Machine Learning for Soil and Crop Management
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Lecture 35
ML and DL for Soil and Crop Image Processing

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Welcome friends to this last lecture of Week 7 of this NPTEL Online Certification Course of Machine Learning for Soil and Crop Management, and this is the 35th lecture. And in our previous lecture of this week, so, the topic of this week is machine learning and deep learning for soil and crop image processing. So, in this week in the previous lectures, we have already discussed some of the very important concepts for deep learning. We have started with the artificial neural network, and then we have discussed about our different structures the structural features of artificial neural network, what is activation function.

And subsequently we have discussed about the convolution neural network and why convolution neural network is very important for image processing we have discussed. We have discussed the structure of the convolutional neural network, we have structured the, we have discussed convolutional layer then pooling layer then we have also discussed simultaneously, we have also discussed the fully connected layer and how these convolutional layer convolutional neural network architecture can help in different image processing for soil and crop we have discussed.

So, and we have also started, we have also discussed the digital image processing. I have discussed what is digital image and how what are the different types of digital images, and then, what are the basic operations you can do with the digital images we have discussed.

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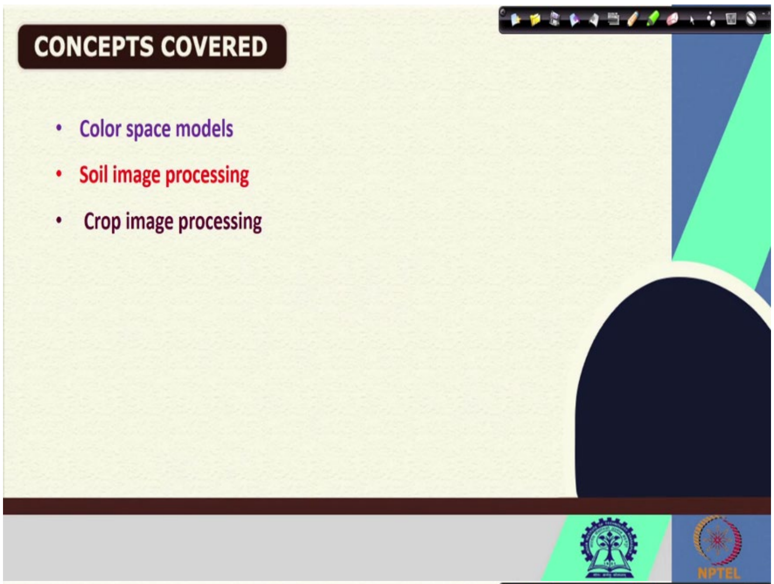

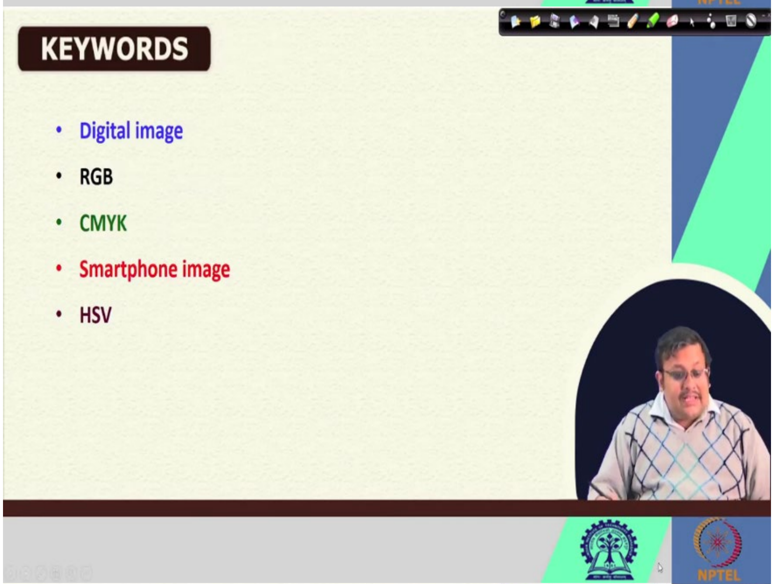

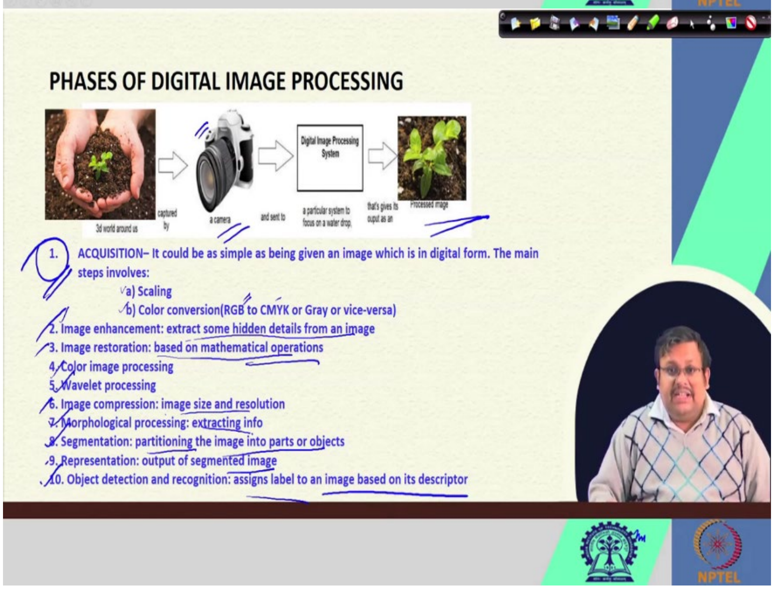

So, we will continue from here, and in this lecture, we are going to cover these concepts. We are going to talk about some color space models, then, we will be talking about soil image processing, and then I will give you an example of crop image processing. So, these are the keywords for this lecture. We are going to talk about more about this digital image, then RGB CMYK, smartphone image and HSV. So, these are the some of the important keywords for this lecture.

So, we have seen what is a digital image and a digital image is consists of millions and millions of pixels or picture elements and so, there are certain phases of digital image processing. So, these are listed here. So, the first step is acquisition that it could be simple image as being given, as being taken from a simple camera or which is in digital form and the major steps which are involved in this acquisition is our scaling, as well as color conversion.

