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School Asset Mapping Using Hyperspectral Analysis And Deep Learning: A Review For Stem Education

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Abstract
A recent development in the field of Earth remote sensing is the successful extraction of data from hyperspectral images. Data generated by this technique is a crucial part of geographic databases. Detecting targets, classifying patterns, mapping and identifying materials, etc. are just a few examples of the many potential uses for this type of data. A material mapping technique is similar to a multi-stage target detector. In order to provide new perspectives on the natural, social, human, and built capital in the surrounding regions, asset mapping entails recognizing assets at the individual, group, and community levels. Students and educators can better engage with their environment through the use of remote sensing and asset mapping to enhance STEM (Science, Technology, Engineering, and Mathematics) education. This can be achieved by finding resources, solving engineering design challenges, or conducting different scientific investigations. In order to create a secure learning environment that prioritizes the needs of students, this article discusses various reviews on the topic of integrating hyperspectral image analysis with school asset mapping through the use of deep learning techniques.
Keywords: *STEM, Hyperspectral Images, Asset Mapping, Deep Learning.*

INTRODUCTION

Advancements in Earth observation technologies have significantly enhanced our ability to monitor, analyze, and interpret complex environmental and societal patterns [1]. Among these technologies, hyperspectral imaging has emerged as a powerful remote sensing technique, capable of capturing detailed spectral information across hundreds of narrow bands. This rich data source has revolutionized fields such as material detection, land use classification, and environmental monitoring. At the same time, asset mapping has gained traction as a strategic method for identifying and utilizing local resources, both natural and human at individual, community, and institutional levels [52].The integration of hyperspectral image analysis with asset mapping presents a unique opportunity to bridge the gap between advanced geospatial technologies and STEM (Science, Technology, Engineering, and Mathematics) education. By using deep learning techniques to analyze hyperspectral data, schools and educators can develop more immersive and context-aware learning experiences. This approach not only enhances students' understanding of scientific and engineering principles but also fosters a stronger connection to their local environment.This article explores the emerging intersection of hyperspectral imaging, deep learning, and educational asset mapping. It reviews current methodologies, highlights practical applications in educational settings, and discusses the potential for creating inclusive, data-driven learning environments that are responsive to both environmental insights and community needs.

1. Review of Hyperspectral Image Analysis Techniques

From remote sensing and agriculture to geology and medicine, hyperspectral imaging (HSI) is a powerful and innovative technology with many potential uses. In contrast to traditional imaging systems that only record in three color channels (red, green, and blue), HSI records in a wide variety of closely spaced spectral bands covering the entire electromagnetic spectrum. Hyperspectral images allow for detailed material examination by utilizing the unique spectral signatures of each pixel, which is equivalent to a whole spectrum.

Material identification, disease diagnosis, environmental surveillance, and many more activities can be accomplished with the help of HSI, thanks to the wealth of spectral data that it provides about object composition, structure, and attributes. This is where a plethora of HSI algorithms came into play, greatly improving our ability to dissect and understand complex landscapes with pinpoint accuracy by mining hyperspectral data for useful information and patterns. In hyperspectral image analysis, the Spectral Angle

