Adaptive transformer architecture for scalable earth observation via hyperspectral imaging

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ABSTRACT

Hyperspectral image (HSI) classification is one of the critical processes involved in remote sensing application that plays a crucial role towards earth observation. Owing to complex spatial-spectral relationship and high dimensionality, it is quite a challenging task to subject HSI content to conventional data analytics or existing methods. Hence, the proposed study introduces a novel computational model known as adaptive spectra-spatial transformer (ASST) to address these ongoing challenges and shortcoming of existing artificial intelligence (AI) based modelling. The proposed model contributes towards a novel transformer-based architecture where a distinct spectral-spatial attention method has been used with transformer encoder. This novel combination facilitates highly adaptive and contextually enriched feature extraction. Tested on universally standard HSI dataset of Pavia University, the proposed ASST model has been benchmarked with notice 97.26% of overall accuracy (OA) and faster processing duration computed via training time (TT) and response time (RT) in contrast to frequently adopted machine learning (ML) and deep learning (DL) models. The accomplished study outcomes truly exhibited highly improved feature representation as well as robust performance against class imbalance problems towards scalable data analysis of HSI contents for earth observation.

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1. INTRODUCTION

A hyperspectral image (HSI) belongs to a specific type of image data that consists of large range of electromagnetic spectrum bands facilitating detailed analysis of surfaces depending upon their spectral signatures [1]. HSI contents facilitates land cover monitoring and precise identification of mineral composition and vegetation health [2]. The enriched quality of HSI is beneficial as well as it is also a major impediment towards the task of classification [3]. Due to increased number of spectral bands, HSI suffers from curse of dimensionality that eventually leads to either degraded model performance or overfitting. The classification accuracy is also complicated by spatial heterogeneity, atmospheric interference, noise, and spectral variability. At present, there were various research attempts being carried out to solve these challenges [4], [5] while artificial intelligence (AI), in the form of machine learning (ML) and deep learning (DL), has shown promising solution towards addressing such form of classification problem. Both ML and DL approaches are quite capable of learning complex patterns associated with HSI contents. There are various frequently adopted methods in ML e.g., support vector machine (SVM), random forest (RF), convolutional neural network (CNN), and many more approaches for this purpose. However, ML models have dependencies of manual feature extraction while DL model requires large scale annotated dataset with potential availability of computational power and resources. Hence, irrespective of potential advantages, ML and DL models have characteristic challenges towards earth observation.

From the context of related work towards ML approaches, there are different variants of learning models implemented till date. SVM is one such supervised ML model which is quite effective for HSI classification as it is quite robust to dimensionality problems, could be used for real-time analysis, lightweight for inference [6], [7]. However, they are very shallow model while no spatial context is model which is essential in earth's observation. RF has also been experimented towards HSI classification as it can handle the high-dimensional data quite well even with small labeled dataset offering scalable outcomes [8]–[10]. However, it has similar problem like SVM i.e., non-inclusion of spatial context consideration while they are less effective for overlapping classes of spectral data. From the perspective of the DL method, it has been noted that CNN has been quite dominantly used adopting two different approaches viz. standalone usage of CNN [11]–[13], hybrid usage of CNN [14]–[16], and mixed dimensional-inclusion in CNN [17]–[19]. The mixed dimensional approaches are of two types further viz. i) standard 3D-CNN [20], [21] and ii) multi-scale 3D-CNN also known as M3D-CNN [22], [23]. Studies have been also carried out using extreme gradient boosting (XGBoost) to find that its predictive performance is quite high and can perform better than RF and SVM too towards HSI classification [24]–[26].