So, color conversion basically converts the color space model like RGB to CMYK or gray or vice versa. So, that any color image can be decomposed into RGB components. I will show you one good picture in coming slides, and then we can convert these color space model to other color space model using some set of equations or algorithms and also or vice versa. The second step is image, another phase is image enhancement.

So, after we take the image we can extract some hidden details from an image, so that is called the image enhancement. The third one is the image restoration. The image restoration is generally based on some mathematical operations. The fourth one is color image processing, the fifth one is wavelet processing, then we can do some image compression like image. We can change the image size and resolution and we can compress the image.

Then, we can do some morphological processing for extracting some of the information then we can do the segmentation which is a very important process of image digital image processing. So, their segmentation basically implies the partitioning of the image into parts or objects. So, and also representation finally which is the output of the segmentation image and the finally, the object detection and recognition which assigns label to an image based on its descriptors.

So, we can see, that all of these are very, very important component of digital image processing. We will start obviously, with the image acquisition using a camera, which can store the image in a digital form. And as you can see that we can take, we are taking an image of the 3D world around us using a camera and then we are sending that image to digital image processing system. And finally, we can derive the image based on our desired outputs.

So, after we take the image, we can do image enhancement, image restoration, color image processing, then we can do the wavelet processing to remove some of the noise and then image compression can be done for easy of storage and execution of different algorithms. And then we can do some morphological processing, segmentation representation and finally, object detection recognition. So, the object detection recognition is our final target or objective for which we do the different image processing, when we combine with different types of deep learning network.

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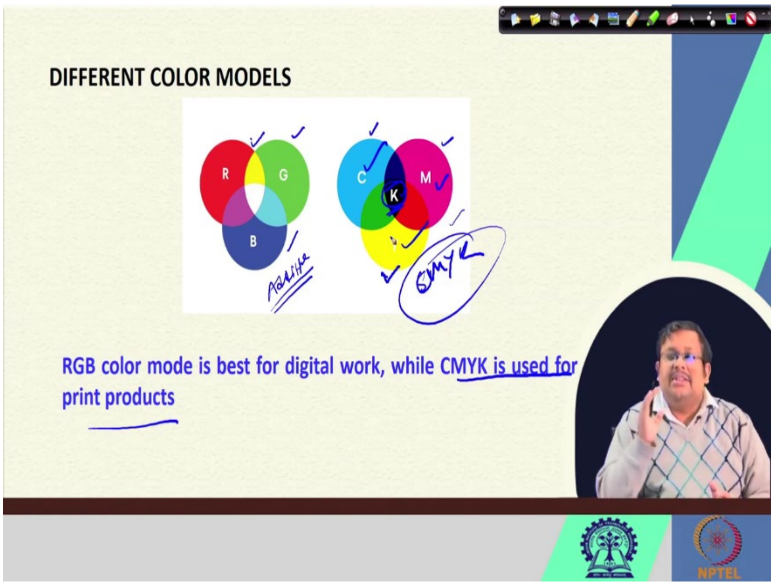

So, there are different types as I have mentioned, there are different types of color models. One is, you can see that is RGB color model, because, we can, any color image can be differentiated into RGB images or RGB component, and they are also known as the additive color, additive color model. Because, when we mix them together in different proportion that will can generate all the other different types of colors. So, RGB color mode and another color mode is CMYK.

This one RGB is a additive color, additive color space model, however, the CMYK is an subtractive color model. So, because, why it is called additive because when you keep on adding these three components a different proportion, it can generate the other color. So, that is why it is called the additive color model.

So, RGB color mode is based for digital work, whereas, the CMYK is used for the print products. So, CMYK is generally used in printers. So, C stands for Cyan, M stands for Magenta, Yellow stands for the Y stands for the yellow and K stands for Black.

So, you can see there are basically four colors, and of course, this is known as the subtractive color models because in the here the concept of the CMYK goes from pure white to pure black. So, that means, when we are mixing this color, so, we are starting with the pure white page in case of digital printer and then we are mixing this color so that we can change the one color to another color.

So, ultimately, when we mix the CMY in equal proportion we will get the finally this K or the finally, the black. So, you can see it can show the transformation from white, which is a mixture of all the colors to the dark black to the black, which, so, in a subtractive way, so, that is why it is known as the subtractive color model.

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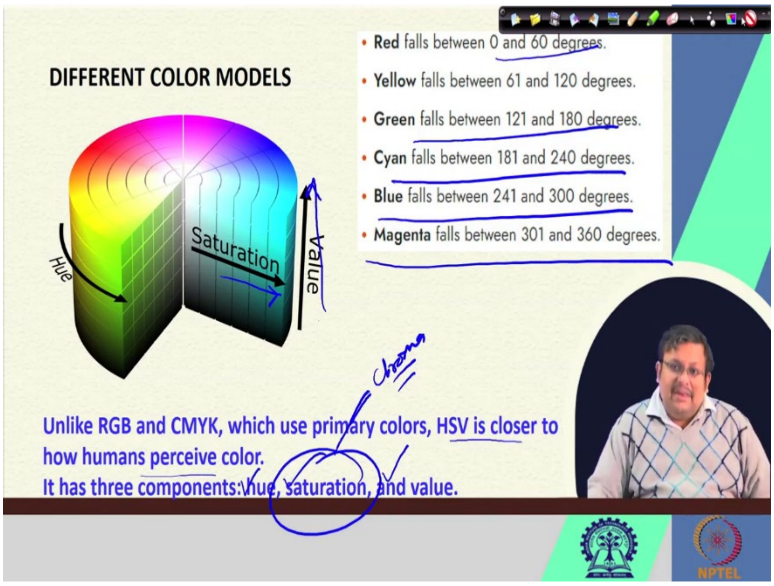

So, this is another important color model, which is known as HSV. So, unlike these RGB and CMYK which uses the primary colors like RGB and then also CMYK, HSV is closer to human perception of color. Remember that while talking about the Munsill soil color chart, I told you that there are three major parameter in the Munsill cell color chart, one is called hue and other is value and the third one is Chroma.