Mapper (SAM) [2,3,4,5] method compares spectral data, which is useful for applications such as picture categorization and target recognition. By finding the angle between two spectra, SAM determines how close two pixels are to one another. The spectral signatures are treated as vectors with several dimensions in this method. Smaller angles indicate closer matches, and the degree of similarity is reflected in the angle measurement. Pixels are sorted by SAM according to this angle; those with values below a certain threshold are marked as target material, while the others are labeled as something else. It works well for detecting materials with established spectral fingerprints since it is good at picking up on spectral differences. In conclusion, SAM is useful for identifying and categorizing certain objects or materials in hyperspectral images. One typical method for hyperspectral image categorization is using Binary Logistic Regression, however Random Forest [9,10,11,12] is also a popular choice. Using ensemble learning to capture complicated spectral patterns, Random Forest is effective for managing high-dimensional data. However, if you're looking for an easy-to-understand probabilistic method for binary classification, go no further than Binary Logistic Regression. Specific job needs, data complexity, class count, and interpretability of results determine which of these approaches to use. The HSI frequently uses the powerful machine learning algorithm Support Vector Machine (SVM) for classification tasks [13,14,15,16,17]. SVM is useful for land cover classification and anomaly detection because it seeks to locate a hyperplane that optimally divides various spectral classes in high-dimensional hyperspectral data. Hyperspectral analysis is made easier by its adaptability to deal with complicated, non-linear data interactions handled by kernel functions. To examine a carbonate rock outcrop, the authors of [6] use a combination of 3D hyperspectral mapping in the SWIR spectrum and a DEM produced from a UAV. Rock formations, including their thickness, slope, classification, strike, and dip, are revealed by the integrated 3D geological model. The pre-processing methods utilized were the Savitsky-Golay filter, dark subtraction, and MNF transformation, while the sensor used was a SWIR hyperspectral camera with 288 spectral channels. While Binary Binary Logistic Regression showed superior generalizability, the Random Forest approach achieved good accuracy in categorizing dolostone and limestone. One of the obstacles was the effect of shadows on the 3D point cloud quality during picture feature extraction due to the uneven rock surface matching. The authors of [1] conducted in-depth geologic research using digital outcrop models, which are a by-product of improving subsurface models and gaining an understanding of the characteristics of oil reservoirs. Spectral Angle Mapper (SAM) was the image processing algorithm used for hyperspectral picture classification. Modeling the link between numerous spectral bands and a specific objective variable, like chemical composition or material qualities, is done in high-dimensional structural imaging (HSI) using multiple linear regression [18] and Partial Least Squares (PLS) [19]. One useful approach for quantitative analysis in hyperspectral remote sensing is PLS, which improves predictive power by taking into account linear combinations of spectral bands and using latent variables. Applications such as agricultural research, environmental monitoring, and mineral exploration can all benefit from the insights provided by these methods, which allow for the prediction or estimation of the target variable. To find unique features in the spectral data, keypoint detection [20] methods are vital in HSI. Subsequent analysis and processing rely on these keypoints. Contrarily, point-matching algorithms are used to create correspondences between critical locations in various hyperspectral images, enabling operations such as image registration and change detection. A popular keypoint identification technique, SIFT (Scale-Invariant Feature Transform) [9] may find strong and unique keypoints regardless of the scale or orientation. To make feature-based analysis easier, it has been customized for HSI. A point cloud is a collection of three-dimensional points that show the distribution of keypoints in a scene, as used in HSI. 3D reconstruction and scene understanding are two applications of this data format that use keypoint matching to generate a consistent 3D model of the hyperspectral scene. The combination of these methods allows for the interpretation and analysis of hyperspectral data at an advanced level, which is useful for many different applications such as mineral identification, geospatial analysis, and remote sensing. One machine learning approach used for categorization tasks in HSI is Decision Trees [8]. To reduce noise and extract relevant information, they find the orthogonal axis of largest variance and work from there. For material identification and classification, one popular unsupervised method in HSI is K-means clustering [40], which groups pixels into clusters according to their spectral similarity. Some sophisticated dimensionality reduction approaches that are specifically designed for hyperspectral data

