Soil Classification and Crop Suggestion using Image Processing

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Soil Classification & Crop Suggestion based on HSV, GLCM, Gabor Wavelet Techniques and Decision Tree Classifier in Image Processing

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Abstract- This paper is intended to support agriculture by classifying 7 different types of soils like Clay, Clayey Peat, Clayey Sand, Humus Clay, Peat, Sandy Clay and Silty Sand, and in suggesting suitable crops that could be grown in those particular soils using image processing. Pre-processing is done by using Low Pass filter. HSV, GLCM, Gabor Wavelet algorithms are used for feature extraction. HSV, GLCM are used to perform colour based feature extraction. Gabor filters are used to perform texture based feature extraction. The features obtained from the test image are then compared with the features obtained from the images in the dataset. Matching of image features is achieved by training the Decision Tree classifier with statistical measurements like mean, standard deviation, skew and kurtosis. Finally the soil is predicted with the help of segmented images that are given as input for simulation using Matlab R2018a and is followed by crop suggestion.

Keywords- Low pass filter**,** HSV, GLCM, Gabor Wavelet technique, Decision Tree classifier.

I. INTRODUCTION

Agriculture is the backbone of India. And several times it becomes difficult to classify soils in different regions of the country with required accuracy. Our project proposes the idea of classifying soil and suggesting suitable crops using image processing. Coolpix Camera is used to take images of 7 different soils. Nearly 200 images are loaded into the dataset. Input image is subjected to pre-processing, feature extraction, classification, testing, and finally the result is produced. The input image is matched with a similar image in the dataset that is image retrieval is being done here. Since Gabor filters are used in our proposed system the efficiency is pretty high. By the process of colour based and texture based feature extraction the accuracy is improved. Our project further extends a helping hand for the farmers by predicting the water absorption rate.

II. PROBLEM DEFINITION

The existing method of soil classification and crop suggestion require manual involvement, human errors, and the results are uncertain. The method is also time consuming and invasive in nature. But our proposed system overcomes all these errors because it takes into account the physical properties of soil for classification and prediction.

III. METHODOLOGY

Following are the various levels involved in image processing:

1. Low level processing
2. Medium level processing
3. High level processing

Figure 1 shows the detailed processes involved in different levels of image processing.

LOW LEVEL PROCESSING:

1. Filtration
2. Enhancement
3. Sharpening
4. Noise reduction

MEDIUM LEVEL PROCESSING:

1. Feature Extraction
2. Classification

HIGH LEVEL PROCESSING:

1. Result Identification

Figure 3.1 Image processing classification process

- Low level processing (LLP): It involves image enhancement, removes noise using Gabor filter and resizes the image.
- Medium level processing (MLP): It involves image segmentation and classification.
- High level processing (HLP): It involves image identification.

Flow Diagram:

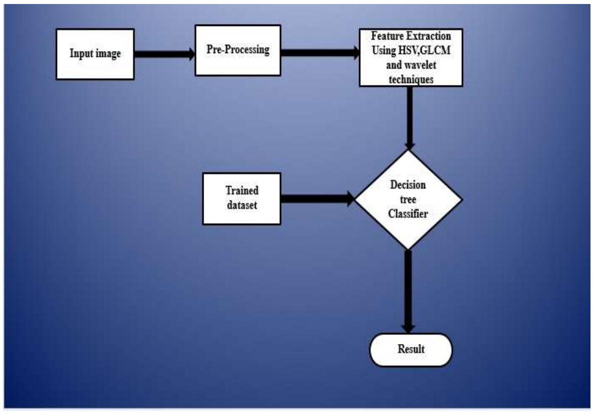


Figure 3.2 Flow Diagram of our proposed system

Filtration:

Filtration in our proposed system is done using Low Pass filter. Low Pass filter is used to pass signals with frequency lower than the cut-off frequency and attenuates all other signals with frequencies greater than the cut-off frequency. In our proposed system Low Pass filter is used to remove unwanted components and features from the signals so as to reduce noise in the signal. Low Pass filter is also used for shade correction, even brightening and for removing artifacts.