So, similar here HSV stands for the same thing hue shows the dominant spectral color and value shows the brightness or darkness, and then Chroma or the saturation shows that the chroma shows the saturation or the purity. So, of course, this HSV color represent the color very close to the human perception.

So, as you can see this in this direction, hues are changing and in this direction, we are changing the purity so of course, saturation is changing and also the values are changing in this vertical direction. So, if we see this circle, of course, this rate falls between 0 to 60 degree, yellow falls between 61 to 120 degree, green falls between 120 to 180 degree, cyan falls between 181 to 240 degrees, blue falls between 241 to 300 degrees and magenta falls between 301 to 360 degrees.

So, it has we can see that these HSV color model also can represent any color from the human perception point of view, and it has also three color. Just like in case of Munsill cell colored chart, it has also hue, saturation and value. So, of Munsill cell color chart, we term this saturation as Chroma, but basically, these two terms are same.

So, this is another important color model. There are other types of color model available. So, there are other types of color model available like LAB color model CILAB color model and also there are other color models which are available. But so, remember that, in case of machine learning-based crop image processing, where the features are basically extracted from any color image, we can extract the color in any of these color model format or we can extract the color in RGB and then we can transform them using a set of predefined algorithms to other color models.

Since these color models can transfer, can be can be transferred from one model to another model, so we can generate any other color model from a specific color model. So, these features are being used in subsequent machine learning algorithms for predicting several soil properties.

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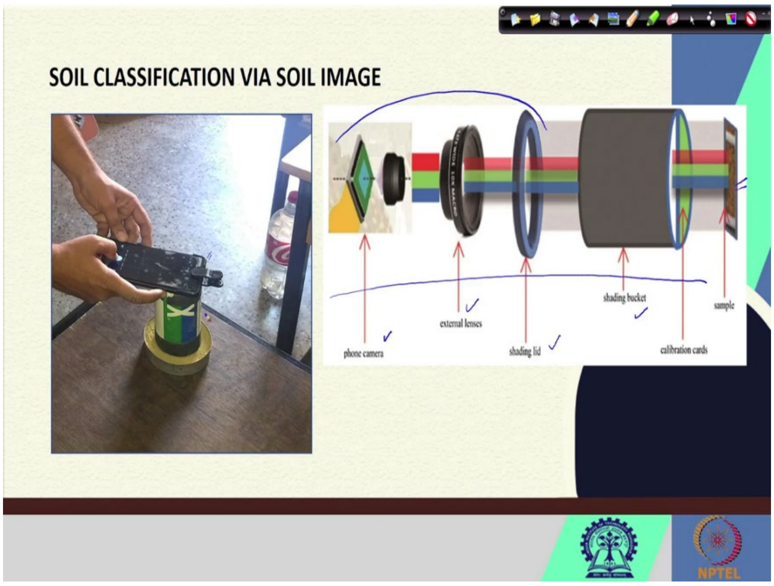

So, just to show you one or two examples, which we have, which we have produced. You can use this soil image for classification purpose. You know what is classification, and in our group we are trying to integrate these mobile-based image or mobile captured image using the arduino and then we are to have we are producing these RGB image and this production of these RGB image using the mobile is based on a lens setup.

So, this external lens setup we are these can be easily procured, and these external lens assembly can be which is composed of these phone camera external lenses and so, that can be, they can be easily procured and they can be used with the shedding bucket and shading lead to offset the interference from the surrounding light and they can capture the image of a soil samples.

So, in our group, we have used these techniques to capture the image of the soil and subsequently after we capture the image of the soil, we did some, we extracted the RGB values of these images and using the RGB values of the images we separated different soil types using the principal component analysis.

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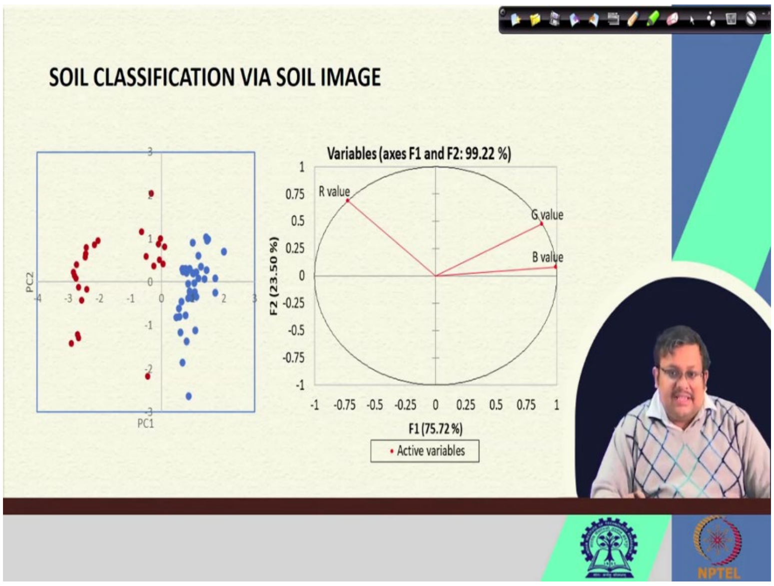

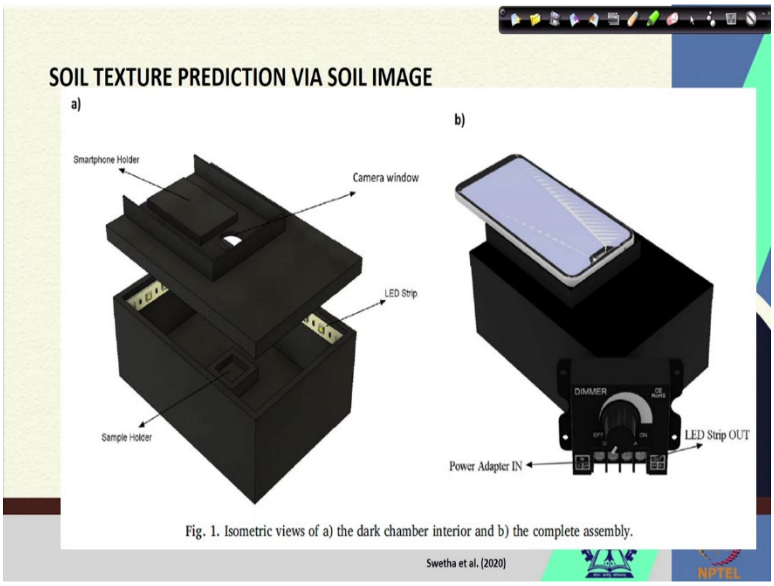

As you can see here, in this picture, we can clearly see the clustering between two types of sample based on their RGB values and from this plot also we can see that while G and B values were high closely related to each other red values are somewhat negatively related to these G and B values. So, based on the soil characteristics and soil colored. So, that shows that image acquisition followed by different types of classification scheme using the imaged extracted features can help to segregate the soil types.