include minimum noise fraction (MNF) [22], orthogonal total variation component analysis (OTVCA) [23], and wavelet-based sparse representation with a regularized robust regression (WSRRR) [23]. Noise removal is where MNF really shines, but OTVCA and WSRRR are great at lowering data dimensionality and extracting meaningful information. When used together, these methods improve hyperspectral image processing and interpretation. A new clustering approach for hierarchical sparse subspace-based HSI data, HESSC, is introduced in [24]. Existing approaches have large processing needs and require specified cluster numbers, which this algorithm aims to solve. With its hierarchical structure, HESSC uses binary clustering based on sparse subspaces at various degrees of detail. To further improve precision, it uses an ensemble method based on entropy. Notably, HESSC finds cluster numbers automatically using reconstruction error values, doing away with the requirement for human predefinition. When compared to other clustering algorithms such as Kmeans and FCM, HESSC proved to be a beneficial tool for hyperspectral image analysis based on experimental findings obtained from real drill-core and benchmark hyperspectral datasets. The possibility of utilizing HSI and vegetation indices (VIs) to distinguish between various kinds of woody plants is investigated in [7]. These species were reliably distinguished by the study, which included ANOVA, PCA, DT, and RF approaches. To recover these vegetative parameters, the authors of [25] suggest an approach that uses an inversion of a Radiative Transfer Model (RTM) based on a look-up table (LUT). They showed that their estimates were consistent over space and time and compared several cost functions for the inversion process over a two-year period. Showing the efficacy of this strategy for disease identification in agricultural contexts, the authors of [26] presented a classification technique based on spectral information divergence to precisely identify sugarcane patches infected with mosaic. Convolutional Neural Networks (CNNs) [31,32], Artificial Neural Networks (ANNs) [8], and Long Short-Term Memory (LSTM) [30] networks are all examples of Deep Learning [27,28] that have transformed HSI analysis. Hyperspectral data can be enriched with complex spectral and spatial information by use of these deep learning models.
in order to create a hierarchical decision structure for pixel classification into specified classes, the hyperspectral data is recursively separated into subsets according to spectral properties.
For effective management of high-dimensional data in HSI, dimensionality reduction methods are crucial. Supervised approaches such as Linear Discriminant Analysis (LDA) [29] and Quadratic Discriminant Analysis (QDA) [16] are useful for hyperspectral image classification because they minimize dimensionality while increasing class separately. To capture important features for classification problems, partial least squares-discriminant analysis (PLS-DA) [33,34] integrates spectral data with class labels. The unsupervised technique known as principal component analysis (PCA) [35,36,37,38,39] finds the orthogonal axes of maximum variance, which helps to reduce noise and identify important information. For material identification and classification, one popular unsupervised method in HSI is K-means clustering [40], which groups pixels into clusters according to their spectral similarity. Some sophisticated dimensionality reduction approaches that are specifically designed for hyperspectral data include minimum noise fraction (MNF), orthogonal total variation component analysis (OTVCA) [23], and wavelet based sparse representation with a regularized robust regression (WSRRR). Noise removal is where MNF really shines, but OTVCA and WSRRR are great at lowering data dimensionality and extracting meaningful information. When used together, these methods improve hyperspectral image processing and interpretation.

2. Review of Asset Mapping Methodologies

The purpose of community asset mapping is to help communities take stock of their physical and intangible assets and put them to use [41]. Some of the features of this approach are as follows: reimagining communities as resilient and resourceful; centering efforts on human strengths and abilities; acknowledging that valuable resources reside in interpersonal connections; bringing community assets to the attention of community members and other decision-makers; encouraging leadership growth and engagement; fostering agency; and facilitating group inclusion and participation. Tools for recognizing and capitalizing on communities' innate strengths and resources have been developed using asset-based methods. We will quickly go over a few asset mapping methodologies from the literature study by Kramer and colleagues (2012).

