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TERRAIN CLASSIFICATION USING TRANSFER LEARNING ON HYPERSPECTRAL IMAGES: REVIEW AND COMPARATIVE STUDY

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1 ABSTRACT

A Hyperspectral image contains much more number of channels as compared to a RGB image, hence containing more information about entities within the image. The convolutional neural network (CNN) and the Multi-Layer Perceptron (MLP) have been proven to be an effective method of image classification. However, they suffer from the issues of long training time and requirement of large amounts of the labeled data, to achieve the expected outcome. These issues become more complex while dealing with hyperspectral images. To decrease the training time and reduce the dependence on large labeled dataset, we propose using the method of transfer learning. The hyperspectral dataset is preprocessed to a lower dimension using PCA, then deep learning models are applied to it for the purpose of classification. The features learned by this model are then used by the transfer learning model to solve a new classification problem on an unseen dataset. A detailed comparison of CNN and multiple MLP architectural models is performed, to determine an optimum architecture that suits best the objective. The results show that the scaling of layers not always leads to increase in accuracy but often leads to overfitting, and also an increase in the training time.The training time is reduced to greater extent by applying the transfer learning approach rather than just approaching the problem by directly training a new model on large datasets, without much affecting the accuracy.

2 INTRODUCTION

Hyperspectral image (HSI) is an image cube made up of hundreds of spatial images. For collecting hyperspectral images, a hyperspectral camera is used to collect a data cube. A normal image has 3 channels of pixel values namely, Red, Green and Blue (RGB). While in the case of hyperspectral images, tens to hundreds of narrow colour channels (i.e. wavelengths) are recorded. By combining all these narrow colour channels we are able to process different qualities of our target image. This forms our basis of classification of Hyperspectral images. The high dimensionality and lack of data samples make these images a highly complex task to classify.

In their survey, *Shao et al.*, have very well explained the application of transfer learning in the context of visual categorization.[1] The training data in the same feature space or with same distribution as the future data can't surely avoid the over-fitting, when the availability of labeled data is low. Transfer learning can help in such situations as related data in different domains can be used to expand the knowledge. Transfer learning helps by extracting useful information from data in a related domain and transferring it to be used in the target domain.

The convolutional neural network (CNN) is a class of deep learning neural networks. CNNs represent a huge breakthrough in image recognition. The use of CNN for HSI classification is also visible in recent works.[2] They're most commonly used to analyze visual imagery and are frequently working behind the scenes in image classification. Making use of CNN would be a brilliant way to implement the classification.

While CNNs have become a standard model for the image classification, the Multi-Layer Perceptron (MLP) models are also extensively used for the HSI classification, especially when the computing resources are limited.[3] MLP classification is recommended for the embedded platforms, as it showcased the shorter run-time as compared to CNN and comparable accuracy.

However, in the case of HSIs, training time is long for the deep learning models, and the demand for the marked data is large. To overcome this issue, we try transfer learning for the problem. Deep learning models are trained on some other dataset and using the learned parameters, the image in the given dataset is classified. This would reduce the training time as well as help us overcome the obstruction of having fairly small dataset given the high dimensionality.

3 MOTIVATION

With the advent of modern remote sensing technology it has become possible to obtain much higher resolution and much better quality satellite images than ever before, as such it is important to scale the software architecture that processes these images to achieve maximal utilization. One category of satellite images is hyperspectral images, these work similarly to ordinary images in that they encode the information available as multiple values which correlate to specific channels of specific pixels of the image, i.e. an image consists of pixels which consist of a set of multiple numeric values. One of the primary differences between hyperspectral images and ordinary images is that ordinary images consist of only three channels: red, green and blue, whereas hyperspectral images consist of many more channels.

Ordinary images are like this due to the fact that human eyes have limits to their capabilities of perceiving wavelengths of the electromagnetic spectrum. However, digital processing tools are not bound by the same limitations, and hence can process the information contained within hyperspectral images and produce greater knowledge about entities within the image. All this intrigues to further explore the hyperspectral images.

4 PROBLEM DEFINITION

Hyperspectral Image is an image captured in such a way that each pixel includes complete spectrum. Thus the Hyperspectral Image forms a three dimensional data (i.e. is in the form of a data cube). In the Hyperspectral Dataset, we have an image along with its correct labels, also known as ground truth values.

Since the availability of the labeled Hyperspectral data is low, so to avoid overfitting and also to reduce the training time, we explore the transfer learning approach. Using related data from a different domain, we expand the knowledge for the problem domain.

The following datasets are used:

- **The Indian Pines (IP)** [4]:
  This dataset has an image with 145x145 spatial dimensions and 224 spectral bands in the wavelength range of 400 to 2500 nm, out of which 24 spectral bands covering the region of water absorption have been discarded. The ground truth available is designated into 16 classes of vegetation.
- **The University of Pavia (UP)** [5]:
  This dataset consists of an image with 610x610 spatial dimension pixels with 103 spectral bands in the wavelength range of 430 to 860 nm. The ground truth is divided into 9 urban land-cover classes.

The deep learning models will be trained for the classification of the Indian Pines dataset. These models will then be used to transfer the knowledge extracted from the Indian Pines dataset, i.e. they will act as a pre-trained model for the classification task of the University of Pavia dataset.

The project aims to compare the different deep learning models coupled with transfer learning, to perform classification of the Hyperspectral Images (the University of Pavia image in our case).

5 LITERATURE REVIEW

With the advent of remote sensing technology, the popularity of Hyperspectral image (HSI) classification has increased. Hyperspectral data possess complex characteristics which transform the task of accurate classification into an interesting and challenging problem especially when restricted to traditional machine learning methods.
Recent developments in the field of machine learning have identified deep learning to be a powerful tool to achieve feature extraction and address nonlinear problems, fur-

thermore deep learning models are already heavily used in several image processing applications. Considering these factors, and especially considering the achievements of deep learning techniques in other, similar applications, deep learning has also been introduced to classify HSIs. Deep learning methods have demonstrated adequately impressive performance. In their survey paper, *Ying Li et al.*, have systematically reviewed several pixel-wise and scene-wise Remote Sensing image classification approaches which use DL methods.[6] The authors performed comparative analysis on Convolutional neural networks, Stacked autoencoders and Deep belief networks. Their paper involved analysis of Spectral feature classification, Spatial feature classification and Spectral-spatial feature classification, their results on the Pavia University dataset show CNNs with Spectral-spatial feature classification to be most accurate. Additionally they found dual channel CNNs to provide the highest accuracy on Indian Pines dataset.

Different deep learning models may be applied for the classification of hyperspectral images that capitalise on both, the spectral and the spatial signatures of the hyperspectral image to obtain state of the art accuracies. A detailed comparative study of the various deep learning models used for hyperspectral classification including deep belief networks(DBN), Generative Adversarial Networks(GAN's), Recurrent Neural Networks(RNNs) and Convolutional Neural Networks(CNNs) and it's different variants like the Gabor-CNN, S-CNN and RESNET, has been presented by *Shutao Li et al.*[7]
It was observed that the CNN based models(S-CNN,Gabor-CNN) were particularly good for the classification task, with most of them having state of the art accuracies (>99%) and apart from the 3-D GAN model all of the deep learning models had a satisfactory accuracy. It was also shown that the deep learning models outperform the traditional machine learning models like SVM, EMP which were also used for the purpose of classifying hyperspectral images.

The Spectral-spatial features are extracted from a target pixel and its neighbours. The convolution on these spectral-spatial features leads to a number of 1D feature maps. The feature maps are stacked into a 2D matrix and can be fed to the Convolutional neural net. This type of model can be reffered as a HSI-CNN model.[8]
For using classifiers like KNN and SVMs one requires a more in-depth knowledge of Hyperspectral images, on the other hand Deep Learning techniques like neural nets allow us to extract complicated features from hidden layers without too much pre-processing of the data.
HSI-CNN is a good trade-off between number of training samples and complexity of the network, and overcomes over-fitting. XGBoost can be considered as a substitution of the softmax layer of HSI-CNN in order to prevent over-fitting.

The Multi-Layer Perceptron (MLP) have also been extensively used for classifica-

tion of the multispectral as well as hyperspectral images. They are relatively fast to train and produce comparable results to the CNNs. A better performance is observed when they are coupled with the PCA.[9]
A study by Beatriz et al. has focused on the time optimization for the classification of HSIs by multilayer perceptron. They proposed 5 different architectures for MLP and compared them with the state of the art SVM model. They also proposed a parallel programming scheme for training the MLP.[10]

A variation can be using SVM in the last layer of the CNN model instead of the traditional softmax layer (SVM-CNN model). The resultant model would now require a lesser training time in contrast to that with the softmax layer, which happens to be more computationally expensive due to the softmax function. The model with the softmax layer has been showed to slightly outperform the SVM-CNN in terms of accuracy, but the SVM-CNN is slightly faster to train.[11]

The paper by *Roy et al.* shows the advantages of using Hybrid Spectral Net (Hybrid SN), a 3D-2D CNN instead of using pure 2D or pure 3D CNN.[2] The pure 2D CNN on its own is not able to extract features regarding the spectral dimensions while pure 3D CNN would become computationally expensive to use and it performs worse for classes having similar textures over many spectral dimensions. The 3D-CNN and 2D-CNN layers are assembled for the proposed model (Hybrid SN) in such a way that they utilise both the spectral as well as spatial feature maps to their full extent to achieve maximum possible accuracy. To reduce the number of spectral bands (more accurately remove the spectral density) PCA is applied over the HSI image.
The HSI data cube is divided into small overlapping 3D patches, their truth labels are decided by the label of the centered pixel. The 2D convolution is applied once before the flatten layer to extract abstract high level features. The research paper confirms the superiority of the proposed method by performing experiments over three benchmark datasets and comparing the results with state of the art methods. The proposed model is shown to be computationally more efficient than the pure 3D CNN model.