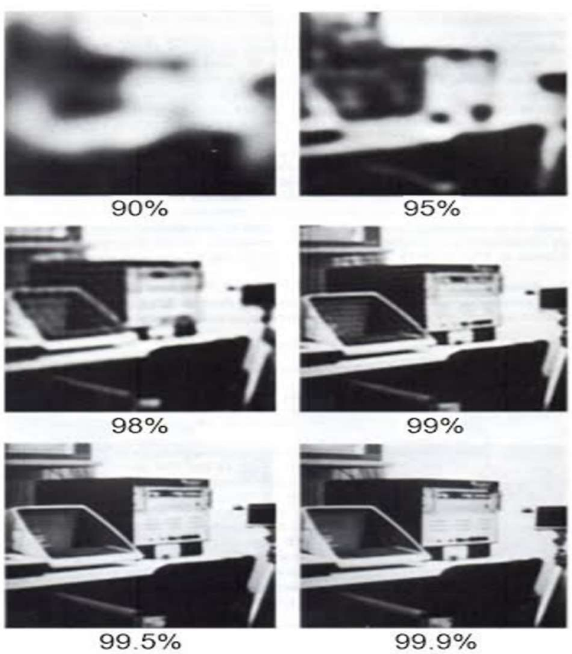


Figure 3.3 Blur Removal- Ideal Low Pass filter

Image Enhancement:

There are two methodologies in image enhancement:

- Frequency domain Processing(FDP)
- Special domain Processing(SDP)

Figure 4 shows the image enhancement steps

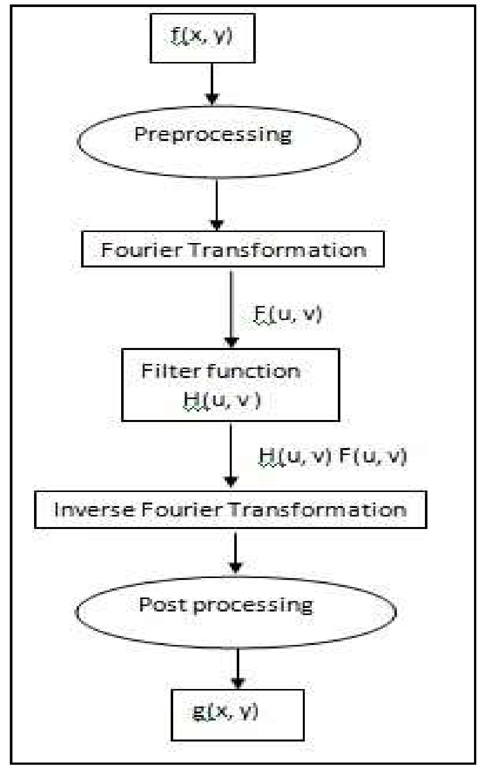


Figure 3.4 Image enhancement steps

FDP: It is basically achieved by filter operation based on Fourier transformation as given in equation no I.

G(u, v)=H(u, v)F(U,V)……………………………………(I)

Where:

F(u, v) : Fourier Transformation
H(u, v) : Filter function
G(u, v) : Yields

SDP: It is based on manipulation of pixel in an image and it is achieved by equation no II

g(x,y) = T[f(x, y)] …………………………………(II)

Where:

f(x,y) = input image
g(x,y) = processed image
T = operator on f, divided over neighbor f(x,y)

Enhancement can be done by using gray level transformation, histogram processing, arithmetic logic operation and special filtering.

Feature Extraction:

Features are the fundamental components of an object. It is used to distinguish one object from the other. Features are also referred to as descriptors. The process of obtaining features from an object is known as description of an object. In our proposed system feature extraction is done by two methods

1. Colour based feature extraction
2. Texture based feature extraction

1. Colour Based Feature Extraction:

Hue Saturation Value (HSV), Gray Level Co-occurrence Matrix (GLCM) are used for Colour based feature extraction in our proposed system. The existing system used few tests including Cone Penetration Test (CPT), Vane Shear Test (VST), Standard Penetration Test (SPT), Pressure Meter Test (PMT). But our proposed techniques are used to extract necessary features so as to suggest crops and the accuracy exceeds the bar which was set by the existing tests.

