Hyperspectral Remote Sensing Image Classification

Team members:

- Padala Viwin Kumar
- Rupendra Shata
- Hariteja U

CODE:B23MG02
MENTOR: Dr.Mrinmoy Ghorai

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Problem Statement

Creating a new novel-backbone network with a focus on the spectrometric and spatial metric characteristics, making it well-applicable to the highly accurate and fine classification of HS images.

Related Work

- The currently available state-of-the-art architectures for this task are:

→CNN

→RNN

→Transformers

Related Work

CNN and it’s Limitations:

→Convolutional neural networks are designed especially for Pattern Recognitions.

→CNNs treat each spectral band as independent features, ignoring the spectral correlations that are important for HSI analysis.

Related Work

RNN and it’s Limitations:

→Recurrent neural networks are designed especially for handling sequential information.

→RNN considers one pixel at a time, and is good for capturing the temporal dependencies, but doesn’t work too well in capturing spatial correlation between pixels.

Approach for experiments

→Consider the Indian Pines dataset whose input size is 145 x 145 x 200.

→For simplicity and generality, we will use Principal Component Analysis for the dimensionality reduction, by choosing the best K value for doing PCA.

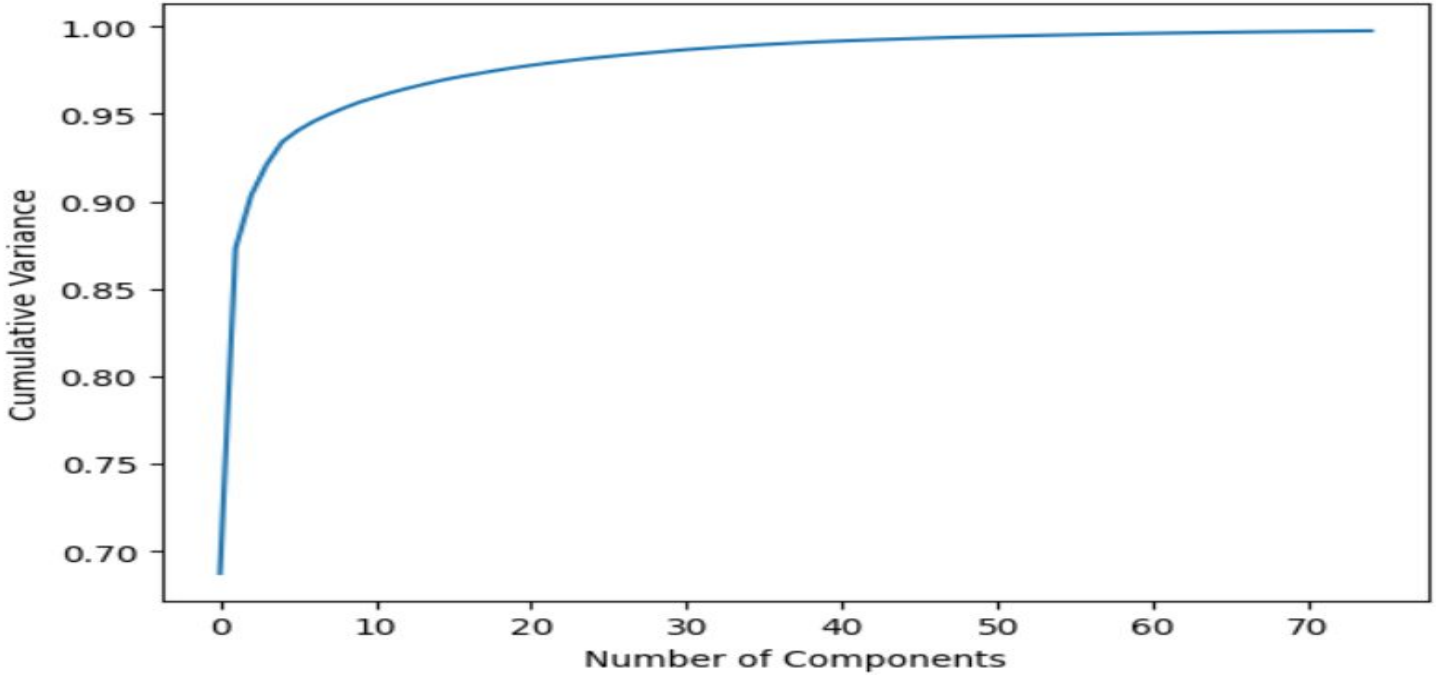
→Preprocess the data.

→Define a model.