The paper by *Xuefeng Jiang et al.* [12] emphasizes a new technique of feature extraction using transfer learning which significantly lowers the training time of the CNN used and reduces its dependency on large labelled datasets. This leverages the Markov property of the images to separate images with class tags and train the CNN on random band samples selected from the datasets.
The paper by *Ke Li et al.* [13] explores another transfer learning approach for hyperspectral image classification using deep belief networks wherein a limited Boltzmann machine Network is trained on the source domain data and its first few layers are extracted to be used for the target domain network. The target domain network is fine tuned further and used for classification of images in the target domain. The

number of layers to be transferred are also varied and chosen for best accuracy.

CNN-based frameworks can achieve high accuracy in an object classification task. But when coupled with transfer learning, they can give high performance in detection tasks as well, while reducing the required training time and computing resources.[14]

Taking inspiration from these papers we use a transfer learning approach coupled with CNN and MLP models, and perform a comparative analysis in the end.

6 PROPOSED METHODOLOGY

6.1 Dataset Preparation

Two datasets, namely the Indian Pines and the Pavia University Hyperspectral datasets, were used, the Indian Pines for training the CNN model from which the CNN stump (the convolutional layers and the pooling layers barring the fully connected layers) was extracted to be trained on the Pavia dataset. Both images have different distributions that thus makes the applicability of Transfer Learning perfectly suitable.

The data used for initial model training was the Indian Pines Hyperspectral Data collected by the AVIRIS sensor over the Indian Pines test site in North Western Indiana. It comprises 145x145 pixels and 224 spectral reflectance bands in the wavelength range 0.4-2.5 μm. Two thirds of the Indian pines is agricultural landscape and the remaining one-third contains perennial vegetation. The ground truth is designated into 16 classes as described by Table 1.

The Pavia University dataset was used to test the model built using transfer learning. It was acquired by the ROSIS sensor over Pavia in northern Italy. It contains 103 spectral bands with 610x610 pixels. The ground truth values for the pixels cover 9 different classes. Table 2 describes the ground truth classes for the Pavia University dataset and their respective sample numbers.

Before model training both datasets were subjected to PCA for dimensionality reduction, which reduces the spectral dimension to 30 for the Indian Pines and the Pavia dataset. This is done so as to facilitate faster training time for the models and reduces the memory cost.

It should be noted that before feeding the dataset for training we need to prepare multiple distinct image cubes from the images, and the size of the image cubes behaves as a hyper-parameter. Increasing the size of the cube though may increase the accuracy but will result in a drastic increase in the requirement of RAM. For this purpose the image cubes are taken of size 5x5x30. Further we also need to flatten

S.No.	Class	Samples
1	Alfalfa	46
2	Corn-notill	1428
3	Corn-mintill	830
4	Corn	237
5	Grass-pasture	483
6	Grass-trees	730
7	Grass-pasture-mowed	28
8	Hay-windrowed	478
9	Oats	20
10	Soybean-notill	972
11	Soybean-mintill	2455
12	Soybean-clean	593
13	Wheat	205
14	Woods	1265
15	Buildings-Grass-Trees-Drives	386
16	Stone-Steel-Towers	93

Table 1: Ground-truth classes for the Indian Pines scene and their respective samples number

the given input image after reducing the dimension using PCA, since unlike a CNN model where we can directly feed an image, a MLP model requires a flat matrix of input parameters.

6.2 Model Training

All of the following models were made in 2 phases. In first phase, the models were trained on the Indian Pines dataset, and then in second phase, transfer learning was applied and models were trained on Pavia University dataset.

6.2.1 CNN Model

Firstly, a CNN model was trained on the Indian Pines dataset. This CNN uses both 3-D and 2-D convolution operations to leverage feature map extraction from both the spatial and the spectral dimensions, in case of just the 2-D convolution however, the spectral information would not have been captured well enough for accurate classification. The model is trained with the 5x5x30 data-cubes obtained from pre-processing the data which is shuffled and split into a train to test ratio of 70:30.

S.No.	Class	Samples
1	Asphalt	6631
2	Meadows	18649
3	Gravel	2099
4	Trees	3064
5	Painted metal sheets	1345
6	Bare Soil	5029
7	Bitumen	1330
8	Self-Blocking Bricks	3682
9	Shadows	947

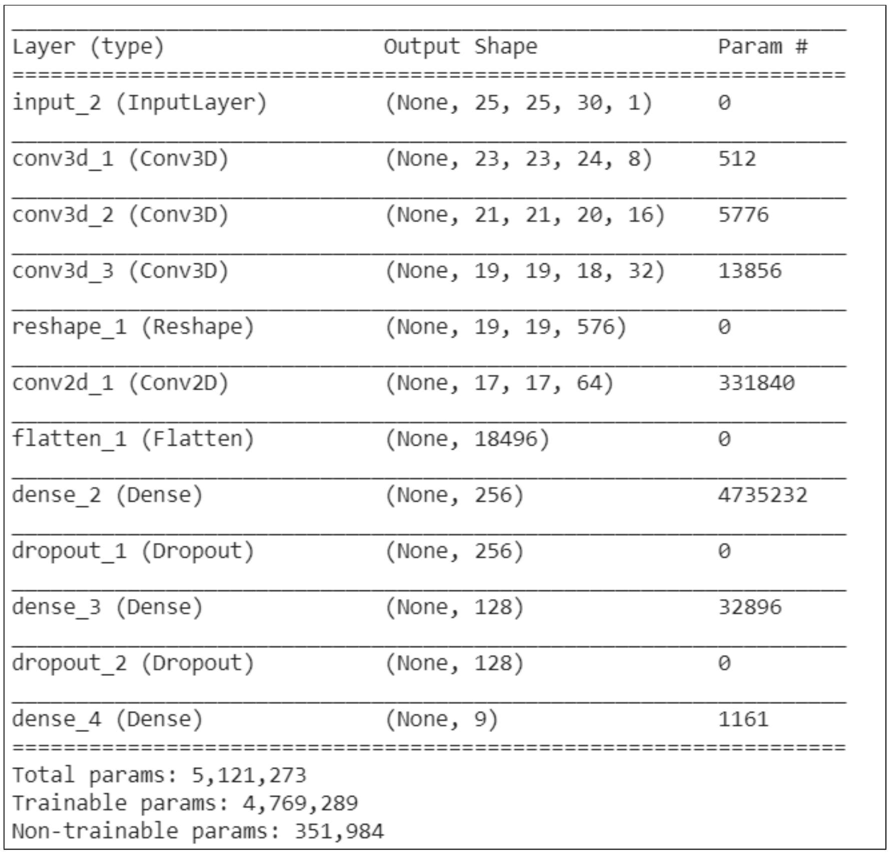
Table 2: Ground-truth classes for the Pavia University scene and their respective samples number

The first 3 layers are convolution 3-D layers, which consist of 8,16 and 32 filters respectively. After this, a convolution 2-D layer is applied which consists of 64 filters and the filter size of 3 by 3. This is the 4^{th} convolution layer. The output from this convolution layer is then flattened (i.e. converted all the activations into 1-D vector) and then fed into the Artificial Neural Net type architecture that mainly consists of fully connected dense layers with ReLU activations.We have 2 dense layers combined with dropout regularization of 0.4. We have made use of Leaky ReLU activation in the 2 dense layer, and finally an output layer that uses a Softmax Activation function for class prediction.We have used Adam Optimizer for training the CNN.

Once the above model is trained on the Indian Pines dataset the CNN stump of the model i.e. the convolutional and pooling layers are extracted and the later layers i.e. the fully connected layers and the softmax layers are stripped. To this convolutional stump, a new set of layers is connected with 3 fully connected layers with ReLU activation and a softmax layer of 9 units are appended. We also use a dropout of 0.4 for the fully connected layers. The layers excluding the fully connected layers and the softmax layers are frozen so that the weights for those layers are not modified and training only takes place for the fully connected layers and the softmax layer. The patches obtained from the Pavia dataset are then split into the training and the test set in a ratio of 40:60, and trained for 3 epochs. Architecture of the Transfer learning based model is summarized in the Fig 1.

6.2.2 MLP Model 1

The MLP model used here is a standard MLP model with three dense layers with 10000, 5000 and 9 layers respectively. The model firstly was trained on Indian Pines dataset and then the last two layers were deleted while making use of the model for



```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_2 (InputLayer)         (None, 25, 25, 30, 1)     0
_________________________________________________________________
conv3d_1 (Conv3D)            (None, 23, 23, 24, 8)     512
_________________________________________________________________
conv3d_2 (Conv3D)            (None, 21, 21, 20, 16)    5776
_________________________________________________________________
conv3d_3 (Conv3D)            (None, 19, 19, 18, 32)    13856
_________________________________________________________________
reshape_1 (Reshape)          (None, 19, 19, 576)       0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 17, 17, 64)        331840
_________________________________________________________________
flatten_1 (Flatten)          (None, 18496)             0
_________________________________________________________________
dense_2 (Dense)              (None, 256)               4735232
_________________________________________________________________
dropout_1 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_3 (Dense)              (None, 128)               32896
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_4 (Dense)              (None, 9)                 1161
=================================================================
Total params: 5,121,273
Trainable params: 4,769,289
Non-trainable params: 351,984
```

Figure 1: Summary of CNN model

prediction on Pavia dataset using transfer learning. The first and the second layers are activated using the ReLu activation function while the last layer that gives the Class identifiers is activated using a SoftMax activation function. The initial model was trained for 20 epochs with a batch size of 128, while on the other hand when the model was used for transfer learning and trained on Pavia dataset only 10 epochs with 128 batch size were performed. The detailed summary of the different layers and the trainable and non-trainable parameters of the above proposed model can be seen in Fig 3.