Hue Saturation Value (HSV):

Using this model, an object with a specific color can be detected and tthe influence of light intensity from the outside is reduced.

Gray Level Co-occurrence Matrix (GLCM):

Given an image composed of pixels, each with an intensity (a specific gray level), the GLCM is a tabulation of, how often different combinations of gray levels co-occur in an image or image section. Texture feature calculations use the contents of the GLCM to give a measure of the variation in intensity.

2. Texture Based Feature Extraction:

Gabor Wavelet Technique:

These are wavelets invented by Dennis Gabor using complex functions constructed to serve as a basis for Fourier transforms in information theory applications. The important property of the wavelet is that it minimizes the product of its standard deviations in the time and frequency domain.

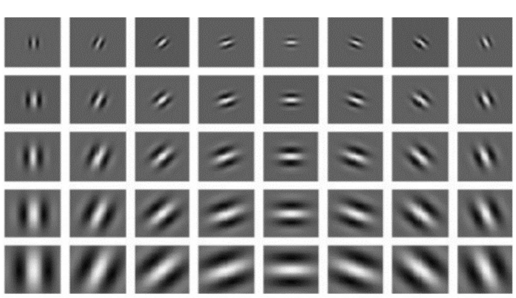


Figure 3.5 Gabor filters of five scales and eight directions

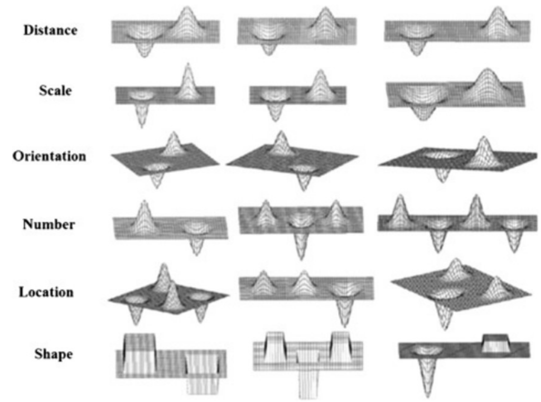


Figure 3.6 Various ordinal filters

Texture Classification*:*

Average Texture Classification Rates for RW and SW with Pre-processing

SEQUENCE

SOIL	LOAMY	CLAY	SANDY	SILTY	PEATY
L3E3	100	91.19	94.261	94.96	83.114
E3L3	100	92.25	93.679	94.24	91.317
L3S3	100	95.84	93.455	96.2	94.849
S3L3	100	95.35	93.693	95.67	94.365
E3E3	100	93	93.475	96.31	92.374
E3S3	100	91.7	98.164	92.83	91.043
S3E3	100	91.08	94.303	92.01	90.589
S3S3	100	94.39	97.918	94.66	93.973

RANDOM

SOIL	LOAMY	CLAY	SANDY	SILTY	PEATY
L3E3	100	89.89	91.583	91.19	88.8
E3L3	100	89.55	91.126	90.91	88.102
L3S3	100	92.09	94.216	90.56	90.587
S3L3	100	91.6	93.161	90.44	90.843
E3E3	100	96.05	92.73	95	94.764
E3S3	100	93.92	96.735	95.14	93.244
S3E3	100	92.48	95.492	93.76	92.232
S3S3	100	94.84	96.993	95.27	94.413

Average Texture Classification Rates for SW with Pre-processing Techniques

MEAN

SOIL	LOAMY	CLAY	SANDY	SILTY	PEATY
L3E3	100	93.184	90.082	62.373	92.159
E3L3	100	94.623	91.014	95.238	89.627
L3S3	100	99.638	97.192	96.970	95.986
S3L3	100	96.801	95.829	96.086	95.776
E3E3	100	99.959	99.925	99.965	99.947
E3S3	100	99.996	99.985	99.988	99.980
S3E3	100	99.980	99.966	99.975	99.979
S3S3	100	99.996	99.995	99.990	99.990
AVG	100	98.022	96.748	97.923	96.680