Now, we have our group has developed another image acquisition setup where we are putting the soil samples inside a black box within a inside this sample holder and then this whole box is lined with the LED strip to for the elimination of the soil samples and this is the camera window where we are putting a mobile phone or smartphone and this is smartphone holder and through this camera window, we are taking the image of the soil which is being illuminated by these LED strips.

The intensity of the LED light is being controlled by these dimmer, external dimer, which you can regulate and we can take the image of the soil sample and after taking the image of the soil samples, we did two or three different types of analysis to predict the soil texture.

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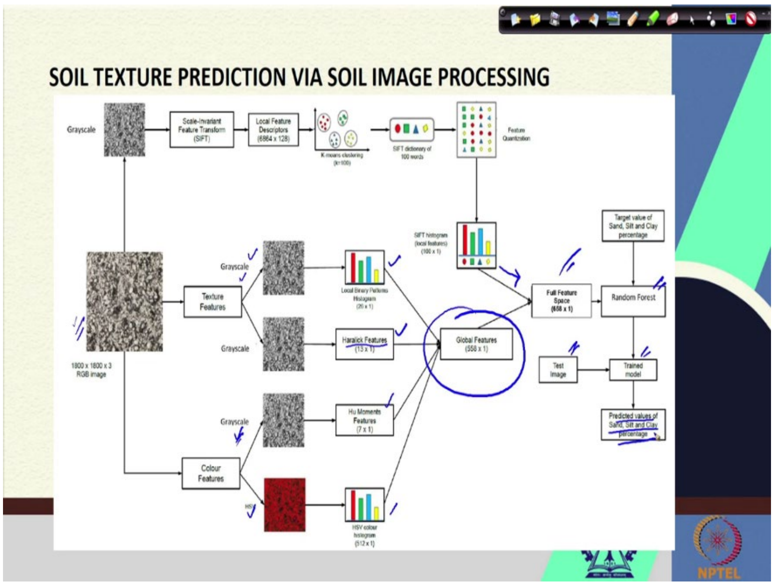

So, you can see here, we started with this 1800 by 1800 RGB image with three channels that is R,G and B and after taking the image this image was transferred to grayscale image. You know about the grayscale now, we have discussed, and also we tried to extract some of the color features. We have extracted these HSV features, we have extracted these grayscale features at hue mobile features also. And not only the color features, but also some textural features of the soil was were extracted like grayscale.

And you can see, we have converted the image into grayscale image and from this grayscale image, local binary pattern and also haralick features, which are the textual features were extracted.

So, we can see here, using the image we have first converted them into HSV as well as the grayscale. From the grayscale, we have extracted the hue moment color features, as well as the HSV color features we have extracted from these HSV image subsequently from the grayscale image, we have computed the local binary patterns histogram, as well as the haralick features.

So, all these features were combined together to produce the global features. Simultaneously, using the bag of visual words algorithm some SIFT features are scale invariant feature transform was used to extract some of the features, which I am going to discuss in the next slide.

And those features were also combined with these global features to get the full feature space, and using the full feature space, subsequently, random forest model was developed. And this random forest model was developed training model was developed, and then it was tested using the testing set or validation set. And then using this trained model, we predicted the sand silt and clay.

So, our results were pretty good, I am going to show you. But this is the snapshot methodological overview, what are the steps we have followed for these image processing.

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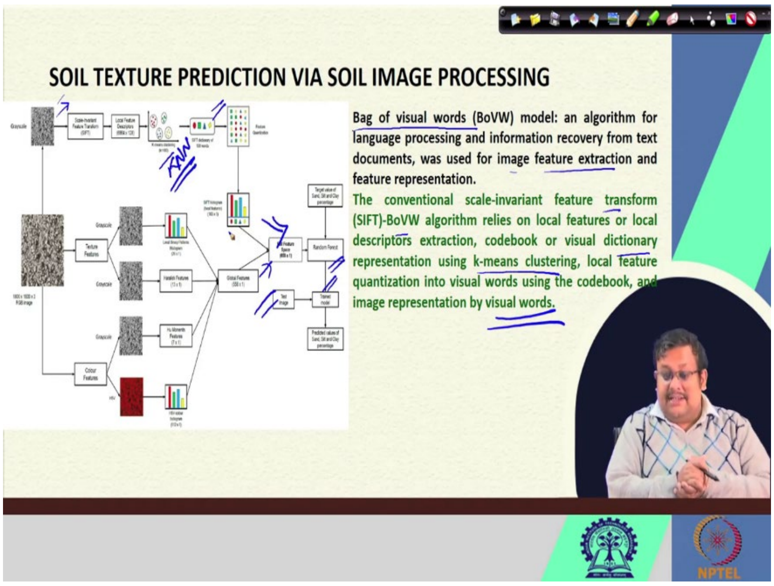

Now, if we want to talk more about these scale invariant feature transform. So, basically, we have used a model called bag of visual words model. Now, these bag of visual words model which is an algorithm for language processing and information recovery from the text documents. So, we use these bag of visual words model to for feature extraction of the image at feature representation.

So, after we extracted this feature, so, this conventional scale invariant feature transform bag of visual algorithms, what they did, they extracted some of the local features or local description. So, these local descriptors or local features were extracted codebook was generated using the k means clustering.

So, suppose some local features, which are composed of both these four to five different types of the features, we basically extract from these grayscale image and then using the K nearest neighbor clustering, we have already discussed this k nearest neighbor in clustering. We have identified these individual features.