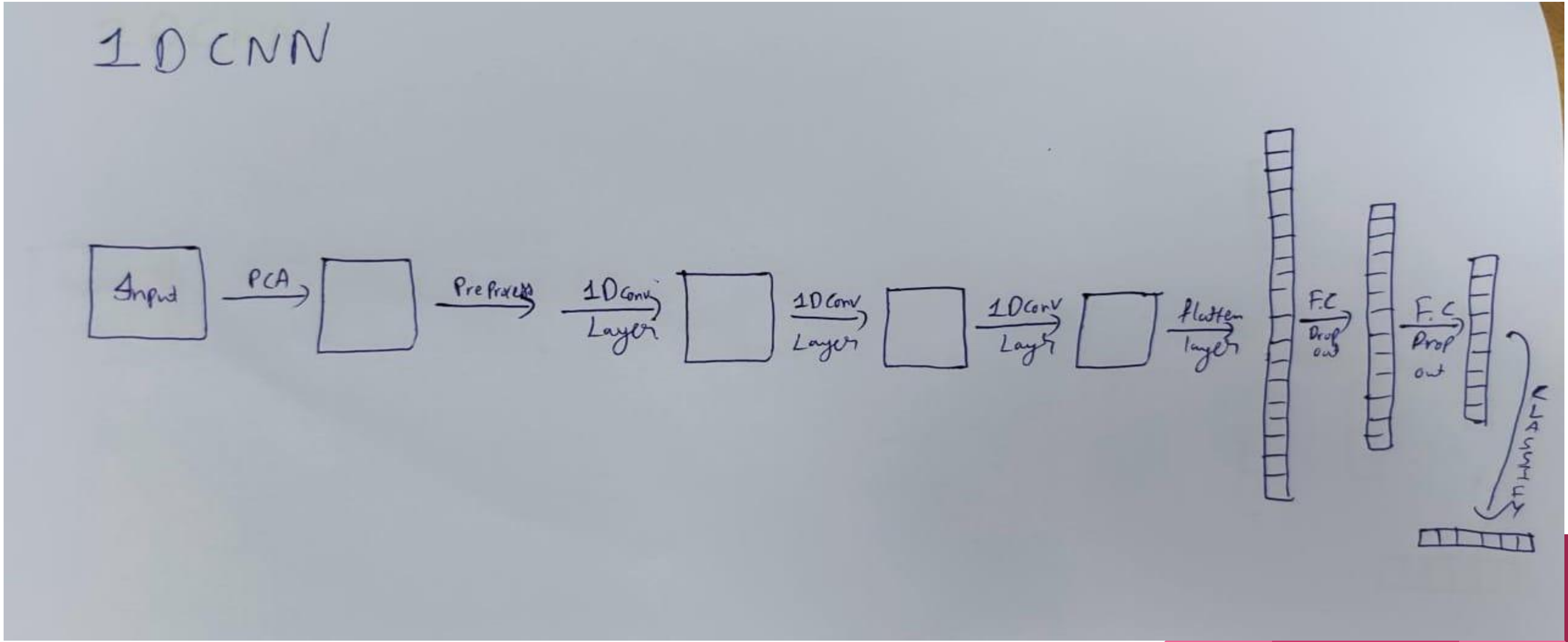
→Train the model.

→Get resulting metrics, Final predicted image using that model.

Cumulative Variance vs Number of components for IP dataset:

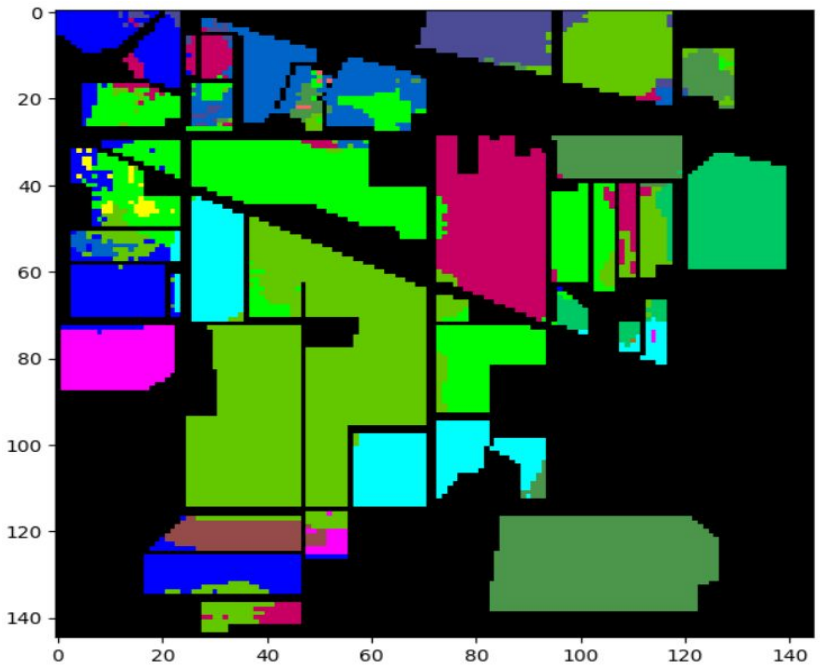


1D CNN:



1D CNN
Input
PCA
Pre Process
1D Conv
Layer
1D Conv
Layer
1D Conv
Layer
Flatten
layer
F.C
Drop
out
F.C
Drop
out
CLASSIFY