The identified research problems from existing approaches are as follows: i) owing to inclusion of deep cube processing, 3D-CNN is computationally expensive, ii) the prime shortcoming of 3D-CNN is associated with higher inclination towards overfitting with less flexibility in handling spectral dependencies of longer ranges, iii) adoption of M3D-CNN could result in maximized architectural complexity which could be mainly due to inclusion of multi-kernel and multi-branch modules for handling large scale of spatial and spectral data in hyperspectral content, and iv) XGBoost has a shortcoming of hyperparameter sensitivity while its tuning is quite computationally expensive and often time consuming. The identified limitation of all the above approaches is addressed by proposed system by incorporating multi-head self-attention that models relationship of global context over spectral and spatial dimension. Apart from this, proposed solution also offers adaptive feature extraction, improved generalization and better interpretability, towards addressing the identified research problems. The next section discusses about the adopted research methodology towards classifying HSI exhibiting addressing the shortcomings associated with existing models.

The aim of the proposed study is to introduce a novel adaptive learning strategy which balances the higher accuracy along with cost-effective computational performance while classifying HSI contents. The accomplishment of this study is carried out by harnessing the potential of DL models. The contribution of the paper is as follows:

i) The proposed study combines both spectral and spatial attention modules for facilitating adaptive focus on critical spatial regions and spectral bands to increase discriminative capability towards learned feature.
ii) The study model introduces a transformer-based global context modelling which uses multi-head self-attention for modelling dependencies of longer ranges over spectral-spatial patches unlike conventional CNN model using only local patterns.
iii) The presented model completely eliminates any reason to select the band manually or any form of dependencies towards handcrafted features as it can perform end-to-end feature learning directly from raw patches of HSI contents.
iv) The proposed design integrates transformer block with shallow conventional layers for accomplishing an optimal balance between model performance and computational efficiency thereby increasing its scope towards practical earth observation scenarios.

2. METHOD

The proposed study aims towards designing a cost-effective as well as adaptive learning strategies essentially meant for analyzing emerging demands towards earth observation. For this purpose, the implementation scheme uses HSI which is frequently used for investigating the topic. HSI image that forms the basis of an earth observation data is quite sophisticated and attributed by enriched spatial and spectral information which can fluctuate over one geographic region to another along with temporal scales. The design of proposed adaptive spectra-spatial transformer (ASST) framework adapts to such form of fluctuation by using both spatial attention and spectral attention. Figure 1 offers a formalization of the adopted design of architecture with various operational components for purpose of classifying HSI content towards earth observation. Following are discussion of the core modules involved in architecture design.

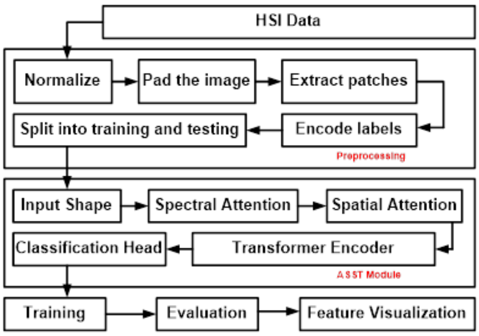


Figure 1. Proposed architecture of ASST

The prime aim of this module is to design a sophisticated relationship within the HSI contents by integrating transformer-based global reasoning, spatial attention, and spectral attention for yielding a unified architecture. This module initially applies spectral attention using 1×1 convolution that highlights essential spectral bands towards each pixel. Further, spatial attention is applied using 3×3 convolution for acquiring boundary information and spatial texture. The joint feature map is then subjected to reshaping while it is passed through a transformer encoder with a deployment of self-attention with multi-heads for learning dependencies over the complete set of patches. The outcome of the module operation is then pooled for designing a feature vector of constant size that is passed through fully connected layers. At the end, SoftMax activation is used for generating probabilities of classes. The implementation steps are as follows:

