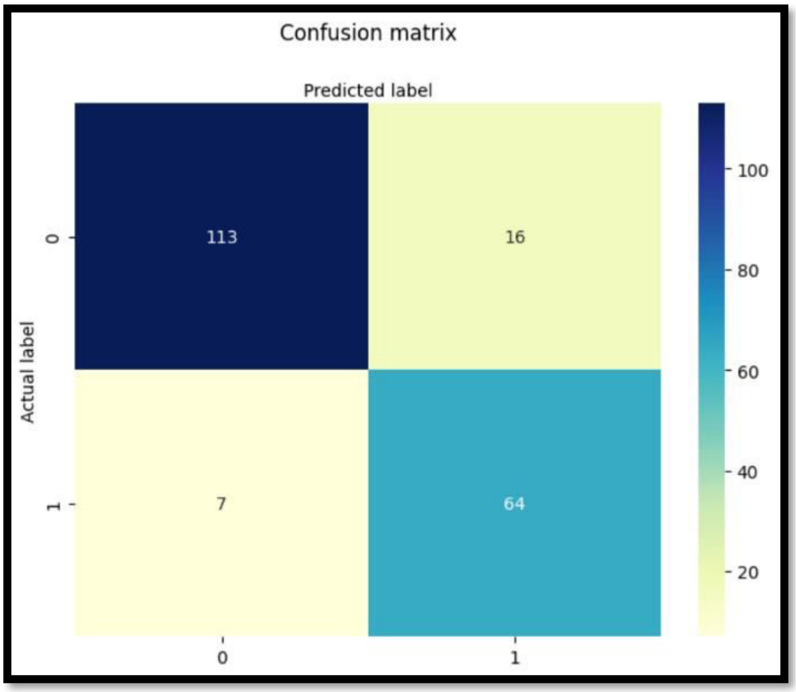

Fig 7. Confusion Matrix for Satellite Imaging

For the satellite imaging model that has been built and can classify agrarian land, the accuracy score can be adjustedin a few ways, for starters we need to alter the data length, increase the size per say or even shifting the sized proportions of the data that has been allotted for training and testing, as is a productive case of CNN. Given the disadvantage of unavailability of open-source satellite data. On the other hand, using CNN has the added advantage of being able to expand the run sets and drafting the model on multiple levels of training and retraining by flowing data through a greater number of epochs while the phase of model training is on. Based on the two distinctions of data a clear comparison of the model performance has been tabulated below.

Table 2. Comparison between Model Performance

Grounds for Comparison	RGB Frames	Satellite Images
Accuracy	Higher: 92.60%	Lower: 88.50%
Justification	Dataset size meets the minimal requirement of the CNN model	Dataset is more effective for a machine learning classification model.
Precision	0.7445	0.8000
F1 Score	0.7873	0.8476
Recall	0.8353	0.9014
Complexity	Higher, credited to time	Lower, credited to data

Furthermore, in the figure below a comparison of data dependence on accuracy has been depicted. Given that RGB frames had a higher preservice of data available for processing in multiple forms, it has performed comparatively better than the satellite data that has covered less than half of the RGB frames.

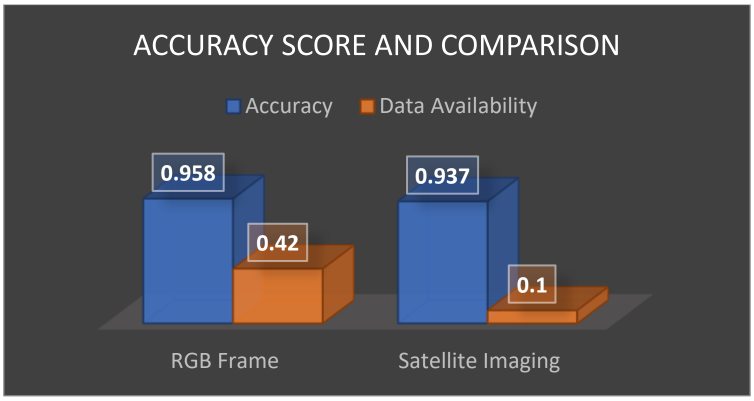

Fig 8. Data Dependence on Accuracy

The paper bears the distinguishing factor of mapping tendency between the images to the model built. Thus, abrief comparison of the existing state of the art imaging procedure, satellite imaging and the RGB added proposed techniques is given below.

Table 3.Comparison between Existing and Proposed System

Parameters	SOA	AI-GIS
Mapping technique	Vertical	Horizontal + Vertical
Algorithm Insight	Precision Agriculture	Terrain Based CNN
End-Use	Utility in AI / ML	Real Time Intel

Accuracy	Subject to environmental conditions	94% Average
Terrain Model	Picturesque	Gray Framing
Randomization	Higher credited to data drawing ability	Lower credited to sample spacing and framing

5. Conclusion and Future Scope

The Artificial Intelligence aided terrain classification model is definitely subject to multiple real time factors based on the requirement in a constrained physical space. The proposed system has achieved a good measure of success given these very constrains and is comparatively reliable than a mapping system that does not input visual data. Thus, based on the classification, two major use cases can be developed given the application as suggested on the proposed system: The foremost would be to virtually assist and even in particular cases help farmers identify land for the agrarian purpose questioning if cultivation is possible. The next level of application would then be from a futuristic perspective to extend this visual mapping to classify which type of land based on area, so the choice of crop for sowing is kept in regard. The proposed system does the work of classification of land keeping the main factors of location and area intact. The potential now lies in the idea of distance mapping of resources which basically is a route-based technique to validate the existence of an agrarian land from a secure distance to resources that will be required to develop it. Safe to say terrain mapping is an easier said than done job when working towards the mapping of resources to viable land.

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