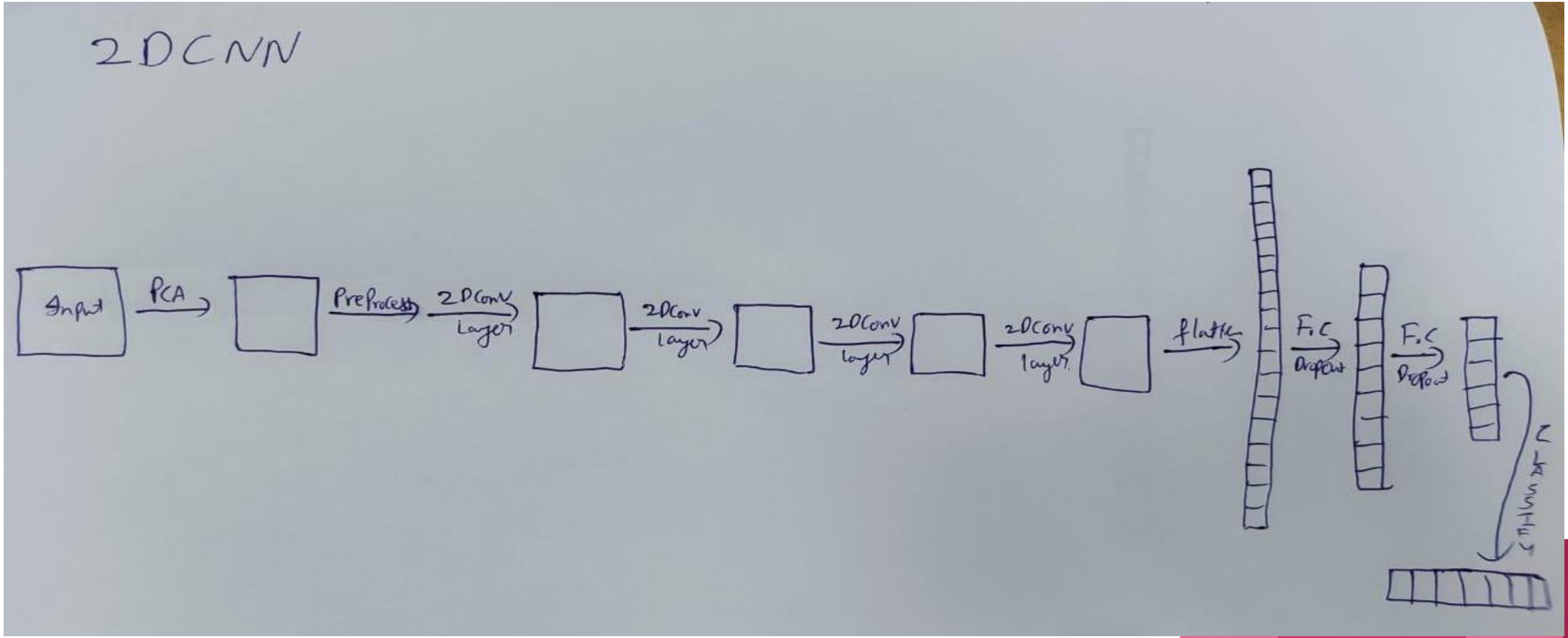
1D CNN Results:



Test loss(%): 54.82582449913025
Test accuracy (%): 83.48214030265808

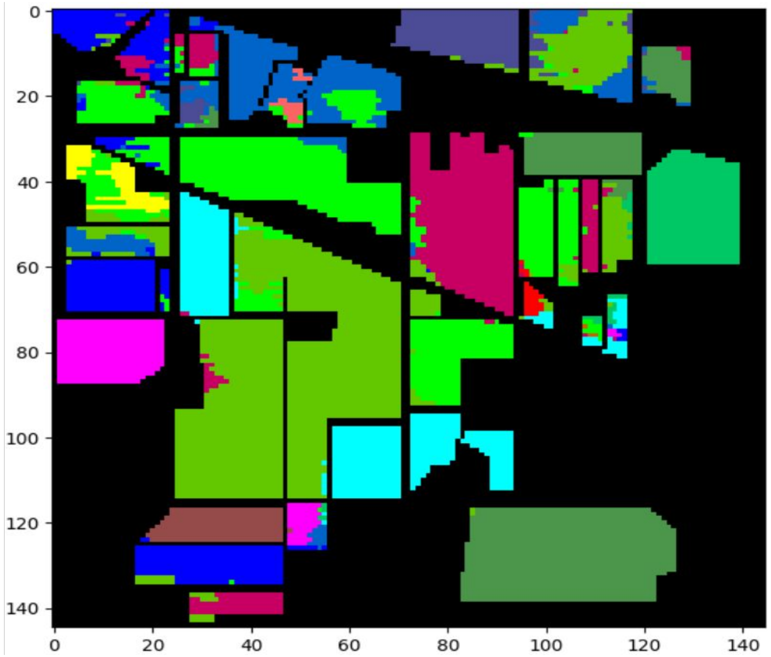
Kappa accuracy (%): 80.9122144381894
Overall accuracy (%): 83.48214285714286
Average accuracy (%): 57.13599038452859