i) Input: the representation of each input patch is given as $P_k \in R^{P \times P \times D}$.
ii) Spectral attention block: the study applies a 1×1 convolution in order to model spectral attention: $F_1 = \sigma(BN(Conv_{1\times1}(P_k)))$, $F_1 \in R^{P \times P \times D}$ where the variable σ represents rectified linear unit (ReLU) activation, while *BN* depicts batch normalization, and d_1 represents the quantity of the output channels (e.g., 64).
iii) Spatial attention block: the system applies a 3×3 convolution: $F_2 = \sigma(BN(Conv_{3\times3}(F_1)))$, $F_2 \in R^{P \times P \times D_2}$.
iv) Transformer encoder block: this module is used for flattening the spatial dimensions towards the multi-head attention $Z = Reshape(F_2) \in R^{P^2 \times D_2}$ while this followed by applying multi-head self-attention $A = MultiHeadAttn(Z, Z) \in R^{P^2 \times D_2}$. Further, normalization and residual connection are applied, $Z_{att} = LayerNorm(Z + A)$ while global average pooling is applied to generate the embedding vector $Z_{embed} = GlobalAvgPool(Z_{att}) \in R^{D_2}$.
v) Classification layer: the embedding is made to pass through fully connected layer viz. $h_1 = \sigma(W_i.Z_{embed} + b_1)$, $h_1 \in R^{256}$, $\acute{h_1} = Dropout(h_1, p = 0.5)$, and $\hat{y} = softmax(W_2.h_1' + b_2), \hat{y} \in R^c$, where the variable $\hat{y}$ represents probabilities of predicted classes, while weight matrices is represented as W_1 and W_2, and (b_1 b_2) represents bias vectors.

The core aim of the next module of training process and loss function is to optimize the ASST module by reducing the frequencies of prediction errors via supervised training adopting labeled patching. The training is carried out for the model using classification loss function that compares true one hot encoded label with the predicted class probabilities. The training of the model is carried out using categorical cross-entropy loss as (1).

$$L_{CE} = -\frac{1}{N}\sum_{k=1}^{N}\sum_{c=1}^{C} y_{k,c}.\log(\hat{y}_{k,c}) \tag{1}$$

In (1), the variable $y_{k,c}$ and $\hat{y}_{k,c}$ represents ground truth one-hot label associated for *c* class and predicted probability towards *c* class respectively. The proposed system also uses early stopping criterion for enhancing the reliability when the performance associated with the validation set resists to improvise while best models are saved using checkpoints and overfitting is resisted by employing dropout. It is essential to understand the significance of this module where the DL models will tend to overfit if they are used without regularization or early stopping criterion is used. This fact is applicable for restricted labeled data present within HSI content. Apart from this, there are also chances of poor generalizability of models without proper validation. Hence, this module ensures of optimal performance by training enhancement carried out here without any need of overtraining. The contribution of this module is that it enhances the convergence to an optimal solution and enhances the model robustness while overfitting is prevented in the vase of classifying HSI contents on data-scarce ecosystem. The next section presents discussion of the result accomplished from implementing the proposed ASST.

3. RESULTS AND DISCUSSION

The proposed system has used Pavia University hyperspectral dataset that has been captured using reflective optics system imaging spectrometer (ROSIS) sensor over the Pavia city, Italy. This consist of 103 spectral bands after opting out for water absorption and noisy band from original 115 bands. The dimension of image is 610×340 pixels while the spatial resolution of an image is 1.3 meters that covers 9 labeled classes such as buildings, trees, meadows, and asphalt that are usually seen over the practical scenarios of urban ecosystem. The ASST model is subjected to comparative analysis with the two conventional scheme i.e., M3D-CNN and 3D-CNN method along with SVM. Although, there are various existing AI schemes deploying ML and DL methods towards analyzing HSI contents leading towards classification, both 3D CNN and M3D-CNN has been particularly selected mainly due to their potential performance as well as quite frequently adopted methods towards acquiring spatial and spectral features from the HSI contents. The study has selected 5×5 as the patch size for acquiring the logical spatial context while resisting possible computational overhead. A batch size of 32 has been considered to provide an equilibrium between gradient stability and training time (TT).