From these individual features we have made a dictionary or codebook, and from this codebook these feature quantization was done. So, you can see that using this model, bag of visual model scale, scale invariant feature transform, we extracted those features and the described those features, develop a dictionary representing the K means clustering, local features quantization were done and then the image, the image was finally, represented by these visual words.

So, after we took we extracted those image, in terms of these visual words, these visual words features were combined with this global feature to finally calculate these random forest model accuracy using the training set as well as the testing set. So, what we did in nutshell? We took the image using the setup, then that image was then the image was processed.

In one process we converted the image into grayscale. From the grayscale we have extracted the textural features, textural features means the size variations, which you can see from in the grayscale image, and simultaneously we have extracted the color features also. So, the extra, so the color features as well as these textual features combined to produce the global features.

Simultaneously we have a gate converted the image into grayscale image. From the grayscale image using the bag of visual words, which is an algorithm for processing the text the language the text, so, we have used that algorithm to generate some to represent the image in terms of some visual words and those were extracted and then combined with the global features to make the full feature space and that feature space was used as the input for predicting the sand, silt and clay using the random forest algorithm.

And then the accuracy of the random forest was calculated by using the testing set. So, this was the actual operation which we have done.

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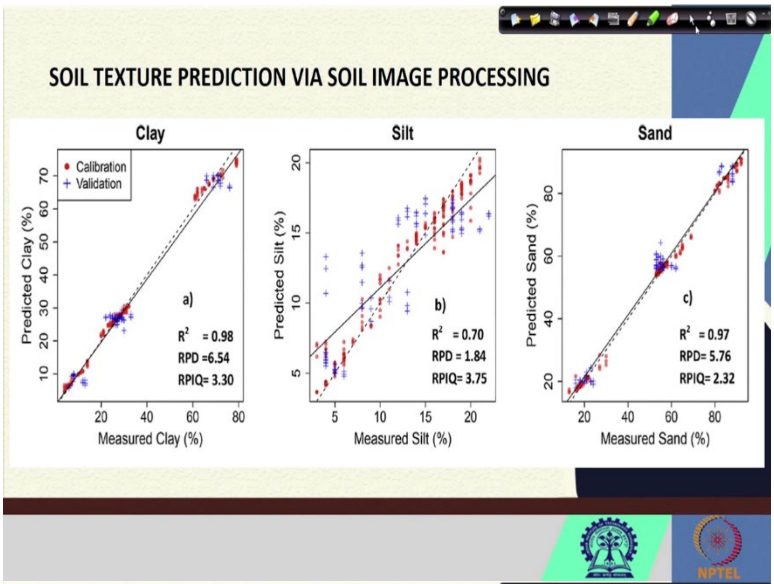

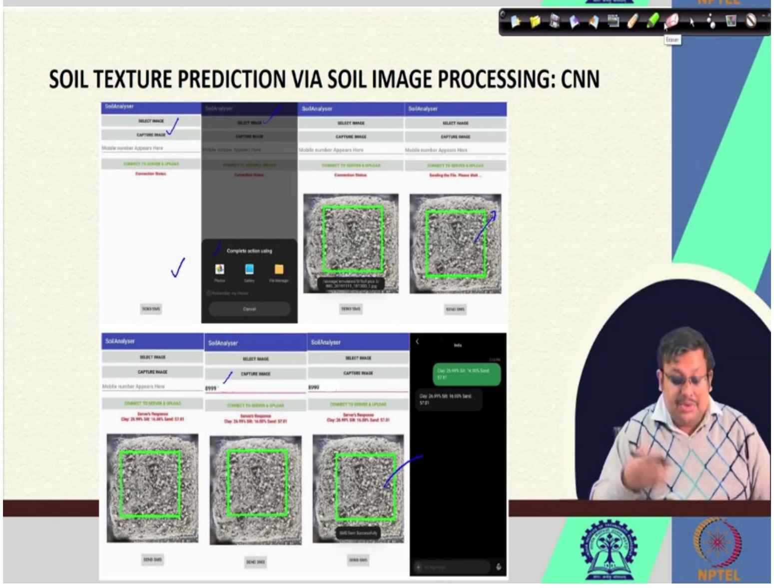

And you can see the results it is clearly visible. Clay and sand produced very good results using the whole feature space, we are getting the R square values of 0.98 and 0.97 which is quite good. RPD values of 6.54 in case of in case of clay and RPD values of 5.76 in case of sand and also in case of silt also we got a decent R square values of 0.70.

Part of the reason is our data set did not contain more silty samples. So, anyway, but still we are getting some decent R square values for the silt. So that shows that this type of image processing followed by machine learning is quite helpful for identification or the prediction of different types of textural features.

Not only we have used this machine learning algorithms, but at the same time we have also used the convolutional neural network, which is a deep learning method. We feed the images directly to the convolutional neural method to predict the textual features and we got the similar very high accuracy, just like as machine learning algorithms.

So, that convolutional neural network algorithm was the trade convolutional neural network was updated in the flask server, which was hosted in Amazon Web Service. And we have developed an app Android app for directly predicting the soil texture using the images taken by the smartphone.

So, using that app, it is now possible to take the image. So, as you can see here, it shows different processes of this app. So, this is the opening screen and then these there are options to you can take either take the photo using, you can either capture the image or you can select the image from your gallery. After you capture or select the image and ROI will be generated to take the ROI will be generated. And from this ROI you can upload these image into the server and then the server will make the calculations and they will send you the results as you can see here clay, silt and sand.

And then you can type the name of the end user so the farmers to whom you want to send these results and it will be directly going to the farmer's mobile. So, it is an overall comprehensive overview of how this app will work. And these apps is really, really helpful for predicting the soil texture using this convolutional neural network and the images which are taken by the smartphone based setup. So, that shows the application of machine learning and image processing for soil property prediction.