2D CNN



2DCNN
Input
PCA
PreProcess
2DConv
Layer
2DConv
layer
2DConv
layer
2DConv
layer
flatten
F.C
Dropout
F.C
Dropout

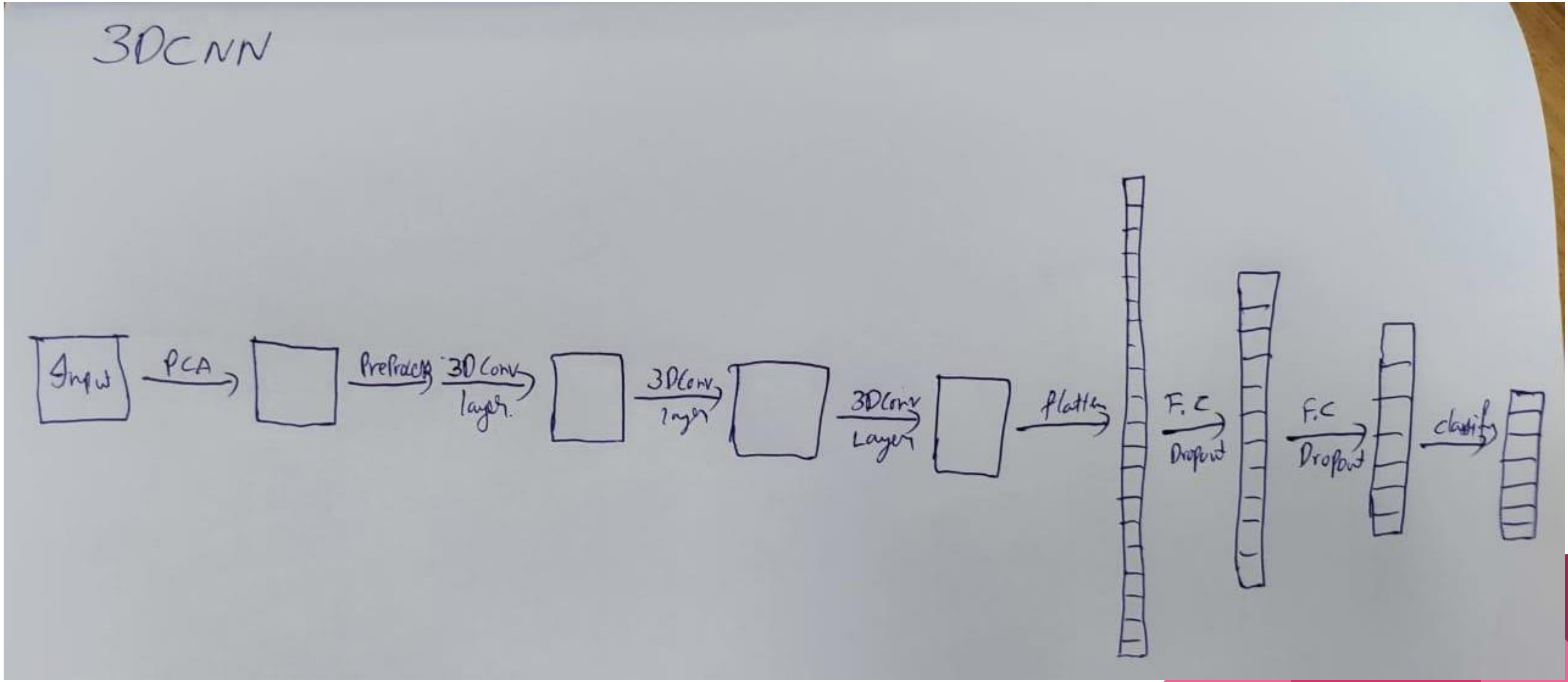
2D CNN Results:



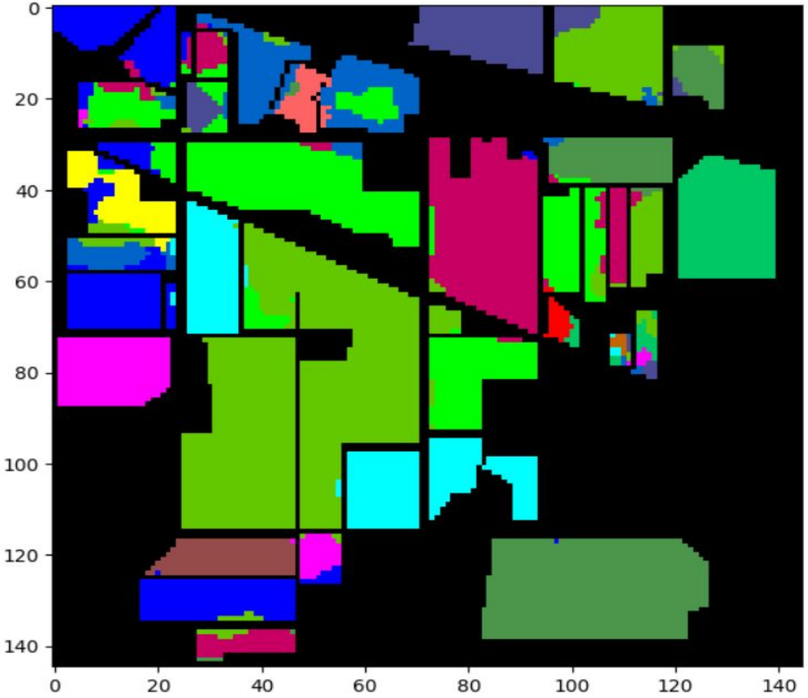
Test loss (%): 51.849520206451416
Test accuracy (%): 86.99776530265808