The accomplished outcome is shown in Table 1. The assessment also considers 0.5 dropout rate for minimizing the overfitting. Adam optimizer is used for its adaptive capability towards minimizing noisy gradients. The rate of learning is kept at 0.001 that offers stable convergence in proposed modelling. All the above-mentioned performance metric has been used for assessing the effectiveness of the proposed ASST model in contrast to existing models of SVM, M3D-CNN, and 3D-CNN. It should be noted that the scores mentioned in Table 1 has arrived after rigorous assessment on multiple rounds to confirm that there is a potential consistency in all the rounds. Overall accuracy (OA) is defined as the ratio of the cumulative number of precisely classified samples to the cumulative number of samples. Kappa coefficient (KC) is a statistical estimate associated with the accuracy corrected or inter-rater agreement for chance. Average accuracy (AA) metric is calculated as mean of the standalone class of accuracy over all the classes. TT refers to total duration consumed by the framework to learn from the training data over all the epochs. Response time (RT) metric is also known as inference time and is stated as duration consumed by the trained model for classifying a batch of sample or a novel input sample.

Table 1. Numerical score accomplished

Model	OA (%)	KC	AA (%)	TT (min)	RT (ms)
ASST	97.26	0.9609	98.45	25	15
SVM	94.34	0.9250	92.98	60	45
M3D-CNN	95.76	0.9450	95.08	75	38
3D-CNN	96.53	0.951	97.57	55	40

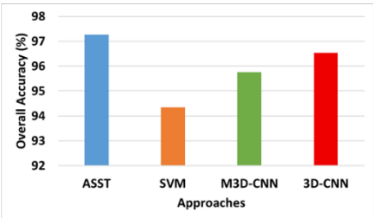
Figure 2 represents the graphical outcome of the comparative analysis being carried out to evaluate the effectiveness of all the considered models. The final training accuracy is noted as 99.3% while final validation accuracy is noted as 98.7%. The optimal epoch being selected is 32 depending upon maximum validation accuracy. The accomplished outcome showcases that proposed ASST model eventually excelled superior performance on all aspects of performance metric in contrast to existing system. The OA, KC, AA, TT, and RT outcomes are shown in Figures 2(a) to 2(e) respectively. The discussion is carried out with respect to all the performance metric as follows:

i) Interpretation of OA scores: the outcome showcases superior ability of the model towards appropriately classifying a major proportion of the hyperspectral pixels over all the classes. The lower performance demonstration of SVM is attributed to their restricted capacity in modelling the complex spatial and spectral dependencies towards the hyperspectral data. On the other hand, these challenges are addressed by DL framework e.g., M3D-CNN and 3D-CNN in much better way in contrast to classical learning models. However, DL models also encounter limitations e.g., overfitting which is mainly due to the inadequate modelling of spectral correlation or inadequate spatial context. The proposed ASST framework has exhibited enhanced performance mainly due to its inclusion of the transformer-oriented design structure that is known to adaptively integrate both spatial and spectral attention methods.
ii) Interpretation of KC scores: the relatively lower value of KC for SVM ($KC_{val} = 0.92$) also demonstrates the challenges associated in accomplishing the consistent classification agreement with respect to the classical methods. For the increased value of OA associated with the proposed ASST model and better strategy towards feature extraction, it is anticipated that KC score will be eventually better than the existing model exhibiting reliability for high-order classification. The features are adaptively weighted by the transformer resulting in minimized misclassification and maximization of consistency towards class agreement.