A_MEAN

SOIL	LOAMY	CLAY	SANDY	SILTY	PEATY
L3E3	100	72.38	94.23	95.81	48.76
E3L3	100	71.62	94.71	91.18	66.34

L3S3	100	94.98	91.08	97.20	83.37
S3L3	100	90.54	93.90	96.36	91.88
E3E3	100	94.34	99.69	97.73	90.78
E3S3	100	97.30	99.51	98.42	94.36
S3E3	100	96.85	99.95	98.35	95.27
S3S3	100	98.36	99.76	98.99	96.90
AVG	100	89.55	96.60	96.76	83.46

STDD

SOIL	LOAMY	CLAY	SANDY	SILTY	PEATY
L3E3	100	67.95	98.39	86.90	25.68
E3L3	100	75.54	99.92	90.95	70.37
L3S3	100	89.65	74.94	97.66	96.77
S3L3	100	93.77	75.36	92.65	84.41
E3E3	100	93.12	99.71	97.30	88.56
E3S3	100	96.89	99.16	98.31	93.36
S3E3	100	96.46	99.62	98.43	94.46
S3S3	100	98.01	99.63	98.87	96.22
AVG	100	88.93	93.34	95.13	81.23

SKEW

SOIL	LOAMY	CLAY	SANDY	SILTY	PEATY
L3E3	100	98.07	96.71	97.43	97.51
E3L3	100	99.04	96.18	97.96	99.02
L3S3	100	99.91	97.80	97.81	98.46
S3L3	100	98.49	97.68	97.86	98.48
E3E3	100	98.77	98.04	99.96	98.68
E3S3	100	98.46	98.57	99.38	98.29
S3E3	100	98.75	99.18	99.50	98.48
S3S3	100	99.12	99.27	99.27	99.46
AVG	100	98.83	97.93	98.65	98.55

KURT

SOIL	LOAMY	CLAY	SANDY	SILTY	PEATY
L3E3	100	90.70	87.63	99.28	94.60
E3L3	100	99.10	78.28	91.41	99.23
L3S3	100	98.47	96.12	95.91	98.87
S3L3	100	98.72	97.43	98.30	97.00
E3E3	100	64.85	60.04	92.88	63.84
E3S3	100	38.47	99.38	52.45	33.73
S3E3	100	28.44	68.80	39.90	23.22
S3S3	100	73.00	96.99	74.34	71.10
AVG	100	73.97	85.58	80.56	72.70

Average Texture Classification Rates for RW with Pre-processing Techniques

MEAN

SOIL	LOAMY	CLAY	SANDY	SILTY	PEATY
L3E3	100	93.19	92.57	97.21	95.66
E3L3	100	96.89	93.75	97.63	89.35
L3S3	100	95.77	91.46	93.22	93.81
S3L3	100	95.09	90.21	93.12	94.11
E3E3	100	99.95	99.97	99.99	99.95
E3S3	100	99.99	99.97	99.98	99.95
S3E3	100	99.97	99.95	99.97	99.98
S3S3	100	99.97	99.95	99.96	99.97
AVG	100	97.60	95.98	97.63	96.60

A_MEAN

SOIL	LOAMY	CLAY	SANDY	SILTY	PEATY
L3E3	100	64.97	95.14	80.86	51.44
E3L3	100	60.22	91.73	78.11	48.97
L3S3	100	84.29	99.00	81.70	74.13
S3L3	100	81.65	94.86	80.63	77.07
E3E3	100	93.52	99.99	97.38	89.96
E3S3	100	95.90	99.51	97.42	93.31
S3E3	100	96.31	99.80	98.00	94.68
S3S3	100	97.96	99.86	98.80	96.74
AVG	100	84.35	97.49	89.11	78.29