We have used Adam Optimizer for training the MLP perceptron layers. Adam is an adaptive learning rate optimization algorithm that's been designed specifically for training deep neural networks. Adam can be considered as a mixture of RMS prop and Stochastic Gradient Descent. It uses the squared gradients to scale the learning rate like RMS prop and it takes advantage of momentum by using moving average of the gradient instead of gradient itself like SGD with momentum. The Loss used is categorical cross entropy and the evaluation metrics is accuracy. Using

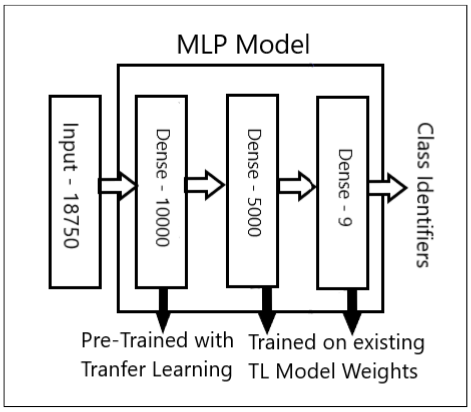
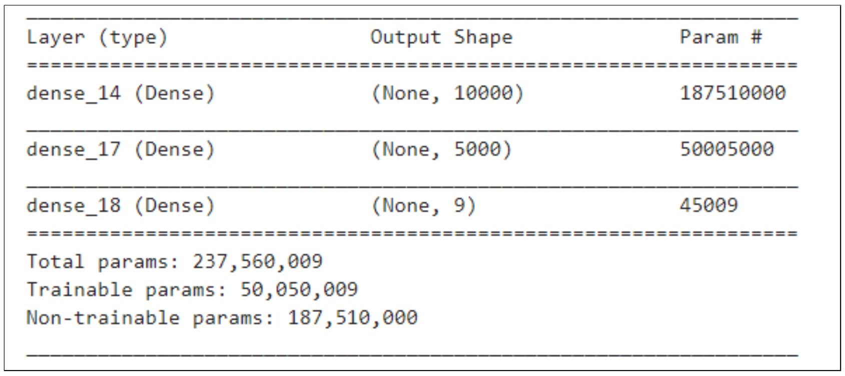


Figure 2: Diagrammatic representation of MLP Model 1



```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_14 (Dense)             (None, 10000)             187510000
_________________________________________________________________
dense_17 (Dense)             (None, 5000)              50005000
_________________________________________________________________
dense_18 (Dense)             (None, 9)                 45009
=================================================================
Total params: 237,560,009
Trainable params: 50,050,009
Non-trainable params: 187,510,000
_________________________________________________________________
```

Figure 3: Summary of MLP Model 1

the above criteria the above model is compiled and trained.

6.2.3 MLP Model 2

Since there is no perfect model that can be defined for any Neural Network problem hence the feasibility of the solution and model depends on whether the error generated by the model is under the permissible parameters of our problem. During our literature survey we found that Terrain Classification on Hyperspectral Images has been under research at IIT Delhi with the association of DRDO. Though not much details about the methodology used was found for it being a closed project, but we used one of architecture of the MLP model that was used for their purpose. The model can be visualised diagrammatically as in Fig 4.

In this model the initial training was done in the Indian Pines dataset with just two Hidden Layers. Later when Transfer learning was performed, the last layer along with its batch normalization extension was chopped off, and three more layers were

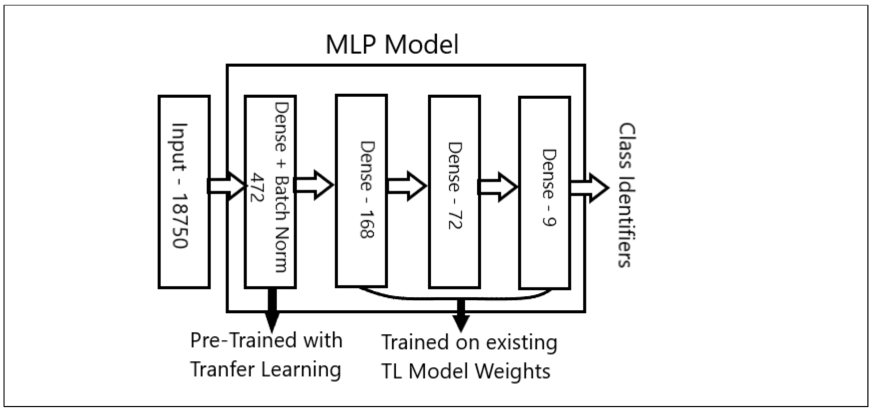


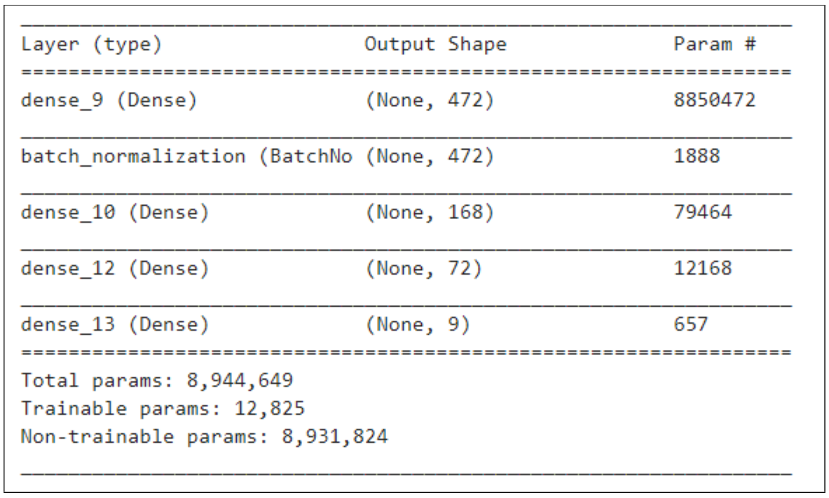
Figure 4: Diagrammatic representation of MLP Model 2

added. The first layer is a Dense Layer of 472 perceptrons, followed by a Batch Normalisation layer. This first layer was left as it is during transfer learning, and three more layers were added with 168, 72 and 9 perceptrons respectively. These layers were the trainable layers that were trained during transfer learning. All these perceptron layers are activated using a ReLu activation function and the optimization technique used while training is Adam Optimization, since it is believed to outperform other optimization techniques like RMSProp. The initial model was trained for 20 epochs with a batch size of 128, while on the other hand when the model was used for transfer learning and trained on Pavia dataset only 10 epochs with 128 batch size were performed. The detailed summary of the different layers and the trainable and non-trainable parameters of the above proposed model can be seen in Fig 5.

6.2.4 MLP Model 3

This model is an extension of the Model 2 with a greater number of pre-trained layers but with lesser number of perceptrons, as models also need to be compared by scaling them horizontally, i.e., adding more layers but reducing the strength of each layer. The visual representation of the model is give in Fig 6.

This model was also first trained with 5 Hidden layers on Indian Pines dataset, but when transfer learning was applied its last two layers were chopped off, and three new dense layers were added. The layers from the saved models were not trained on the Pavia dataset, while the three dense layers were trained. The pretrained layers consisted of Dense layers with 1024, 512, 256 and 128 perceptrons, with each layer being followed by an appropriate Batch Normalization layer. All the perceptron layers are activated using a ReLu activation function and the optimization technique used while training is Adam Optimization, much like the previous model. The initial



```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_9 (Dense)              (None, 472)               8850472   
_________________________________________________________________
batch_normalization (BatchNo (None, 472)               1888      
_________________________________________________________________
dense_10 (Dense)             (None, 168)               79464     
_________________________________________________________________
dense_12 (Dense)             (None, 72)                12168     
_________________________________________________________________
dense_13 (Dense)             (None, 9)                 657       
=================================================================
Total params: 8,944,649
Trainable params: 12,825
Non-trainable params: 8,931,824
_________________________________________________________________
```