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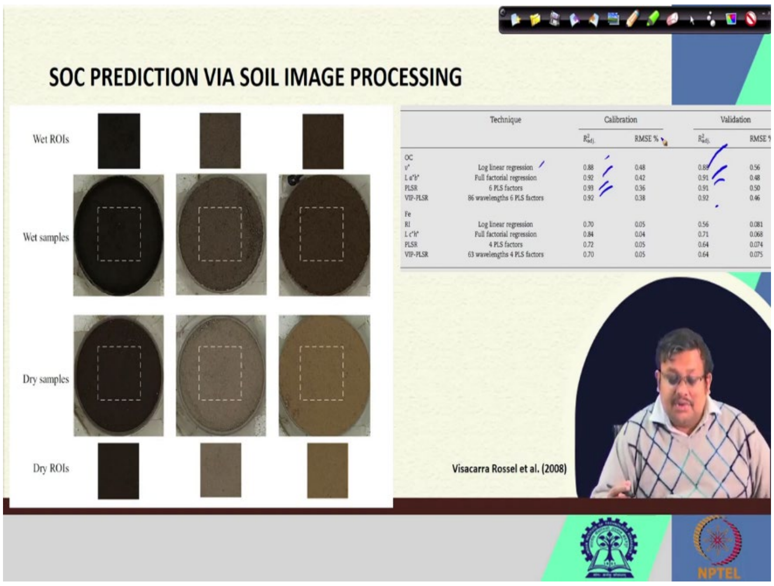

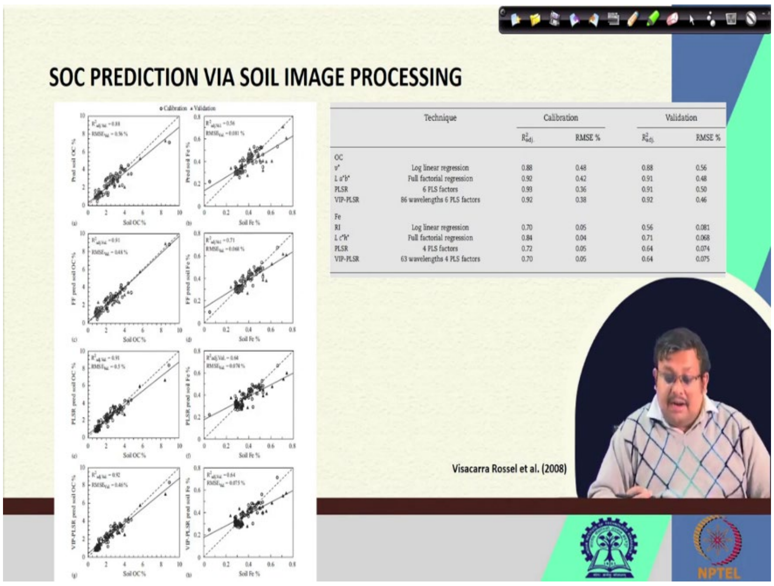

Another research, was published by Visacarra Rossel et al in 2008. There are numerous research I am just showing a couple of them. So, they have used the digital image of both dry soil samples and wet soil samples, and they have developed different types of calibration model to predict the organic carbon and iron content of the soil.

As you can see here, they are using the, they have used these different types of color features. And then using the color features, they have used different types of technique like long linear regression, full factorial regression, 6 PLS factors, then 86 wavelets 6 PLS factors, so, different types of techniques, they have used using different types of features.

And using those features, they have tried to produce the calibration equation and validate the calibration equation you can see for organic carbon these results were quite a promising and, so, that research was published in 2008. And after that, these exploration of image-based soil property prediction was tried a couple of times by different scientific groups of the world.

So, these are the prediction models, which have been generated by these in this research. You can see that the calibration samples and the validation samples are being shown in this figure, and they have modeled both soil organic carbon and soil iron content. For soil iron content the adjusted validation goes up to 0.70 and so that also shows that some decent validation score was observed especially, in case of full factorial regression using the LCH features.

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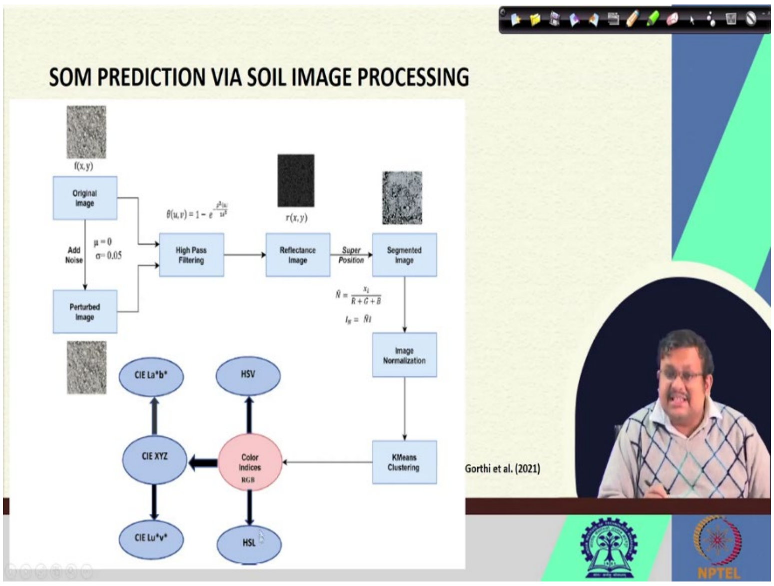

Our group has also did some research for using the smartphone captured image from the same setup and in combination with some image processing. So, you can see that, after we took the image we did some image processing like we pass the image through high pass filtering. I will tell you what is high pass filtering. So, when the image was passed to the high pass filters, we retain only the reflectance image and we removed the intensity values from the image.

Because the intensity, so, what is the purpose of this research because, we have seen that in the real field condition one of the major problem is variable sunlight intensity. So, where the variable color intensity is there, it is not possible, it is operationally difficult to produce a model because our inputs illumination will be variable.

So, to remove these variable illumination concept or component, we pass the images through high pass filters. So, we only kept the reflectance image and subsequently the images were segmented and then image normalization and K means clustering was done to get the color indices in terms of RGB. Once we got the RGB we have converted these RGB to other features like HSVC. Lab, CXYZ, CIE Luv, HSL and so on. And then using these data set, we have tried to predict the soil organic matter.