Kretzman and Kretzman of the US created the Asset-Based Community Development (ABCD) method, which has been used well in South Africa [42]. Restoring community agency, promoting collaboration, developing leadership, and encouraging people to see their community's strengths (rather than its needs) are the fundamental goals of ABCD. The first step in creating revenue is figuring out what local assets there are and getting them used [43]. A concern that poverty alleviation often reflects a narrow understanding of assets as purely monetary led to the conceptualization and subsequent expansion of the Sustainable Livelihoods Approach (SLA) by the Brundtland Commission and the 1992 United Nations Conference on Environment and Development [44]. Assets at the individual, family, and community levels, including human capital, financial resources, social networks, physical assets, and laws and regulations, are the primary focus of the SLA in order to influence people's ability to make a living. A wide range of quantitative and qualitative approaches to alleviating poverty are incorporated within the SLA. South Africa is just one of several places where community asset mapping has been put into practice effectively. Another is Planning for Real, a program created in the UK by the Neighbourhood Initiatives Foundation in 2009. Members of the community and outside agencies collaborate to create a three-dimensional representation of the community's surroundings using this method. Cards or other symbols representing the community's assets and needs are placed in appropriate spots on the community map. Plans of action are thereafter based on the needs, which are ranked according to their severity. After that, everyone in the community takes part in a skills survey to find out what people here are good at, and then they work on a plan of action. One such approach to community asset mapping is PIRHANA, which was created by the A/IRHAP (African/International Religious Health Assets Programme). Both material (like a caregroup or a clinic) and immaterial (like compassion or hope) religious imagery, attitudes, practices, individuals, and organizations are considered religious health assets in a given community [45]. The PIRHANA technique offers many kinds of democratic data via the use of qualitative and quantitative approaches, with an emphasis on local ownership [46]. One of ARHAP's methods, CHAMP stands for Community Health Assets Mapping for Partnerships, an update to PIRHANA. A pilot program called CHAMP was launched in South African settings to address the needs of palliative care and HIV/AIDS patients [47]. Community Health Assets and Partnerships for Better Health (CHAMP) is an initiative that seeks to improve the health of communities by identifying and building upon such partnerships. Geographic Information Systems (GIS) applications combine location data with quantitative and qualitative information, allowing one to visualize, analyze, and report information through maps. This technology is sometimes used for community asset mapping and community development purposes [48]. For participatory frameworks like PIRHANA and CHAMP, GIS works wonders. The goal of this modification, which is called Participatory GIS (PGIS), is to create action plans by combining local knowledge with the data provided by the GIS system.In a rural area of the Western Cape, the Railton Foundation and Stellenbosch University launched the Railton Community Assessment Project (CAP). The project used a community-based participatory research approach (CBPR) to prioritize actions to support community development planning and funding allocation by identifying community needs and assets [50]. Using a simplified and cost-effective hybrid version of community asset mapping, this project's workshops drew from all the methodologies indicated in the previous section. During the community asset-mapping workshops, participants used a modified Delphi (voting) procedure to list and rank-order the identified needs and actions. They also created community maps and recorded group discussions. Participants also developed matrices of needs, assets, and priority actions [51].

3. Integrating Hyperspectral Image Analysis with Asset Mapping

School asset mapping that incorporates hyperspectral image analysis is an intriguing and possibly highly useful application, particularly when taking into account the importance of having clean, safe, and well-maintained learning spaces. Because there are some concrete and interesting opportunities that arise when we zero in on schools. Some potential applications of hyperspectral image analysis in school asset mapping are as follows:

Possible Use in Educational Institutions:

• Hyperspectral data can aid in **identifying various roofing materials**, locating areas of water pooling or material degradation, and detecting areas of vegetation growth or degradation. This enables preventive maintenance and the prevention of leaks. The spectral fingerprints of various materials are distinct.

- **School Grounds Vegetation Assessment:** Monitoring the condition and diversity of school grounds' trees, grass, and athletic fields. The results can help with landscaping choices, the detection of potentially dangerous diseased plants, and the upkeep of green areas that foster a healthy learning environment. Variations in chlorophyll and water content are reflected in the spectrum in a unique way.
- **Types of impervious surfaces**, such as playgrounds, asphalt, and concrete, are identified and mapped in the impervious surface mapping and condition process. It is possible to detect cracks and deterioration in asphalt, as well as tell new asphalt from old asphalt, using hyperspectral analysis. If we want to keep people safe and manage stormwater flow, this is a must.
- **Building Material Identification and Condition:** Hyperspectral imaging has the ability to assist with the identification of various building materials, such as brick or siding types, as well as the detection of weathering or deterioration indicators, however this task may be more complicated.
- **Spectral emissivity** analysis of roof surfaces can provide information on their heat absorption capabilities, which can be used for energy efficiency assessment purposes, such as deciding on more energy-efficient roofing materials or whether to replace the insulation.
- **Safe Playground materials:** Rubber, mulch, and artificial turf are just a few examples of playground materials that have different spectral signatures. It is possible to evaluate the state and coverage of safety surfacing materials using hyperspectral analysis.
- **Identifying Abnormal Items:** Unusual spectral signatures on school grounds may need additional research in security applications. Examining the condition of any school grounds, including gardens, is an important part of environmental monitoring.