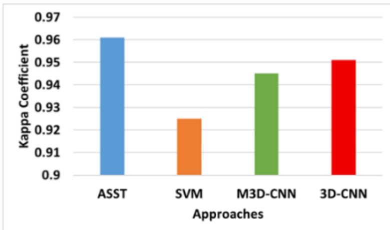
iii) Interpretation of AA scores: the prime cause of shortcomings associated with the existing system originates from uneven performance that is noted over varied classes especially for those with less or sometimes none number of labeled samples. The struggle towards generalization is higher in CNN models for minority classes while sophisticated feature learning is seriously lacking in SVM model which leads to skewed mean accuracy. The discriminating capability towards features over all the classes are improved upon by the attention-based method of ASST model. This is done by adaptively emphasizing on informative cues of spectral and spatial attribute. The issues of class imbalance effect are potentially mitigated by the attention-guided learning and yields to more consistent accuracy performance over all the classes.

iv) Interpretation of TT/RT scores: ASST demands only 25 minutes and 15 seconds for completing the training cycle and generating final response respectively which are much lower duration involved in contrast to existing models. From the context of existing models, 3D-CNN has exhibited 55 minutes which is better in contrast to its counterpart 3D-CNN and SVM models. Similarly, there is no significant difference for performance of RT for M3D-CNN and 3D-CNN much which is again slightly higher than SVM model. The prime reason for this is found to be involved higher cost of computation associated with the DL approaches mainly due to the complex architectures of deep layers and convolution that can restrict their practical deployment when it comes to resource-constrained systems. The deep networks are potentially avoided by this architecture while it still maintains its expressiveness yielding to more cost-effective computational solution towards classification of HSI contents.

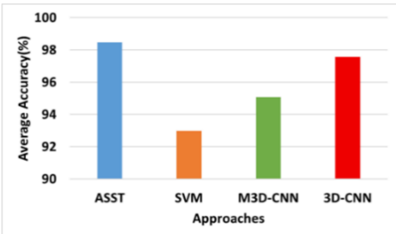
The novelty of an outcome is its minimized computational burden, that is evidently witnessed from reduced duration scores, without compromising with the accuracy scores. This ground of outcome structure offers evidence towards higher applicability. It relates to resource-constraint applications in earth's observation.



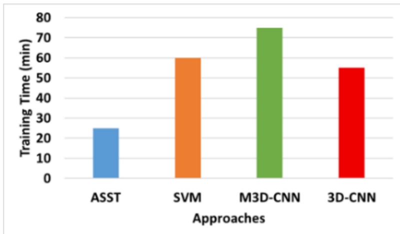
(a)



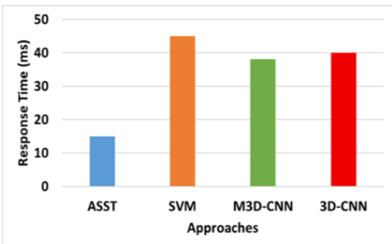
(b)



(c)



(d)



(e)

Figure 2. Benchmarked outcome of (a) OA, (b) KC, (c) AA, (d) TT, and (e) RT

4. CONCLUSION

This paper has presented a novel model named as ASST that is meant for classifying HSI content in order to fulfil the core purpose of remote sensing application that plays a critical role in earth observation.

The study is meant for mitigating the ongoing challenges associated with computational inefficiency, limited labeled data, and high dimensionality. The attention method and transformer encoders were utilized to combine spatial and spectral information by the model. Benchmarked dataset of Pavia University has been used to find that ASST exhibits better performance on accuracy-based metric and duration-based metric in contrast to frequently adopted classification models using ML/DL methods. The OA recorded for proposed model is 97.26% while it has been proven to significantly minimize both training and response duration. The architectural design presented by ASST not only enhances the classification performance but also offers faster convergence performance too. With a rigorous analysis, it is noted that ASST model accomplishes higher extent of robustness to class imbalance thereby making it increasingly applicable for real-world deployment too. An interesting learning outcome of this model is to know that transformer-based architecture is capable of adapting towards spatial-spectral model very effectively. The future work of this study will be further to optimize the learning model in presence of more complex set of information and testifying them on more complex form of objective function.

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AUTHOR CONTRIBUTIONS STATEMENT

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Devendra Kumar Saragoor Madanayaka	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Devanathan Muthukrishnan		✓				✓		✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [DKSM], upon reasonable request.

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