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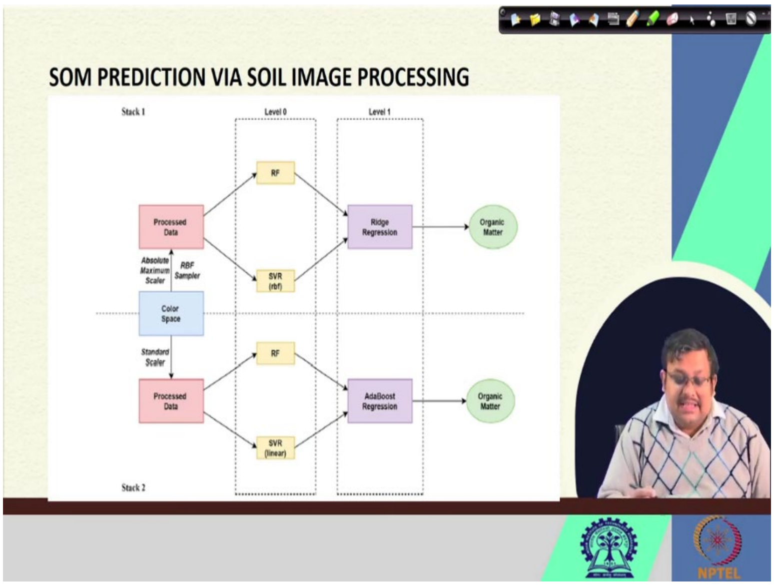

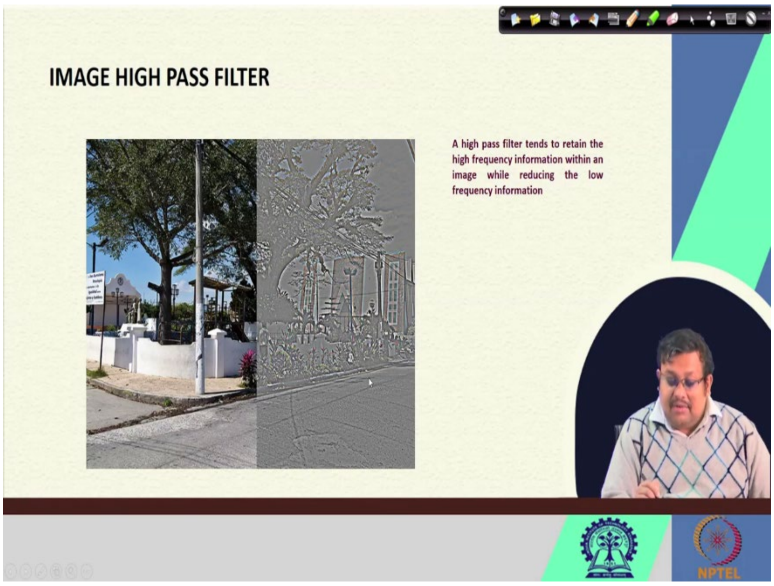

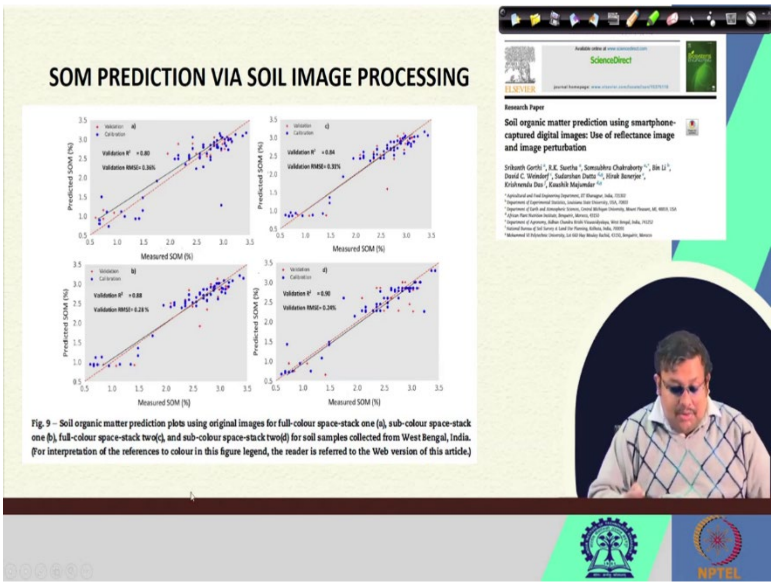

Now, what is high pass filters? A high pass filter tends to retain the high frequency information within the image while reducing the low frequency information. So, you can see this is an original image and if this image is passed to the high pass filter, it will only retain the high frequency components within an image, while reducing the low frequency components.

So, this is called the high pass filter. So, in this process also, we pass the image through high pass filter, so that we can keep only the high density components for subsequent image processing and image segmentation, and also the extraction of different types of color features.

So, after we did all these operations, we use different stacking of different types of machine learning algorithms. You can see they did there are two type two levels of machine algorithms we have tried. What is level 0 models another is level 1 model. In the level 0 we have tried random forest, support vector regression with the radial basis function then random forest and also support vector regression with linear kernel.

So, at the end these predictions of these models when used as an inputs it does level 1 for ridge regression and AdaBoost regression to predict the organic matter. So, ultimately our target was organic matter, we tried to predict the organic matter using the random forest and SVR, predicted there is two ridge regression and also random forest and SVR prediction through AdaBoost regression.

And we got very good R square values as you can see, validation R square varied from 0.8 to 0.84 to 0.88 to 0.90. So, that shows that the it is possible to use the smartphone captured image with the convolutional with different types of machine learning algorithms to predict the soil organic matter, it was published in the journal of biosystems engineering.