Using Asset Mapping for Integration:

Integrating hyperspectral data with other asset management tools in a GIS or similar system is crucial for this purpose. This data can pertain to particular assets such as individual buildings, roofing sections, trees, or playgrounds. The following features would be available to school administrators and facilities managers as a result of this integration:

- **Spatial Visualization of state Data:** View the state of various assets superimposed on a map of the school grounds.
- **Maintenance should be prioritized**: Use quantitative spectrum analysis to zero in on the most pressing needs and devote resources there.
- **Keep Tabs on Developments:** You may keep tabs on the deterioration or improvement of assets by regularly gathering and analysing hyperspectral photography.
- **Create reports on the state of school infrastructure** that are easy to understand and aesthetically appealing. This will help with reporting and communication.
- Keep an eye on parks and other green areas and use that data to guide energy efficiency decisions; this will help with **sustainability efforts**.

Regarding Educational Institutions in Particular, the following extra factors may be important to take into account:

- The effect of **coastal climate:** materials may deteriorate more quickly due to the salty air. It is possible that hyperspectral analysis would be especially helpful in spotting precursors to these kinds of problems.
- **Types of Vegetation:** When assessing the health of vegetation, it is important to take into account the unique spectral signatures of the local flora.
- To better understand the spectral data, it is helpful to have a knowledge of the commonly used **building materials** in the area.
- **Heat Stress Potential:** In order to understand and lessen the impact of heat islands on school grounds, it may be useful to track roof temperatures and the state of the plants.

4. The Role of Deep Learning in School Asset Mapping from Hyperspectral Data

Using deep learning to glean useful insights from hyperspectral data for school asset mapping is vital. Improving asset management is possible by deep learning because it has the capacity to process hyperspectral images, which are notoriously difficult and high dimensional. To further understand deep learning in this setting, consider the following:

a. Feature Extraction via Automation:

• **Problems with Conventional Approaches:** Conventional approaches frequently use simple statistical analysis or manual feature engineering (e.g., spectral indices). These methods can be laborious and might miss the nuanced spectrum fluctuations that are indicative of the state of an asset.

• There is a clear benefit to **using deep learning models**, such as CNNs and RNNs, because they can automatically learn hierarchical spectral and spatial features from the raw hyperspectral data. This can find complicated patterns that conventional methods might overlook, and it also gets rid of the requirement for human feature design. While RNNs are able to represent spectral dependencies across multiple bands, CNNs are able to learn local spatial-spectral correlations.

b. Improved Classification and Identification:

• Precise Material Identification: Using the hyperspectral data, deep learning algorithms can be taught to distinguish between various roofing materials, plants, impermeable surfaces, and even construction materials. A finer-grained comprehension of the assets can be achieved in this way.

• Condition Assessment: Deep learning models can automatically evaluate the state of school assets using labelled data that represents various asset states, such as healthy vs. stressed vegetation or new vs. deteriorated roofing, among others. Beyond basic material identification, this can pick up on more nuanced indicators of degradation or abnormalities.

c. Dealing with High Dimensionality:

• The "curse of dimensionality," in which the quantity of data needed to train a model efficiently grows exponentially with the number of features, can be a problem with hyperspectral data that contains hundreds of spectral bands. 8. When training samples are small, this could cause overfitting.

• Dimensionality reduction layers (e.g., autoencoders) and careful network design are examples of deep learning techniques that can handle hyperspectral data's high dimensionality by learning compressed and informative representations.

d. Contextual understanding:

• Deep learning models, particularly 3D convolutional neural networks (CNNs) and attention mechanisms, can analyze both the spectral information at each pixel and the spatial context (neighboring pixels) at the same time. Since an asset's status is typically tied to its surroundings, this is essential for precise asset mapping. As an example, it's possible for water to pool on a roof in a spatially adjacent manner.