Figure 5: Summary of MLP Model 2

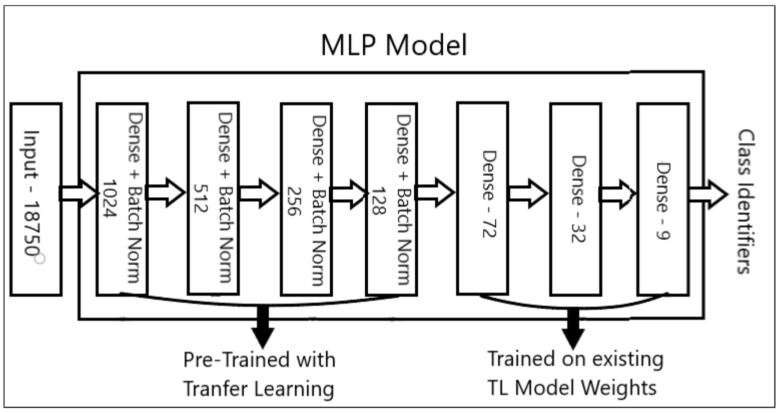
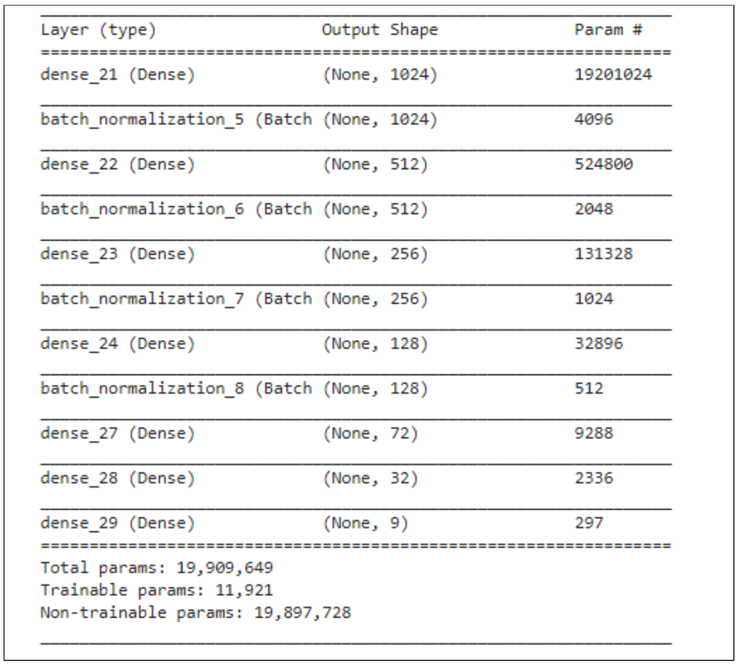


Figure 6: Diagrammatic representation of MLP Model 3

model was trained for 20 epochs with a batch size of 128, while on the other hand when the model was used for transfer learning and trained on Pavia dataset only 10 epochs with 128 batch size were performed. The detailed summary of the different layers and the trainable and non-trainable parameters of the above proposed model can be seen in Fig 7.



```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_21 (Dense)             (None, 1024)              19201024
_________________________________________________________________
batch_normalization_5 (Batch (None, 1024)              4096
_________________________________________________________________
dense_22 (Dense)             (None, 512)               524800
_________________________________________________________________
batch_normalization_6 (Batch (None, 512)               2048
_________________________________________________________________
dense_23 (Dense)             (None, 256)               131328
_________________________________________________________________
batch_normalization_7 (Batch (None, 256)               1024
_________________________________________________________________
dense_24 (Dense)             (None, 128)               32896
_________________________________________________________________
batch_normalization_8 (Batch (None, 128)               512
_________________________________________________________________
dense_27 (Dense)             (None, 72)                9288
_________________________________________________________________
dense_28 (Dense)             (None, 32)                2336
_________________________________________________________________
dense_29 (Dense)             (None, 9)                 297
=================================================================
Total params: 19,909,649
Trainable params: 11,921
Non-trainable params: 19,897,728
_________________________________________________________________
```

Figure 7: Summary of MLP Model 3

7 REQUIREMENTS

7.1 Hardware Requirements

- Machine supporting GPU for training the Transfer Learning model
- Core i5 or i7 CPU
- Minimum 8 GB RAM

7.2 Software Requirements

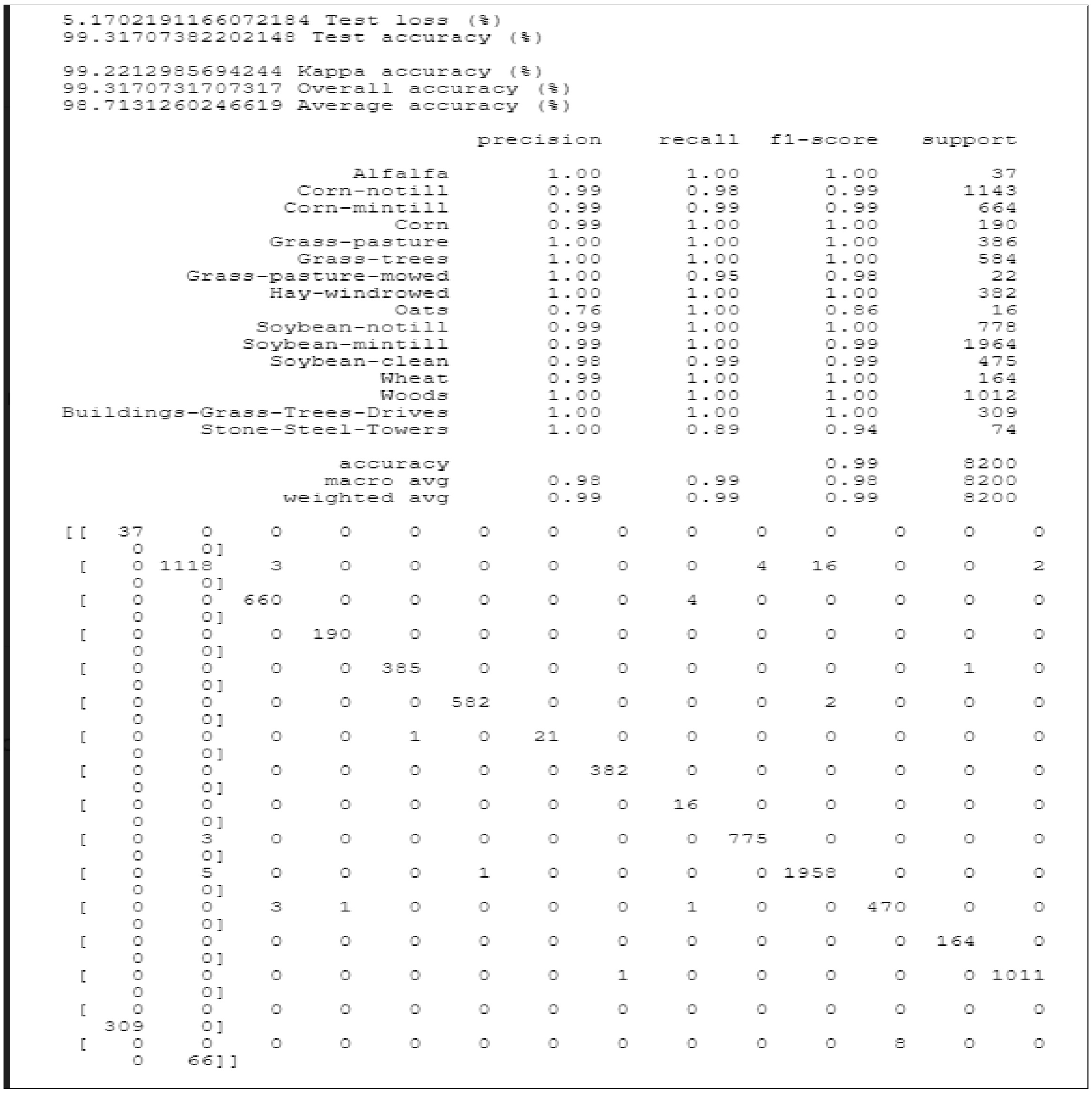
- Python 3.7
- OS supporting Google Chrome Web Browser
- Tensorflow, Keras
- NumPy, pandas, scikit-learn, Matplotlib python libraries
- Google Collab
- Spectral - python module for processing Hyperspectral Image Data.

8 RESULTS

8.1 CNN Model

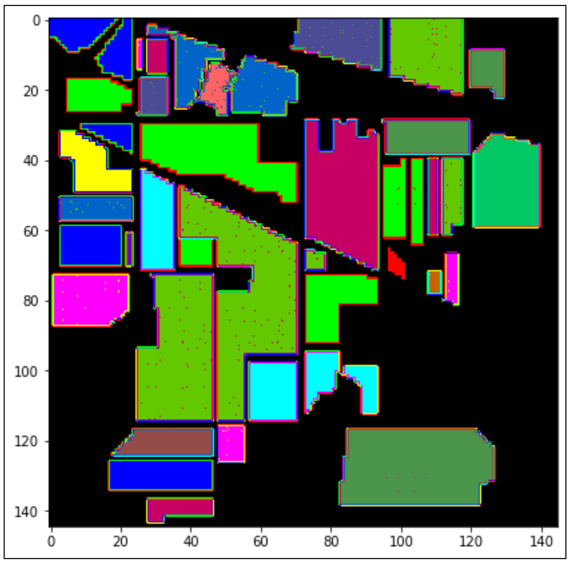
Firstly, the Indian Pines dataset is applied to the CNN model and the confusion matrix obtained is shown in Fig 8.