SKEW

SOIL	LOAMY	CLAY	SANDY	SILTY	PEATY
L3E3	100	98.84	97.34	99.08	98.98
E3L3	100	98.83	97.31	98.87	99.06
L3S3	100	96.00	91.92	93.63	95.20
S3L3	100	95.09	91.33	93.36	94.55
E3E3	100	99.86	93.68	99.12	99.70
E3S3	100	98.33	96.90	97.49	98.34
S3E3	100	97.81	93.94	96.85	97.83
S3S3	100	98.39	97.01	97.85	96.84
AVG	100	97.89	95.68	97.03	97.59

KURT

SOIL	LOAMY	CLAY	SANDY	SILTY	PEATY
L3E3	100	93.89	80.33	92.04	93.63
E3L3	100	90.83	80.38	92.32	92.54
L3S3	100	83.41	85.98	81.16	75.17
S3L3	100	72.11	83.67	79.72	74.21
E3E3	100	99.31	99.77	82.00	95.63
E3S3	100	73.02	93.39	83.85	68.44
S3E3	100	53.88	84.22	58.76	52.22
S3S3	100	79.56	94.37	82.43	79.20
AVG	100	81.38	81.89	82.78	78.94

Classification:

Classification is based on features of image and category of organized data. Basically classification method has two phases:

- Training phase
- Testing phase

Types of classification:

Supervised classification
Unsupervised classification.
Statically process

Classification can be done by following six steps as shown in figure 5

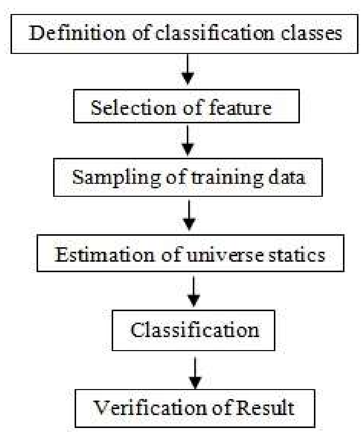


Figure 3.7 Steps of classification

The most basic classification techniques are

- Multilevel slice classification
- Minimum distance classification

- Maximum distance

Other classification like expert system, fuzzy system etc. Distance may be based on nearest neighbour method, farthest neighbour method, Centroid method, Group average method, Wand method.

Classifier:

Decision Tree Classifier is used in our proposed system. Decision tree builds classification models in the form of a tree structure. It breaks down a data set into smaller and smaller subsets while at the same time an associated decision tree is incrementally developed. A decision node has two or more branches. Leaf node represents a classification or decision.

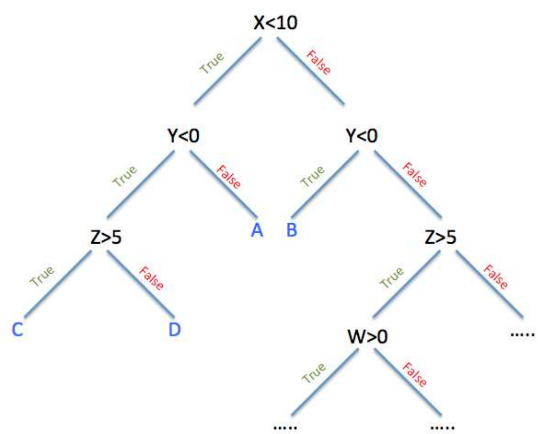


Figure 3.8 Decision Tree Classifier

Decision Tree Classifier: A Concise Technical Overview

Decision Tree Induction Algorithm

```
INPUT: S, where S = set of classified instances
OUTPUT: Decision Tree
Require: S ≠ ∅, num_attributes > 0
procedure BUILDTREE
    repeat
        maxGain ← 0
        splitA ← null
        e ← Entropy(Attributes)
        for all Attributes a in S do
            gain ← InformationGain(a, e)
            if gain > maxGain then
                maxGain ← gain
                splitA ← a
            end if
        end for
        Partition(S, splitA)
    until all partitions processed
end procedure
```

Figure 3.9 D-Tree Induction Algorithm

Decision Tree Raising Algorithm

```
INPUT: D, where D = Unpruned Decision Tree
OUTPUT: Pruned Decision Tree
procedure PRUNETREE
    for all Nodes n in D do
        for all Children c of n do
            if Replacing n with c does not lower accuracy of D then
                Replace n with c
                Reclassify former sibling nodes of n
            end if
        end for
    end for
end procedure
```