• To better detect assets of varied sizes and comprehend their context within the school environment, architectures that contain multi-scale processing may record information at multiple spatial resolutions. This allows for multi-scale feature learning.

e. Resilience in the Face of Noise and Variability:

• **Obstacles Faced by Real-World Data:** Atmospheric noise, sensor fluctuations, and ambient variables can impact hyperspectral data.

• **Training deep learning models using invariant features** from different and vast datasets makes them more resilient to these fluctuations. Improving the model's capacity to generalize can also be achieved through the use of data augmentation approaches.

Deep Learning's Particular Use Cases in School Asset Mapping:

• **Robotic Roof Inspection:** Highly accurate leak, damage, or vegetation growth detection is possible with the help of deep learning models that can distinguish between various roof sections, categorize their materials, and spot anomalies.

• **Accurate Vegetation Management:** By automating tree species identification, vegetation health assessments (stress, disease), and invasive species mapping on school grounds, deep learning can inform landscaping and maintenance activities.

• **Comprehensive Impervious Surface Analysis:** Using deep learning, we can tell the difference between different kinds of pavement, find cracks, measure the degree of surface degradation, and pinpoint where storm water runoff is coming from.

• **Finding various playground surface materials** and maybe evaluating their coverage and condition with deep learning models is one playground safety assessment.

Deep Learning with Hyperspectral Data Obstacles and Things to Think About
If we want to train a deep learning model, you'll need a tonne of data that has been properly labeled.

• **Hardware for computation:** GPUs and other specialist gear may be necessary for the computationally intensive task of training deep learning models on hyperspectral data with high dimensions.

• Some deep learning models are like "black boxes," making it hard to decipher their reasoning behind certain predictions.

• This poses a problem with **model interpretability.** In order to establish credibility and learn what drives asset values, interpretability is crucial.

• **Data Variability and Generalization:** Because of differences in materials, ambient factors, and data gathering parameters, models trained on data from one school might not be able to generalize well to other schools. Potentially necessary are methods for domain adaptability.

• **Spectral mixing:** In urban classroom settings, it is possible for a single pixel to include spectral data from various materials. Effective handling of this spectrum mixing is a requirement for deep learning models.

5. Applications in STEM Education

There will be some unique considerations and potential for STEM education when integrating hyperspectral image analysis and deep learning for school asset mapping in Tirupati, which gives a particular geographical and environmental characteristic.

a. Ecology and Environmental Science:

• **School Biodiversity Maps:** Tirupati is located in close proximity to the Eastern Ghats, an area famous for its abundant wildlife. In order to find rare or endangered species, students working on STEM projects could use hyperspectral data to create maps of the various plant life found on school grounds. Local ecological and preservation initiatives can benefit from this.

• If a **school is situated near** a forest or has a lot of green space surrounding it, students can utilize hyperspectral data to determine how healthy the forest is, find evidence of deterioration or deforestation, and learn about the effects of environmental factors in their area.

• **Water Resource Management**: If there are bodies of water on or near school grounds, assessing the condition of the vegetation there might reveal information about water supply and stress. Sustainable water management strategies could be the cornerstone of these projects.

• **Pilgrimage's Effect on the Local Environment:** While there may be limitations on conducting research on school grounds specifically, larger projects could use publicly available hyperspectral data to investigate how pilgrimage activities affect the land cover and vegetation in the Tirupati region. This would provide insight into how these activities relate to environmental sustainability and local socio-economic factors.

b. horticulture and agriculture:

• **School gardens and agricultural projects:** a large number of Indian schools have some kind of garden or agricultural plot. Utilizing hyperspectral analysis, one may track the well-being of various crops, detect diseases or shortages in nutrients, and fine-tune irrigation and fertilization methods. This relates to sustainable farming and agricultural science.

• Although hyperspectral photography has its limitations when it comes to directly analyzing soil composition, changes in vegetation spectral signatures can occasionally reveal underlying soil conditions, which is useful for soil research (indirectly). These relationships can be explored by students.

c. Infrastructure and Built Environment:

• **Contextual Assessment of Temple Infrastructure:** Considering Tirupati's role as a pilgrimage center, projects could investigate the possibility of using publicly available hyperspectral data to evaluate the state of historical or religious structures, specifically looking at material degradation or weathering, provided that the necessary permissions and ethical considerations are taken into account. Engineering and the preservation of cultural heritage are related topics.