Kappa accuracy (%): 85.10060063489163
Overall accuracy (%): 86.99776785714286
Average accuracy (%): 67.23601512075784

3D CNN



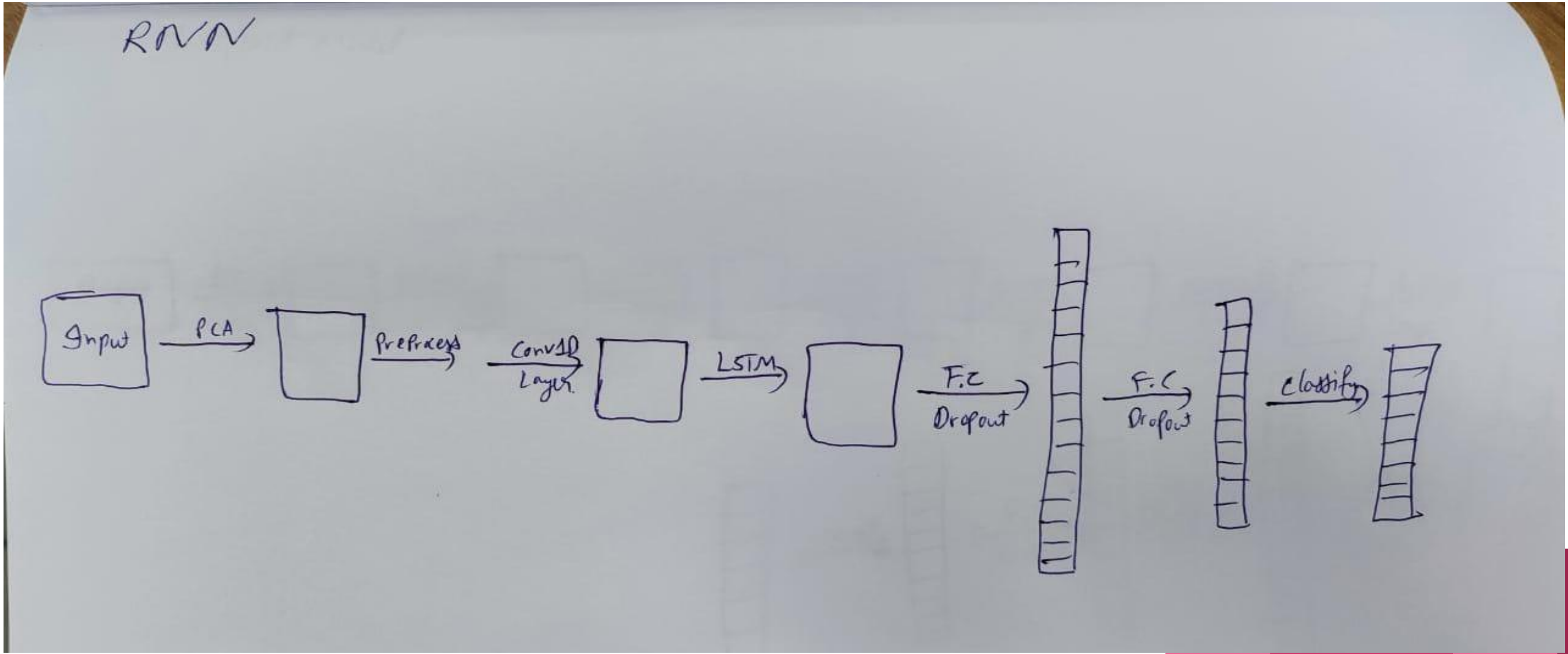
3D CNN Results:



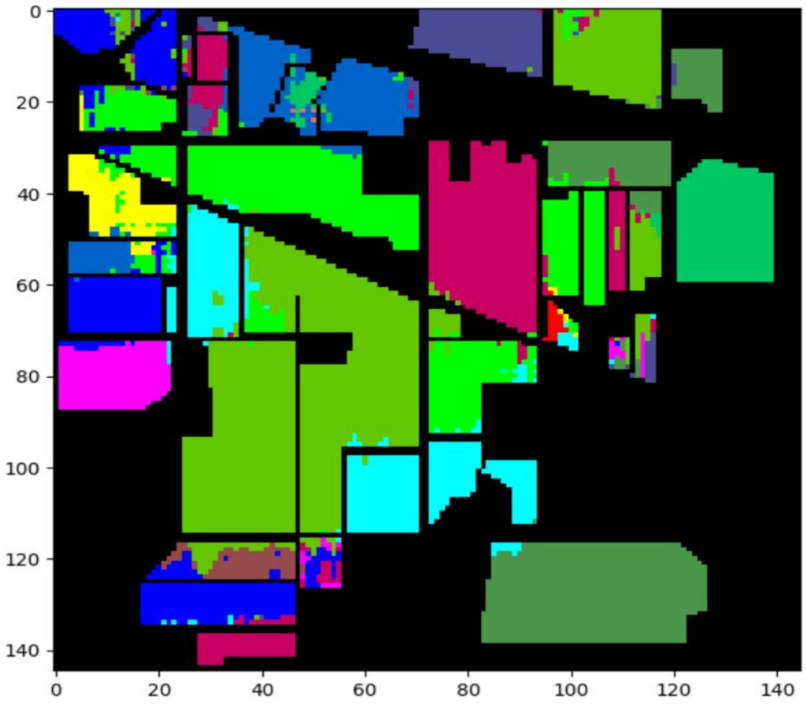
Test loss (%): 33.30453038215637
Test accuracy (%): 89.78794813156128

Kappa accuracy (%): 88.29625531990828
Overall accuracy (%): 89.78794642857143
Average accuracy (%): 76.46379422968337

RNN:


RNN
Input
PCA
Preprocess
Conv1D
Layer
LSTM
F.C
Dropout
F.C
Dropout
classify

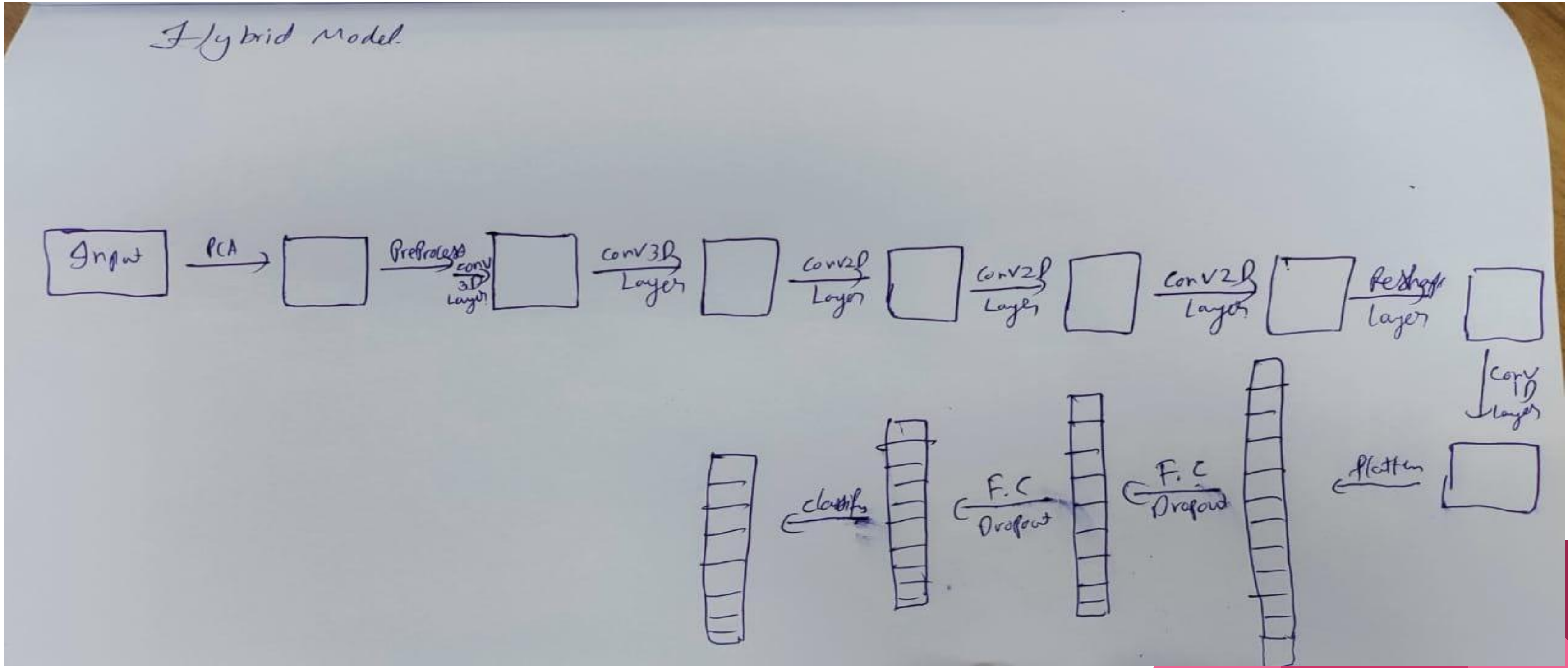
RNN Results:



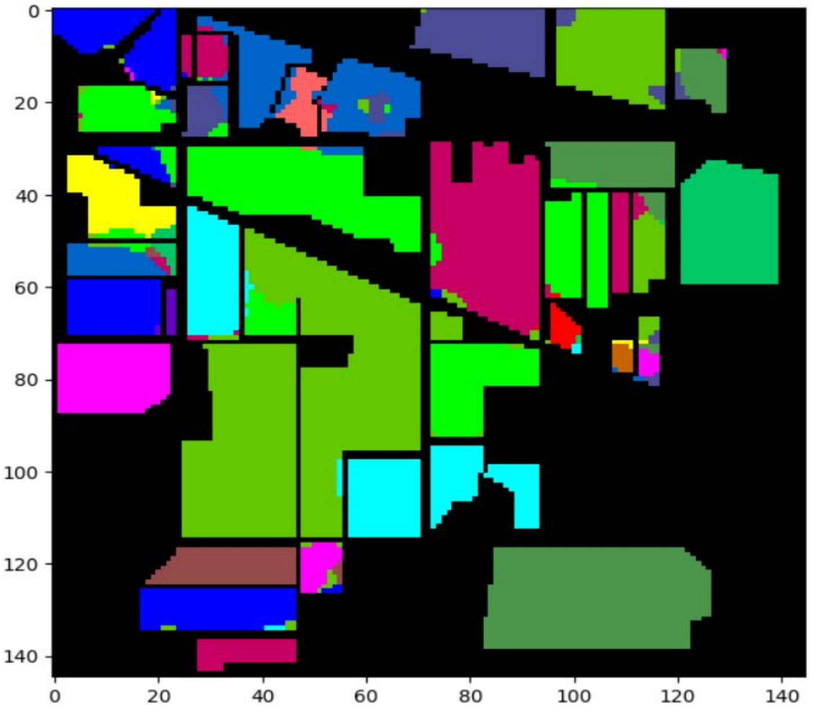
Test loss (%): 50.63251256942749
Test accuracy (%): 86.94196343421936

Kappa accuracy (%): 84.99856721377277
Overall accuracy (%): 86.94196428571429
Average accuracy (%): 64.20153663930923

Hybrid Model:



Hybrid Model Results:



Test loss (%): 30.368894338607788
Test accuracy (%): 94.02901530265808

Kappa accuracy (%): 93.18182222258571
Overall accuracy (%): 94.02901785714286
Average accuracy (%): 88.2427911854418

Main Problem:

The main problem here is that both the CNN architecture and the RNN architecture are lagging behind in their performance due to their limitations in capturing both spectral and spatial information at the same time.

What next?

→We want to do experiments on the Transformers architecture next, which is said to be a latest promising architecture as they not only can handle variable-length sequences like RNNs but also capture spatial information like CNNs by taking the advantage of its self-attention mechanism.

→And then model a new architecture that is well suited for this task based on the conclusions derived from all the results combined.

Indian Pines Dataset:

- The HS image consists of 145 × 145 pixels at a ground sampling distance (GSD) of 20m, and 220 spectral bands covering the wavelength range of 400nm to 2500nm with a 10nm spectral resolution.

- After removing 20 noisy and water absorption bands, 200 spectral bands are retained, i.e., 1-103, 109-149, 164-219. There are 16 mainly-investigated categories in this studied scene.

Pavia University Dataset:

❖ This HS scene was acquired by the Reflective Optics System Imaging Spectrometer (ROSIS) sensor over Pavia University and its surroundings, Pavia, Italy