Test set accuracy came out to be **99.31%** which is quite high, but the model had to be trained for 100 epochs which took around 15 minutes to run on Google Colaboratory. This trained model was saved to be used for transfer learning purposes in future. The Fig 9a shows the ground truth for Indian Pines and the prediction is shown in Fig 9b.



```
5.170219166072184 Test loss (%)
99.31707382202148 Test accuracy (%)

99.221298569424 Kappa accuracy (%)
99.3170731707317 Overall accuracy (%)
98.7131260246619 Average accuracy (%)
                                  precision    recall  f1-score   support

                     Alfalfa       1.00      1.00      1.00        37
                 Corn-notill       0.99      0.98      0.99      1143
                Corn-mintill       0.99      0.99      0.99       664
                        Corn       0.99      1.00      1.00       190
               Grass-pasture       1.00      1.00      1.00       386
                 Grass-trees       1.00      1.00      1.00       584
         Grass-pasture-mowed       1.00      0.95      0.98        22
               Hay-windrowed       1.00      1.00      1.00       382
                        Oats       0.76      1.00      0.86        16
              Soybean-notill       0.99      1.00      1.00       778
             Soybean-mintill       0.99      1.00      0.99      1964
               Soybean-clean       0.98      0.99      0.99       475
                       Wheat       0.99      1.00      1.00       164
                       Woods       1.00      1.00      1.00      1012
Buildings-Grass-Trees-Drives       1.00      1.00      1.00       309
          Stone-Steel-Towers       1.00      0.89      0.94        74

                    accuracy                           0.99      8200
                   macro avg       0.98      0.99      0.98      8200
                weighted avg       0.99      0.99      0.99      8200

[[  37    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0]
 [   0 1118    3    0    0    0    0    0    0    4   16    0    0    2
     0    0]
 [   0    0  660    0    0    0    0    0    4    0    0    0    0    0
     0    0]
 [   0    0    0  190    0    0    0    0    0    0    0    0    0    0
     0    0]
 [   0    0    0    0  385    0    0    0    0    0    0    0    1    0
     0    0]
 [   0    0    0    0    0  582    0    0    0    0    2    0    0    0
     0    0]
 [   0    0    0    0    1    0   21    0    0    0    0    0    0    0
     0    0]
 [   0    0    0    0    0    0    0  382    0    0    0    0    0    0
     0    0]
 [   0    0    0    0    0    0    0    0   16    0    0    0    0    0
     0    0]
 [   0    3    0    0    0    0    0    0    0  775    0    0    0    0
     0    0]
 [   0    5    0    0    0    1    0    0    0    0 1958    0    0    0
     0    0]
 [   0    0    3    1    0    0    0    0    1    0    0  470    0    0
     0    0]
 [   0    0    0    0    0    0    0    0    0    0    0    0  164    0
     0    0]
 [   0    0    0    0    0    0    0    1    0    0    0    0    0 1011
     0    0]
 [   0    0    0    0    0    0    0    0    0    0    0    0    0    0
   309    0]
 [   0    0    0    0    0    0    0    0    0    0    0    8    0    0
     0   66]]
```

Figure 8: Confusion matrix obtained for CNN model trained on Indian Pines dataset


(a) Ground Truth

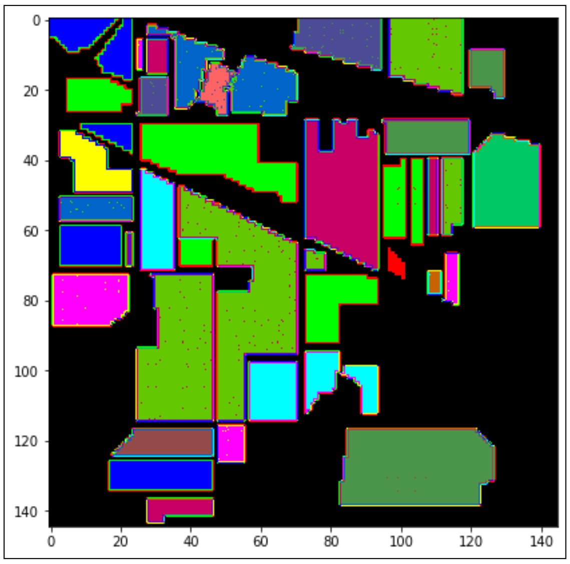
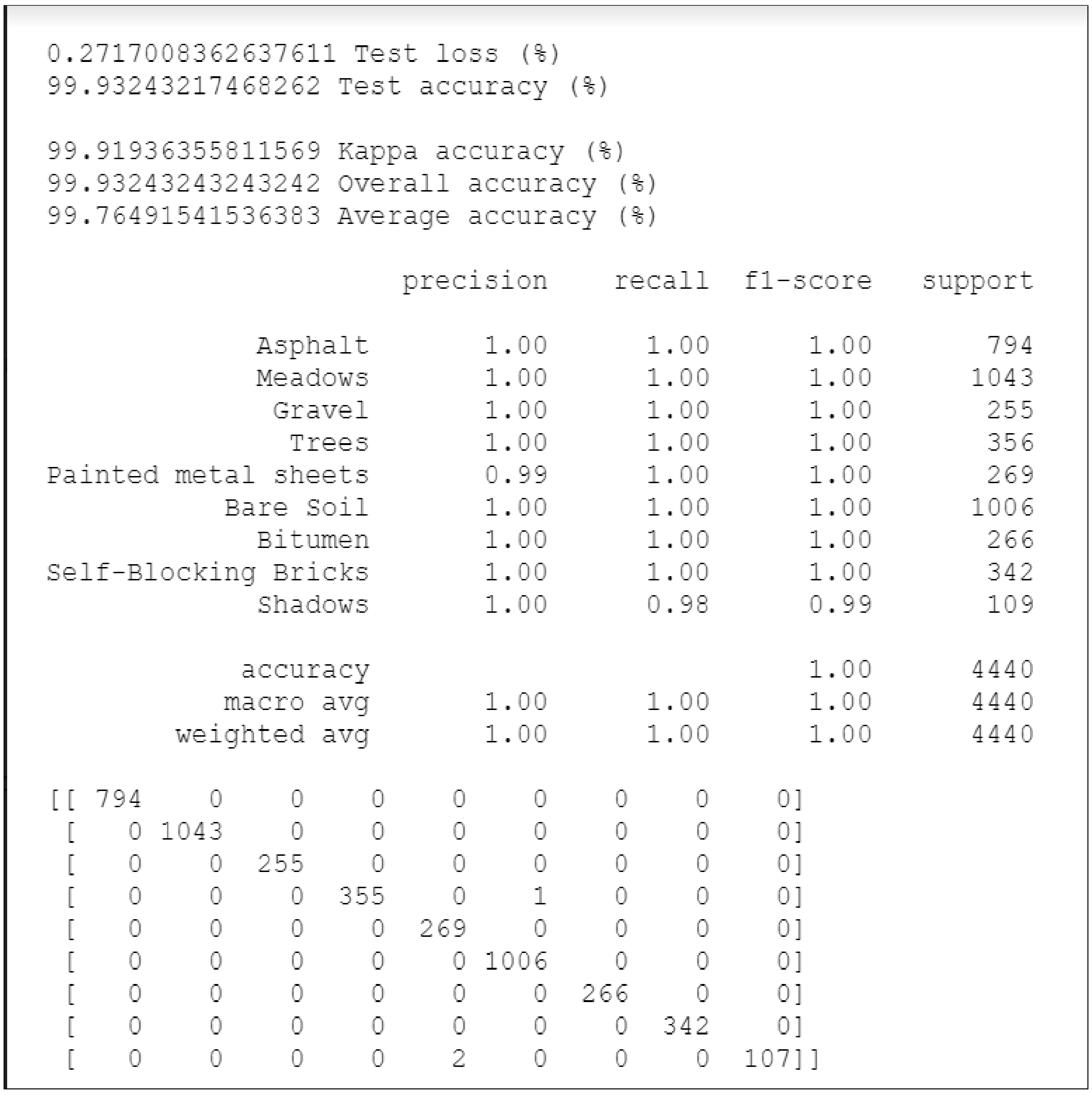

(b) Prediction

Figure 9: Indian Pines dataset

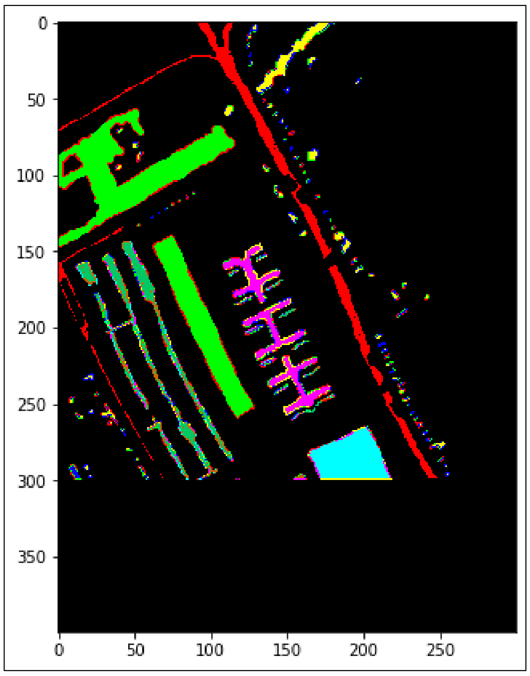
For training over the Pavia University dataset, the above model was loaded and the last few layers were popped off, as they were specifically trained on Indian Pines Dataset. New layers were added so that they could be trained specifically on the Pavia University dataset, the confusion matrix of the same is shown in Fig 10.

The test set accuracy for the Pavia University dataset came out to be **99.93**% and it had to be trained only for 3 epochs that took approximately 30 seconds, which is significantly better than the last model. The ground truth and the prediction made are shown in Fig 11a and Fig 11b respectively.