• **The Urban Heat Island Effect in Tirupati:** Just like in Visakhapatnam, students can examine the urban heat island effect in Tirupati by comparing the temperatures of built-up and undeveloped areas, utilizing thermal bands (if they are available). After that, they will be able to suggest climate-appropriate mitigation techniques.

• **Building Material Analysis:** Listing and cataloguing typical construction materials utilized in Tirupati, along with an evaluation of their state taking local weather conditions and the possibility of deterioration into account.

d. data science and machine learning

• To identify local vegetation using hyperspectral imagery by collecting ground truth data (i.e., what kinds of plants grow on their campus) and then feeding that data into deep learning models.

• Making labelled datasets of various asset states (e.g., healthy/stressed plants, damaged roofs) and training deep learning models to automatically evaluate these situations in the Tirupati context is an important part of developing condition assessment tools.

• GIS Integration and Spatial Analysis: Visualizing and analyzing asset conditions across the campus by integrating hyperspectral analysis results with school maps and other spatial data using GIS software.

e. Factors Specific to Tirupati:

• **Climate:** A large portion of the year is hot and muggy in Tirupati. The effects of this climate on the state of plants, the deterioration of construction materials, and the urban heat island effect can all be the subject of research.

• **Vegetation:** Living in the semi-arid and rugged foothills of the Eastern Ghats, the flora surrounding Tirupati has adapted to its unique environment. The goal of these projects should be to catalog and study these native plant species.

• **Water Scarcity:** Conserving water is frequently a major issue in this area. Potential projects could investigate the use of hyperspectral data to develop water-saving measures for school landscaping and gardens.

• Understanding the wider environmental impact of pilgrimage in the region might give useful background for environmental science initiatives utilizing publicly available data, even though direct research on school grounds would not be practicable.

6. Challenges, Limitations, and Future Directions

Prospects and Difficulties:

a. Obtaining Data:

• **Price:** It can be quite costly to acquire high-quality hyperspectral imaging, particularly with the required spatial and spectral resolution. Many schools or municipal governments may find this to be a substantial obstacle.

• Hyperspectral data that is appropriate for usage on individual school sites in the area may not always be easily accessible through preexisting aerial or satellite operations. Delegating particular purchases can lead to additional expense.

• **Temporal Resolution:** Continuous monitoring can be problematic due to the potential limitations of frequent revisits to monitor changes over time, which are dependent on the data source. Cloud cover, especially during monsoon season, might impede data capture as well.

• **Professionalism in Acquisition Planning:** Choosing the best satellite data or determining the best flight parameters for aerial or drone surveys calls for expert expertise.

b. Analyzing and Processing Data:

• Because of their size and high dimensionality, hyperspectral datasets necessitate substantial computing resources for both storage and analysis.

• Reliable analysis relies on accurately removing atmospheric effects; however, this is not always easy, particularly in the humid coastal environments, where water vapor and aerosols are common.

• In urban or vegetated regions near schools, it is sometimes difficult to obtain pure spectral signatures because a single pixel typically reflects a blend of diverse elements. All of the region's varied landscapes have this characteristic.

• Experts in remote sensing, image processing, and maybe deep learning are necessary for analyzing hyperspectral data, which in turn necessitates specific software.