Figure 3.10 D-Tree Raising Algorithm

Advantages and disadvantages of different classifiers:

Methods	Advantage	Disadvantage
K-NN	1. It is easy to implement. 2. Training is done in faster manner.	1. It requires large storage space. 2. Sensitive to noise. 3. Testing is slow.
Decision Tree	1. There are no requirements of domain knowledge in the construction of decision tree. 2. It minimizes the ambiguity of complicated decisions and assigns exact values to outcomes of various actions. 3. It can easily process the data with high dimension. 4. It is easy to interpret. 5. Decision tree also handles both numerical and categorical data.	1. It is restricted to one output attribute. 2. It generates categorical output. 3. It is an unstable classifier i.e. performance of classifier is depend upon the type of dataset. 4. If the type of dataset is numeric than it generates a complex decision tree
Support Vector Machine	1. Better Accuracy as compare to other classifier. 2. Easily handle complex nonlinear data points. 3. Over fitting problem is not as much as other methods.	1. Computationally expensive. 2. The main problem is the selection of right kernel function. For every dataset different kernel function shows different results. 3. As compare to other methods training process take more time. 4. SVM was designed to solve the problem of binary class. It solves the problem of multi class by breaking it into pair of two classes such as one-against-one and one-against-all.
Neural Network	1. Easily identify complex relationships between dependent and independent variables. 2. Able to handle noisy data.	1. Local minima. 2. Over-fitting. 3. The processing of ANN network is difficult to interpret and require high processing time if there are large neural networks.
Bayesian Belief Network	1. It makes computations process easier. 2. Have better speed and accuracy for huge datasets.	1. It does not give accurate results in some cases where there exists dependency among variables.

Figure 3.11 Advantages and Disadvantages of Classifiers

IV. IMPLEMENTATIONS

Mat lab 2018(A)

MATLAB is a scientific programming language and provides strong mathematical and numerical support for the implementation of advanced algorithms. It is for this reason that MATLAB is widely used by the image processing and computer vision community. New algorithms are very likely to be implemented first in MATLAB, indeed they may only be available in MATLAB. We used Computer Vision and Image Processing Tools.

System Requirements

- Windows 7 (or) higher
- 64 bit operating system
- Disk Space
  - 2 GB for MATLAB only,
  - 4–8 GB for a typical installation.
- Minimum 2GB RAM needed
- No specific graphic cards required

V. RESULT ANALYSIS

Processing of Images:

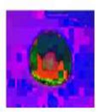
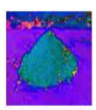
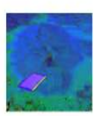
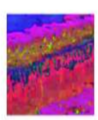
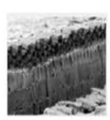
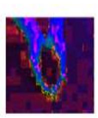
INPUT IMAGE	ENHANCED IMAGE	FEATURE EXTRACTED (HSV) IMAGE	GRAY SCALE IMAGE
			
			
			
			
			

Figure 5.1 Pre-processing of images

Output Obtained:

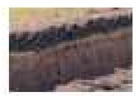
INPUT IMAGE	TYPE OF SOIL	CROPS SUGGESTED
	CLAY	1. BROCCOLI 2. SPROUTS 3. CABBAGE
	SANDY CLAY	1. LETTUCE 2. COLLARD GREENS
	SILTY SAND	1. POTATOES 2. WHEAT 3. SUGAR BEET
	CLAYEY PEAT	1. ERICACEOUS SHRUBS 2. SEDGES 3. SPHAGNUM MOSS
	HUMUS CLAY	1. CROTONS 2. FLOWERING PLANTS

Figure 5.2 Obtained output

VI. CONCLUSION

The proposed system has added features like crop suggestion, prediction of water absorption by plants which couldn't be found in existing systems. Accuracy is more because feature extraction is based on colour and texture of the input images. Thus our proposed idea will make sure to help farmers, agriculture activists in efficient soil classification and crop suggestion.

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