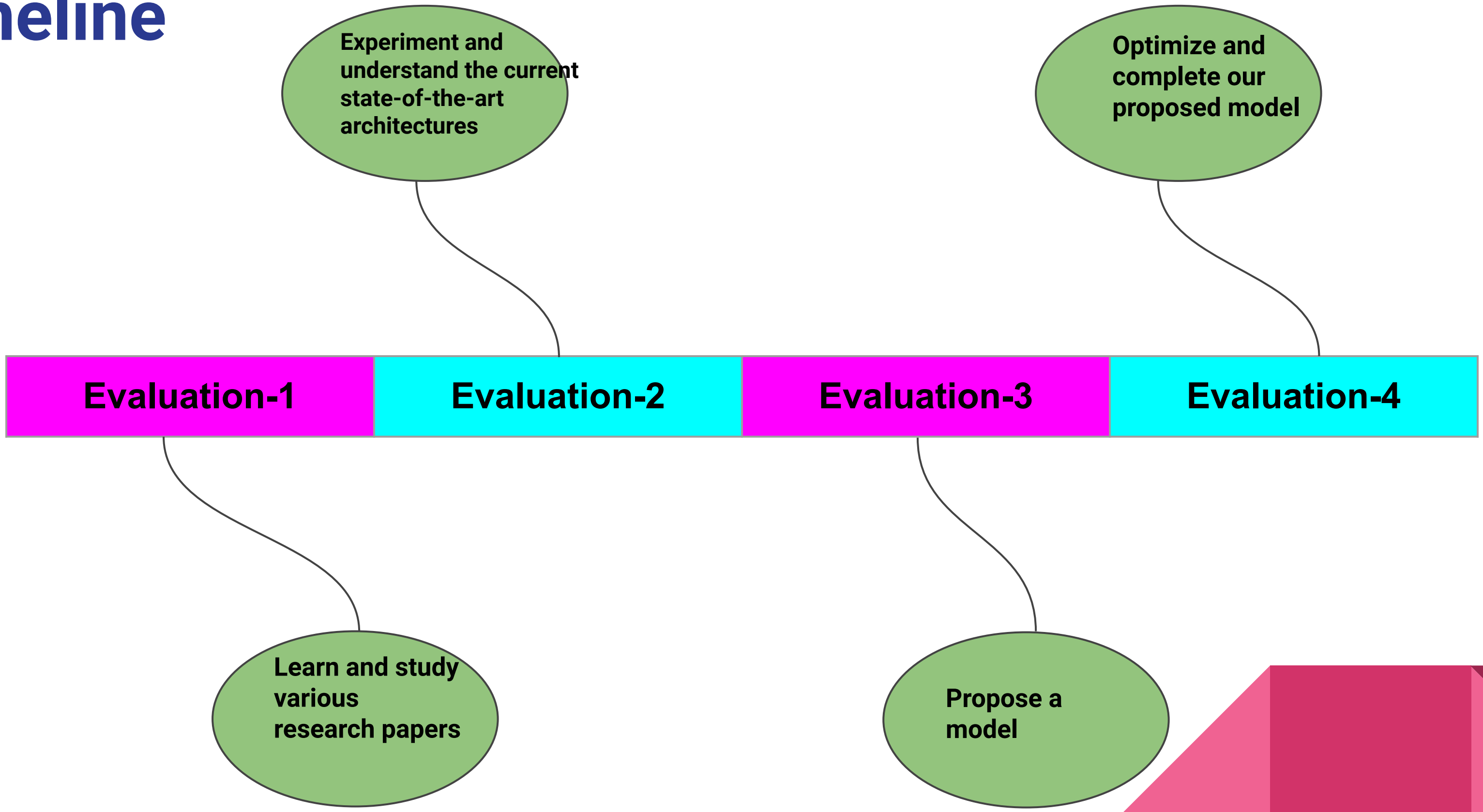
❖ The sensor can capture 103 spectral bands ranging from 430nm to 860nm, and the image consists of 610 × 340 pixels at a GSD of 1.3m. This scene includes 9 land cover classes

Houston 2013 Dataset

❖ This dataset was acquired by the ITRES CASI-1500 sensor over the campus of the University of Houston and its neighboring rural areas, Texas, USA.

❖ The HS cube comprises of 349×1905 pixels with 144 wavelength bands in the range of 364nm to 1046nm at 10nm intervals. And also it is a cloud-free version.

Timeline



Experiment and understand the current state-of-the-art architectures
Optimize and complete our proposed model
Evaluation-1
Evaluation-2
Evaluation-3
Evaluation-4
Learn and study various research papers
Propose a model

References

→Luo, Y., Zou, J., Yao, C., Zhao, X., Li, T., & Bai, G. (2018). HSI-CNN: A Novel Convolution Neural Network for Hyperspectral Image. 2018 International Conference on Audio, Language and Image Processing (ICALIP). doi:10.1109/icalip.2018.8455251

→Hierarchy for Hyperspectral Image ClassificationHybridSN: Exploring 3-D–2-D CNN Feature Hierarchy for Hyperspectral Image Classification

→X. Zhao, R. Tao, W. Li, H.-C. Li, Q. Du, W. Liao, and W. Philips, "Joint classification of hyperspectral and lidar data using hierarchical random walk and deep cnn architecture," IEEE Trans. Geosci. Remote Sens., vol. 58, no. 10, pp. 7355–7370, 2020.

→R. Hang, Q. Liu, D. Hong, and P. Ghamisi, "Cascaded recurrent neural networks for hyperspectral image classification," IEEE Trans. Geosci. Remote Sens., vol. 57, no. 8, pp. 5384–5394, 2019.

→Spectral Former: Rethinking Hyperspectral Image Classification with Transformers Danfeng Hong, Senior Member, IEEE, Zhu Han, Student Member, IEEE, Jing Yao, Lianru Gao, Senior Member, IEEE, Bing Zhang, Fellow, IEEE, Antonio Plaza, Fellow, IEEE, and Jocelyn Chanussot, Fellow, IEEE

→ Multimodal Fusion Transformer for Remote Sensing Image Classification, Swalpa Kumar Roy, Student Member, IEEE, Ankur Deria, Danfeng Hong, Senior Member, IEEE, Behnood,Rasti, Senior Member, IEEE, Antonio Plaza, Fellow, IEEE, and Jocelyn Chanussot, Fellow, IEEE Hyvrid SN

THANK YOU