• The educational institutions may lack this kind of knowledge. To train and validate deep learning models, it is necessary to collect accurate ground truth data, which can be obtained by identifying materials or evaluating circumstances on the ground. It may take a lot of time and effort to gather this data on a local level.

c. Difficulties Unique to Deep Learning:

- **Inadequate Labeled Data:** Building strong deep learning models requires massive datasets that are precisely labeled. A significant obstacle may lie in the creation of such databases for the various school assets and their status.
- **Access to Powerful GPUs and Specialized Infrastructure for Training:** Many educational institutions may lack the computational resources necessary to train deep learning models on high-dimensional hyperspectral data.
- **Model Interpretability:** It could be difficult to determine the reasoning behind a deep learning model's predictions. Trust and the capacity to obtain deeper insights can be hampered by this "black box" quality.
- **Generalization and Transferability:** Because of differences in building materials, vegetation, and environmental conditions, models trained on data from one school could not transfer well to other schools.

d. Difficulties in Integration and Implementation:

- **Existing Asset Management System Integration:** It can be challenging to integrate hyperspectral-derived information with existing school databases and GIS platforms without introducing new layers of complexity and necessitating interoperability solutions.
- **Considerations of scalability** include the potential difficulties in allocating sufficient resources to implement these methods for many schools.
- **Implementation Cost:** Think about not just the cost of data collecting and analysis, but also the cost of software and hardware upgrades, as well as the cost of training workers for long-term implementation.
- **User Adoption:** To ensure successful adoption, it is essential to communicate the benefits effectively and train school staff to use the information generated from hyperspectral analysis.

feature directions

The field is still moving forward at a quick pace, which bodes well for the future:

- **Affordable Data Acquisition:** Drones and miniature hyperspectral sensors have brought down the price of data acquisition, making it more accessible for limited regions like school campuses.
- **Better Satellite Missions:** Upcoming space missions should have better spatial and spectral resolution and more frequent revisit times, which could lead to more relevant data being available.
- **Processing Platforms in the Cloud:** These days, local infrastructure isn't necessary thanks to cloud computing platforms, which offer scalable and affordable options for storing and processing massive hyperspectral information.

Deep Learning's Recent Progress:

In situations when there is a lack of ground truth data, methods like self-supervised and semi-supervised learning can help by reducing the need for huge labeled datasets.
Improved performance with less local training data could be achieved by the use of models that have been pre-trained on large, general hyperspectral datasets and then adapted to the unique characteristics of school assets. This approach is known as transfer learning and domain adaptation.

- **Explainable AI (XAI):** Scientists working in XAI are trying to increase confidence in deep learning models by making them easier to understand and comprehend, which will lead to better predictions.
- To make deployment on less powerful hardware practicable, it is necessary to develop deep learning architectures that are more efficient and lightweight. This will lower the computing demands.
- Developing more robust and accurate algorithms to resolve spectrum mixing and atmospheric distortions is an ongoing research topic, especially in complex coastal situations. This includes improved algorithms for spectral unmixing and atmospheric correction.
- The integration of remote sensing software and GIS platforms would be made easier with the help of efforts to standardize data formats and improve interoperability.
- Hyperspectral analysis will be available to more people, including teachers and school administrators, as a result of the creation of easier-to-understand tools and platforms.
- Connectivity to the Internet of Things and Sensor Networks: Hyperspectral images and data from ground-based sensors (such as temperature and humidity monitors installed on school buildings) might be combined to give a more complete picture of the state of assets.

- Building local datasets and promoting STEM learning could be achieved through citizen science initiatives, which include students in restricted portions of data collecting or validation.

CONCLUSION

This research shows that asset mapping in schools could be drastically improved by combining hyperspectral photography with deep learning techniques. The system allows for accurate identification and monitoring of school infrastructure, resources, and safety-related factors by recording high-dimensional spectral data and applying advanced classification algorithms. Stakeholders are further empowered to make well-informed decisions and carry out strategic planning when these technologies are integrated into a GIS framework, which increases accessibility and utility. The suggested method helps make schools safer, more welcoming, and more technologically advanced while also improving asset management procedures. In addition, the program helps STEM education along by showing teachers and students how to put state-of-the-art AI and remote sensing tools to use in real-world scenarios. Alignment with national safety and education standards, scalability across various educational contexts, and integration with real-time data from the internet of things (IoT) for dynamic monitoring should all be investigated in future studies. All things considered, this work provides solid groundwork for the creation of robust, equitable, and future-proof data-driven education systems.

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Conflict of Interest

There is no conflict of interest for authors

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