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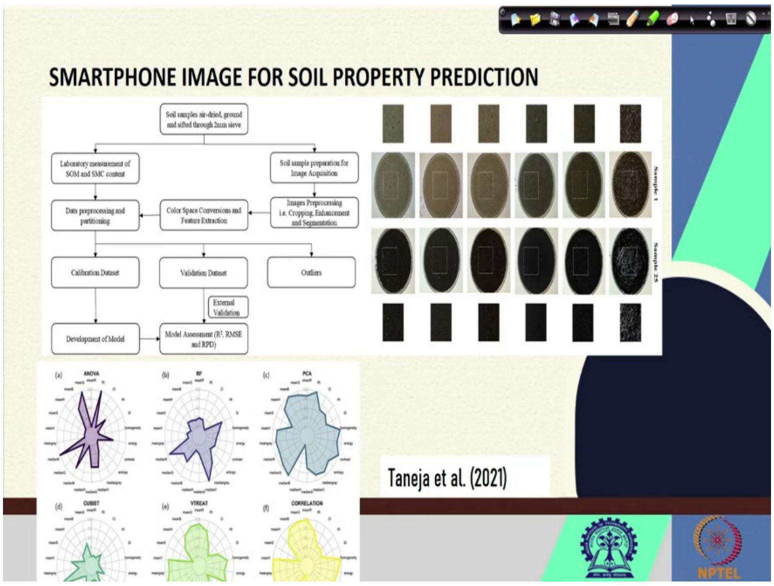

Other groups are also trying to predict the soil organic carbon using the smartphone images, so soil samples were ground, so this research was executed by Taneja et al in 2021. So, soil samples were air dried and then they have, they took the image of the soil samples and then image processing was done and then they developed.

So, soil samples preparation they did and then the image was taken and then image processing like cropping enhancement, segmentation was done, color space conversion and feature extraction was done and then data P pronouncing and partitioning.

Now, one important feature of this experimental setup is they have tried different levels of moisture to incorporate the variable moisture effect on the soil color. So, after they did all this preprocessing and partitioning they divided the color, divided the dataset into calibration data set and validation data sets and finally they did external validation to get the results of R square and MSC, RPD. So, this is how different groups in the world are trying to use the images for subsequent prediction of different soil features irrespective of variable light intensity. So, that shows the impact of this image-based soil property prediction.

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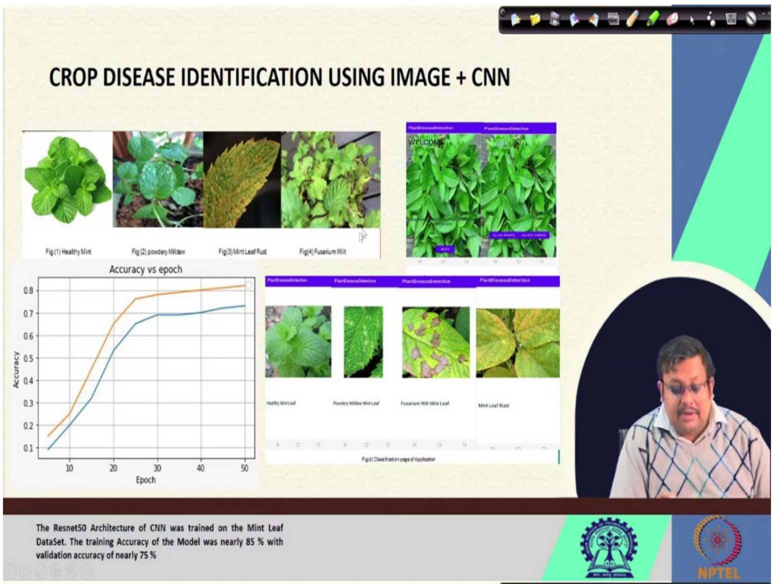

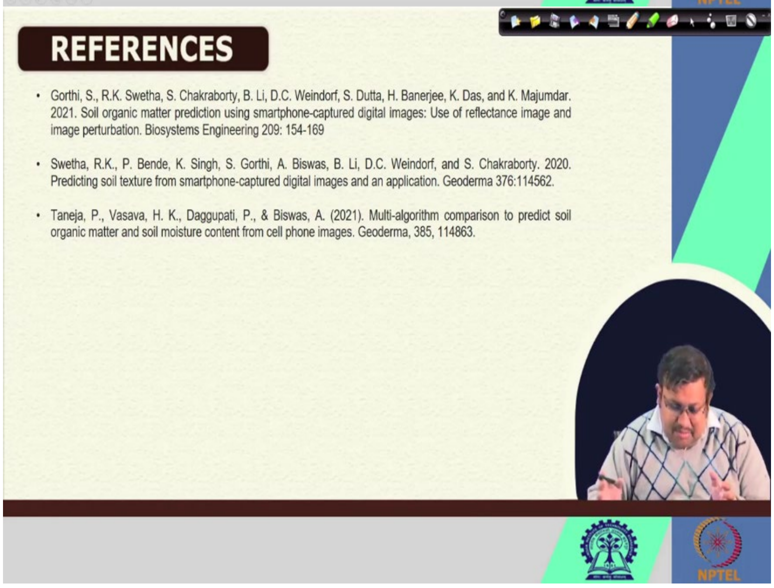

Just to show these the last slide. So, also researchers are used are using these crop image. So here you can see there are different types of healthy mint leaf, also these are the different disease leaf like powdery mildew, mint leaf rust, fusarium wilt, so different types of diseases of the mint. And using these images and convolutional neural network, what app is being developed, which will be useful for plant disease. I did plant leaf disease identification for mint.

So, you can see that these are the different steps of these the Android app which has been generated. So, you can see the for these convolutional neural network these ResNet 50 architecture of this convolutional neural network was trained for weekly data saved at the training accuracy of the model was nearly 85 percent, as you can see from here, accuracy versus epoch graph, and also the validation accuracy was nearly 75 percent.

We will talk about this type of classification in our upcoming weeks in details. But just to show you one example, where crop image is also being used in combination of convolutional neural network models to predict or classify different features from the crop.

So, guys these are the references, let us wrap up our lecture. I hope that you have understood some of the information which are really due to you. And of course, it is always advised. I will always advise you to go and explore the huge amount of material which are available online for gaining more and more knowledge in this aspect. Because whatever I am giving you it is an overview, but if you want to explore more, and you want to feel more confident about this type of application, you have to read those resources, and then only you can have a total understanding of what is really going on over there.

I will try to give you as much as information as possible, so that you can identify or you can understand the basics, but at the same time, I will always tell you to go and read those resources to clarify your doubts. Anyway, you are more than welcome to send me your queries and I will be answering your queries. And I hope that you have learned something new. And let us wrap up this week. And let us we will go from here in the next week and then in the next week we will be discussing more application of image add deep learning for desired feature extraction, and also classification and regression. Thank you.