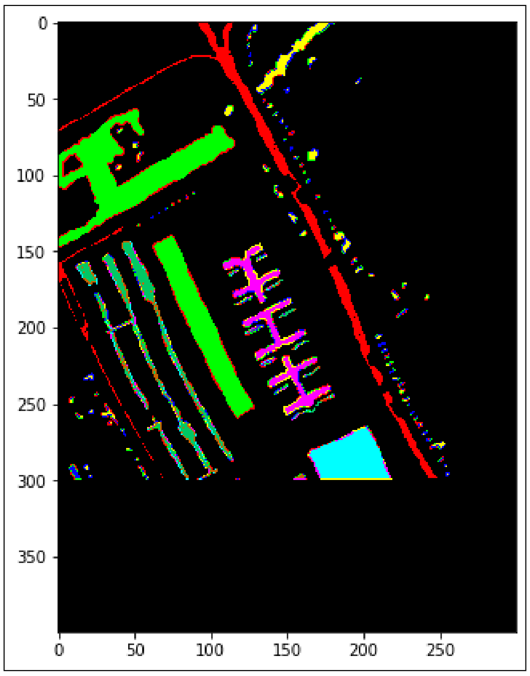


```
0.2717008362637611 Test loss (%)
99.93243217468262 Test accuracy (%)

99.91936355811569 Kappa accuracy (%)
99.93243243243242 Overall accuracy (%)
99.76491541536383 Average accuracy (%)

                      precision    recall  f1-score   support

             Asphalt       1.00      1.00      1.00       794
             Meadows       1.00      1.00      1.00      1043
              Gravel       1.00      1.00      1.00       255
               Trees       1.00      1.00      1.00       356
Painted metal sheets       0.99      1.00      1.00       269
           Bare Soil       1.00      1.00      1.00      1006
             Bitumen       1.00      1.00      1.00       266
Self-Blocking Bricks       1.00      1.00      1.00       342
             Shadows       1.00      0.98      0.99       109

            accuracy                           1.00      4440
           macro avg       1.00      1.00      1.00      4440
        weighted avg       1.00      1.00      1.00      4440

[[ 794    0    0    0    0    0    0    0    0]
 [    0 1043    0    0    0    0    0    0    0]
 [    0    0  255    0    0    0    0    0    0]
 [    0    0    0  355    0    1    0    0    0]
 [    0    0    0    0  269    0    0    0    0]
 [    0    0    0    0    0 1006    0    0    0]
 [    0    0    0    0    0    0  266    0    0]
 [    0    0    0    0    0    0    0  342    0]
 [    0    0    0    0    2    0    0    0  107]]
```

Figure 10: Confusion matrix obtained for Transfer Learning model trained on Pavia University dataset



(a) Ground Truth



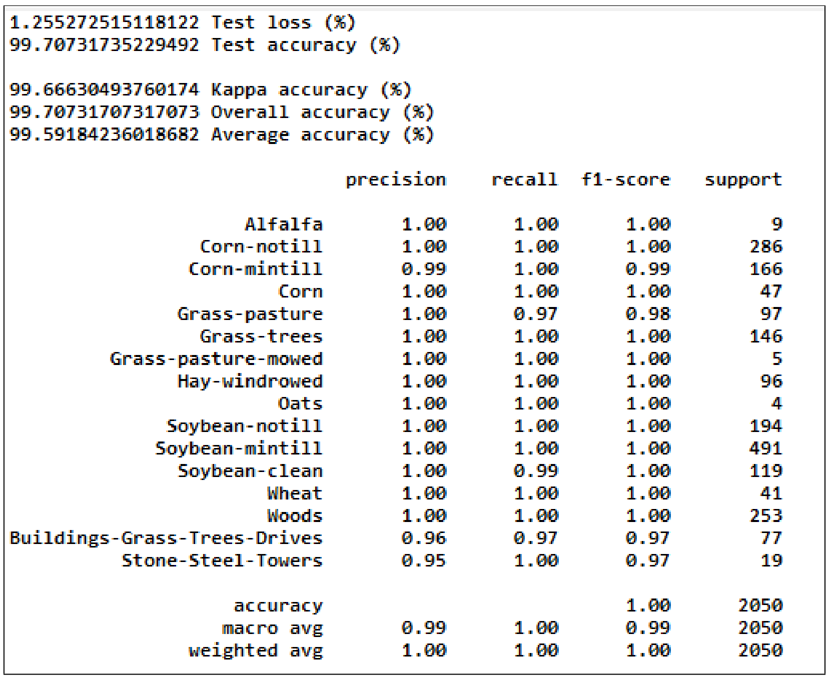
(b) Prediction

Figure 11: University of Pavia dataset

8.2 MLP Model 1

The MLP model was a very basic model with varying activation functions, and it was first trained on the Indian Pines dataset and the confusion matrix hence obtained is shown in the Fig 12.

It can be seen that the average accuracy of the model is 99.70% which is acceptable,

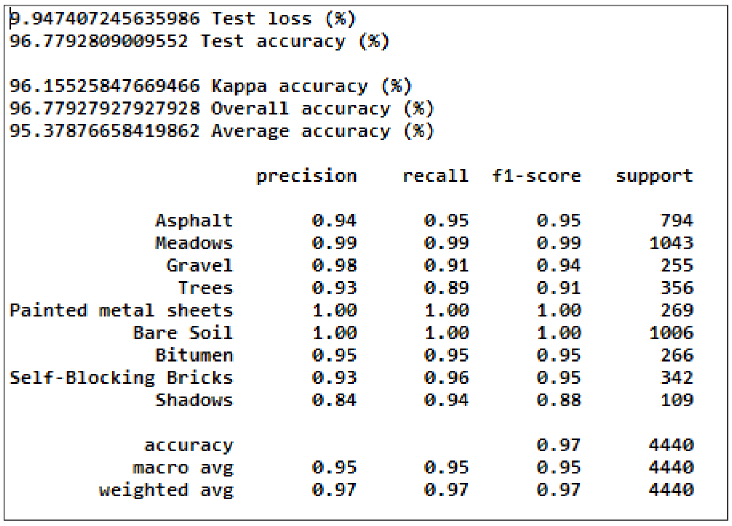


```
1.255272515118122 Test loss (%)
99.70731735229492 Test accuracy (%)

99.66630493760174 Kappa accuracy (%)
99.70731707317073 Overall accuracy (%)
99.59184236018682 Average accuracy (%)

                              precision    recall  f1-score   support

                     Alfalfa       1.00      1.00      1.00         9
                 Corn-notill       1.00      1.00      1.00       286
                Corn-mintill       0.99      1.00      0.99       166
                        Corn       1.00      1.00      1.00        47
               Grass-pasture       1.00      0.97      0.98        97
                 Grass-trees       1.00      1.00      1.00       146
         Grass-pasture-mowed       1.00      1.00      1.00         5
               Hay-windrowed       1.00      1.00      1.00        96
                        Oats       1.00      1.00      1.00         4
              Soybean-notill       1.00      1.00      1.00       194
             Soybean-mintill       1.00      1.00      1.00       491
               Soybean-clean       1.00      0.99      1.00       119
                       Wheat       1.00      1.00      1.00        41
                       Woods       1.00      1.00      1.00       253
Buildings-Grass-Trees-Drives       0.96      0.97      0.97        77
          Stone-Steel-Towers       0.95      1.00      0.97        19

                    accuracy                           1.00      2050
                   macro avg       0.99      1.00      0.99      2050
                weighted avg       1.00      1.00      1.00      2050
```

Figure 12: Confusion matrix obtained for MLP model 1 trained on Indian Pines dataset

and it should be noted that since the model was not having too many hidden layers it only took around 10 minutes to be trained for 20 epochs on Google Colaboratory even at high configurations.

Once we had the above trained model, we used the same for transfer learning by editing the last layer, and adding new trainable layers with trainable parameters. The model hence was then trained on the Pavia dataset, upon whose training and validation, the confusion matrix in Fig 13 was obtained. It should be noted that



```
0.947407245635986 Test loss (%)
96.7792809009552 Test accuracy (%)

96.15525847669466 Kappa accuracy (%)
96.77927927927928 Overall accuracy (%)
95.37876658419862 Average accuracy (%)

                      precision    recall  f1-score   support

             Asphalt       0.94      0.95      0.95       794
             Meadows       0.99      0.99      0.99      1043
              Gravel       0.98      0.91      0.94       255
               Trees       0.93      0.89      0.91       356
Painted metal sheets       1.00      1.00      1.00       269
           Bare Soil       1.00      1.00      1.00      1006
             Bitumen       0.95      0.95      0.95       266
Self-Blocking Bricks       0.93      0.96      0.95       342
             Shadows       0.84      0.94      0.88       109

            accuracy                           0.97      4440
           macro avg       0.95      0.95      0.95      4440
        weighted avg       0.97      0.97      0.97      4440
```

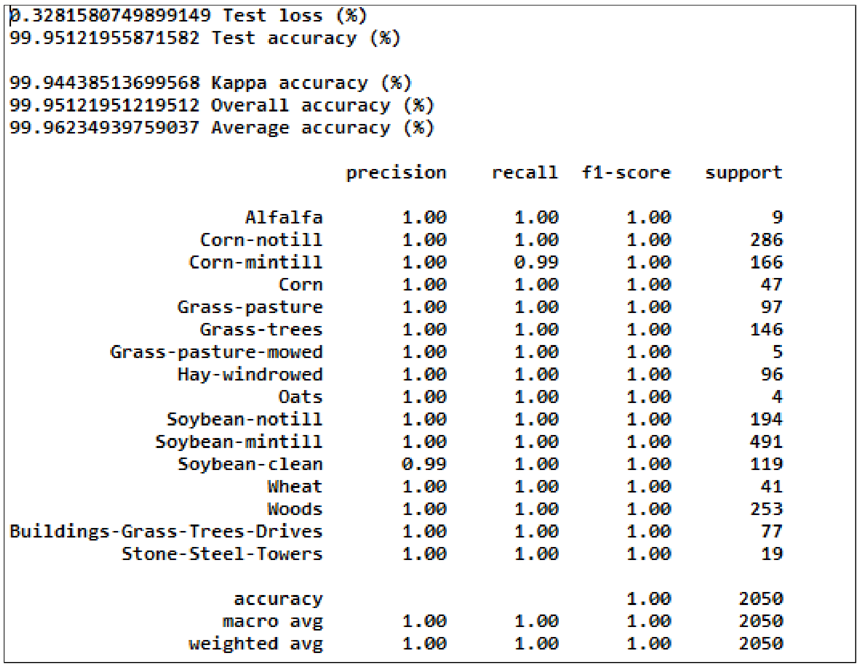
Figure 13: Confusion matrix obtained for MLP model 1 trained on Pavia University dataset

during the transfer learning the model was trained only for 10 epochs and the accuracy that we received out of the model on the Pavia dataset is close to 96.78% which is acceptable when we see in the context of transfer learning. It should be noted that the accuracy decreased before and after applying the transfer learning because the initial layer was still trained with weights of the previous Indian Pines dataset, and this decrease in accuracy on applying transfer learning algorithm is very commonly observed.

8.3 MLP Model 2

The MLP model was first trained on the Indian Pines dataset and the confusion matrix hence obtained is shown in the Fig 14.

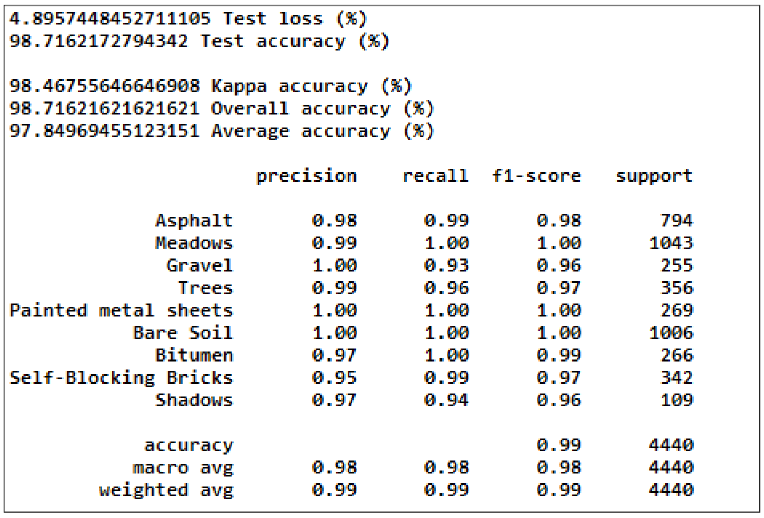
In the above figure, we can see that the average accuracy of the model is 99.95%



```
0.3281580749899149 Test loss (%)
99.95121955871582 Test accuracy (%)

99.94438513699568 Kappa accuracy (%)
99.95121951219512 Overall accuracy (%)
99.96234939759037 Average accuracy (%)

                              precision    recall  f1-score   support

                     Alfalfa       1.00      1.00      1.00         9
                 Corn-notill       1.00      1.00      1.00       286
                Corn-mintill       1.00      0.99      1.00       166
                        Corn       1.00      1.00      1.00        47
               Grass-pasture       1.00      1.00      1.00        97
                 Grass-trees       1.00      1.00      1.00       146
         Grass-pasture-mowed       1.00      1.00      1.00         5
               Hay-windrowed       1.00      1.00      1.00        96
                        Oats       1.00      1.00      1.00         4
              Soybean-notill       1.00      1.00      1.00       194
             Soybean-mintill       1.00      1.00      1.00       491
               Soybean-clean       0.99      1.00      1.00       119
                       Wheat       1.00      1.00      1.00        41
                       Woods       1.00      1.00      1.00       253
Buildings-Grass-Trees-Drives       1.00      1.00      1.00        77
          Stone-Steel-Towers       1.00      1.00      1.00        19

                    accuracy                           1.00      2050
                   macro avg       1.00      1.00      1.00      2050
                weighted avg       1.00      1.00      1.00      2050
```

Figure 14: Confusion matrix obtained for MLP model 2 trained on Indian Pines dataset

which is quite high, but it should be noted that the model had to be trained for 20 epochs which took around 10 minutes to run on Google Colaboratory even at such high configurations.This trained model was saved to be used for transfer learning purposes in future.
Once we had the trained model, we used the weights of that model for the transfer learning purpose as it would not only reduce the time it takes for the model to train on the Pavia dataset, which was substantially larger than the Indian Pines dataset. The confusion matrix that was obtained after applying transfer learning and training the model on the Pavia dataset is shown in Fig 15. It should be noted that during



```
4.8957448452711105 Test loss (%)
98.7162172794342 Test accuracy (%)

98.46755646646908 Kappa accuracy (%)
98.7162162162162 1 Overall accuracy (%)
97.84969455123151 Average accuracy (%)

                     precision    recall  f1-score   support

             Asphalt       0.98      0.99      0.98       794
             Meadows       0.99      1.00      1.00      1043
              Gravel       1.00      0.93      0.96       255
               Trees       0.99      0.96      0.97       356
Painted metal sheets       1.00      1.00      1.00       269
           Bare Soil       1.00      1.00      1.00      1006
             Bitumen       0.97      1.00      0.99       266
Self-Blocking Bricks       0.95      0.99      0.97       342
             Shadows       0.97      0.94      0.96       109

            accuracy                           0.99      4440
           macro avg       0.98      0.98      0.98      4440
        weighted avg       0.99      0.99      0.99      4440
```

Figure 15: Confusion matrix obtained for MLP model 2 trained on Pavia University dataset

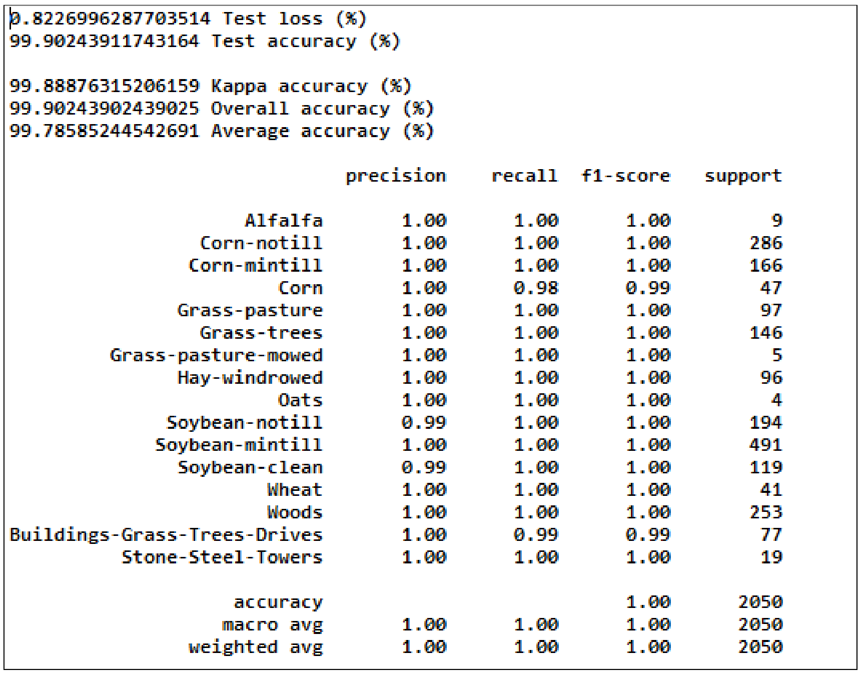
the transfer learning the model was trained only for 10 epochs and the accuracy that we received out of the model on the Pavia dataset is close to 98.71% which is still quite high when we see in the context of transfer learning. The accuracy was also a substantial leap from that of the basic model, and hence we can say that this model out-performed the previous model.

8.4 MLP Model 3

This MLP model was similar to a horizontally scaled architectured form of the second model, and it was also first trained on the Indian Pines dataset and the confusion matrix hence obtained is shown in the Fig 16.

In the above figure, we can see that the average accuracy of the model is 99.90% which is still quite high, but it should be noted that the last model had already achieved a greater accuracy, and this model in turn had also to be trained for 20 epochs which took a greater time, about 15 minutes to run on Google Colaboratory even at such high configurations.This trained model was again saved to be used for transfer learning purposes in future.

Once we had the trained model, much like we did with the previous two models, we used the weights of that model for the transfer learning purpose on the Pavia dataset. The confusion matrix that was obtained after applying transfer learning and training the model on the Pavia dataset is shown in Fig 17. It should be noted that during the transfer learning the model was trained only for 10 epochs and the accuracy that we received out of the model on the Pavia dataset is close to



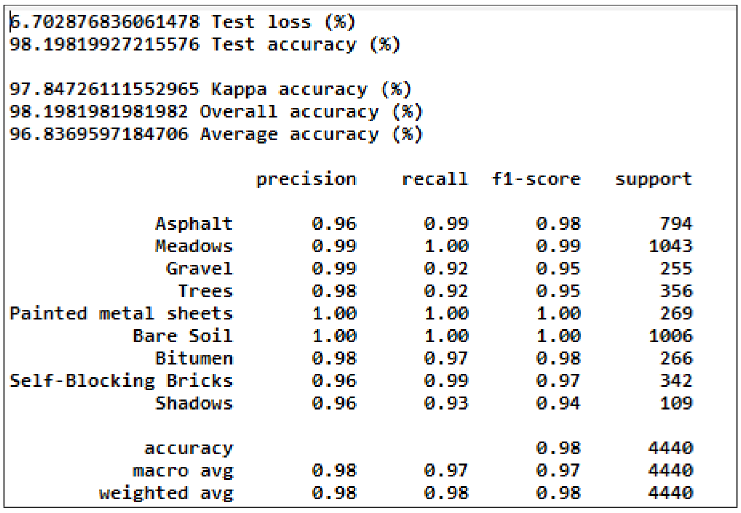
```
0.8226996287703514 Test loss (%)
99.90243911743164 Test accuracy (%)

99.88876315206159 Kappa accuracy (%)
99.90243902439025 Overall accuracy (%)
99.78585244542691 Average accuracy (%)

                          precision    recall  f1-score   support

                 Alfalfa       1.00      1.00      1.00         9
             Corn-notill       1.00      1.00      1.00       286
            Corn-mintill       1.00      1.00      1.00       166
                    Corn       1.00      0.98      0.99        47
           Grass-pasture       1.00      1.00      1.00        97
             Grass-trees       1.00      1.00      1.00       146
     Grass-pasture-mowed       1.00      1.00      1.00         5
           Hay-windrowed       1.00      1.00      1.00        96
                    Oats       1.00      1.00      1.00         4
          Soybean-notill       0.99      1.00      1.00       194
         Soybean-mintill       1.00      1.00      1.00       491
           Soybean-clean       0.99      1.00      1.00       119
                   Wheat       1.00      1.00      1.00        41
                   Woods       1.00      1.00      1.00       253
Buildings-Grass-Trees-Drives   1.00      0.99      0.99        77
      Stone-Steel-Towers       1.00      1.00      1.00        19

                accuracy                           1.00      2050
               macro avg       1.00      1.00      1.00      2050
            weighted avg       1.00      1.00      1.00      2050
```

Figure 16: Confusion matrix obtained for MLP model 3 trained on Indian Pines dataset

98.19% which is quite lower than what we had already achieved. This was probably seen because the pre-trained model had three large perceptron layers that were not trained during transfer learning, so the model was actually overfitting the Indian Pines dataset and the extra few layers that were later trained on the Pavia dataset, were not able to align the weights and capture the true features.

Comparison

Now since we have seen the separate outputs of the three different MLP models, we also need to compare the three to decide the one whose architecture best fits our objective. In the table 3, we have compared the tree models in a tabular form, and though by looking at the output predicted images, being it of the Indian Pines or the Pavia dataset, all three seems to be exactly the same, but when we see the test accuracy and the average accuracy store we find a difference there. The first model being a very basic model is out-performed by the second model, which though requires a higher computational power and time for training but also provides a higher accuracy. In case of the third model, we saw that mere horizontally scaling and increasing the number of perceptron layers did not result in increase in the accuracy but rather decreased the accuracy due to overfitting over the dataset and the same can be seen when the model was tested after transfer learning.



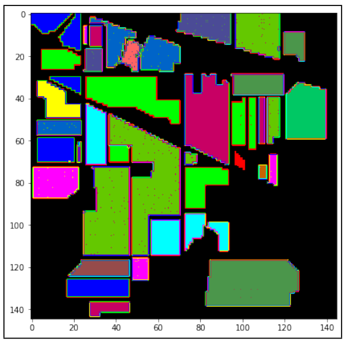
```
6.702876836061478 Test loss (%)
98.19819927215576 Test accuracy (%)

97.84726111552965 Kappa accuracy (%)
98.1981981981982 Overall accuracy (%)
96.8369597184706 Average accuracy (%)

                      precision    recall  f1-score   support

             Asphalt       0.96      0.99      0.98       794
             Meadows       0.99      1.00      0.99      1043
              Gravel       0.99      0.92      0.95       255
               Trees       0.98      0.92      0.95       356
Painted metal sheets       1.00      1.00      1.00       269
           Bare Soil       1.00      1.00      1.00      1006
             Bitumen       0.98      0.97      0.98       266
Self-Blocking Bricks       0.96      0.99      0.97       342
             Shadows       0.96      0.93      0.94       109

            accuracy                           0.98      4440
           macro avg       0.98      0.97      0.97      4440
        weighted avg       0.98      0.98      0.98      4440
```

Figure 17: Confusion matrix obtained for MLP model 3 trained on Pavia University dataset

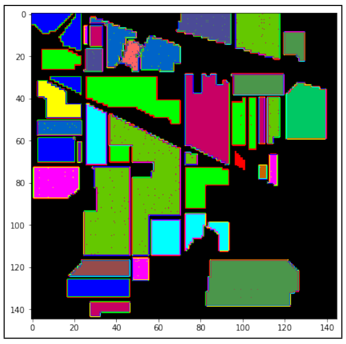
Model	MLP Model 1	MLP Model 2	MLP Model 3
Layers	3	4	7
Architecture	(18750,10000,5000,9)	(18750,472,168,72,9)	(18750,1024,512,256,128,72,32,9)
Trainable Params	50,050,009	12,825	11,921
IP Test Accu.	99.70%	99.95%	99.90%
IP Avg. Accu.	99.59%	99.96%	99.78%
Pavia Test Accu.	96.78%	98.71%	98.19%
Pavia Avg. Accu.	95.37%	97.84%	96.83%

Table 3: Comparison of MLP models

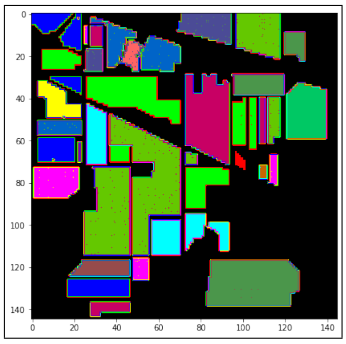
With the above comparison, it is conclusive that the second MLP model that we proposed is the better of the three, with a test accuracy of 99.95% on Indian Pines and of 98.71% on the Pavia Dataset. When we compare the above result with the one that we had obtained while addressing the same problem by using a CNN based transfer learning approach, where we obtained a test accuracy of 99.91% on Indian Pines and 99.93% on the Pavia dataset, we can conclude that the MLP model though was faster in terms of training and the convergence to the optimum result was faster than what it took in case of CNN. The CNN also captures the spatial features of the image dataset, apart from just the spectral ones, whereas the MLP model only captures the spectral features.



(a) MLP model 1

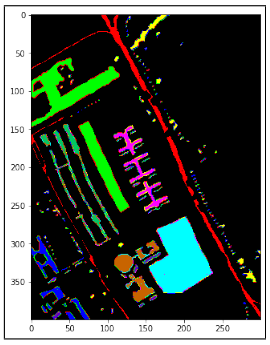


(b) MLP model 2

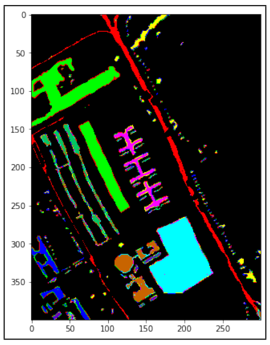


(c) MLP model 3

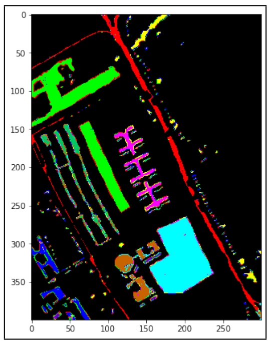
Figure 18: Predicted Images of Indian Pines dataset



(a) MLP model 1



(b) MLP model 2



(c) MLP model 3

Figure 19: Predicted Images of Pavia University dataset

9 CONCLUSION

The MLP based models are straight-forward and are used in a wide range of image classification objectives. Unlike the CNN, they require a smaller training time since there are no tasks to capture the spatial features like convolution or pooling. Scaling the MLP architecture, either vertically or horizontally does lead to increase in the accuracy of the model, at the cost of time, but there is an upper limit to it, after which the model starts to experience overfitting and performs worse in the case of transfer learning. These facts were evidently seen with the detailed comparison of the three different MLP models that were implemented and discussed.
The use of transfer learning substantially decreases the training time required for the model, on larger datasets like Pavia by extracting weights and knowledge from smaller datasets like the Indian Pines dataset. The crux of transfer learning lies in

fact that we take advantage of the inner layers trained in the previous model and use it's general information (in our case about the hyperspectral images) to train the outermost few layers. Thus, saving time by not having to train the inner layers again.
One more argument that arose was whether a CNN based transfer learning model or a MLP based transfer learning model.The decision of which model to prefer is based on the application and objective and also may vary with the available resources. In case when the terrain classification is to be used for purposes like agricultural research, the spatial features need to be taken care of and hence a CNN based model would work better in this case. On the other hand, in applications involving military remote sensing the spectral features overlook the spatial ones, and hence the MLP based model should be preferred over CNN in this case.

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