Deep Ensemble Method for Healthcare Asset Mapping Using Geographical Information System and Hyperspectral Images of Tirupati Region

P. Bhargavi[1], T. Sarath[2], Gopichand G[3]*, G V Ramesh Babu[4], T Haritha[5], A.Vijaya Krishna[6]
Assistant Professor, Dept. of. Computer Science, Sri Padmavathi Mahila Visvavidyalayam, Tirupati, India[1]
Research Scholar, School of Computer Science and Engineering and Information Systems,
Vellore Institute of Technology, Vellore, India[2]
Assistant Professor Senior Grade - 2, School of Computer Science and Engineering,
Vellore Institute of Technology, Vellore, India[3]
Associate professor, Department of Computer Science, Sri Venkateswara University Tirupati, India[4]
Assistant professor, Department of CSE, Sree Rama Engineering College, Tirupati, India[5]
Assistant Professor-Department of Information Technology,
G. Narayanamma Institute of Technology and Science for women, Hyderabad, India[6]

***Abstract*—The ever-increasing capabilities of deep learning for image analysis and recognition have encouraged some researchers investigates potential benefits of merging Hyperspectral Images (HSI) and Geographic Information Systems (GIS) with deep learning in the healthcare industry. Healthcare is an ever-changing sector that constantly adopts new technologies to improve decision-making and patient service. This research digs into the role that GIS and Remote Sensing (RS) play in modern healthcare and their significance. By delivering data from faraway places and enabling spatial analysis, the combination of RS and GIS has transformed healthcare. This GIS & RS data will have the numerous quantity of data so big data analytics can be helpful for storing and retrieving of data. This analysis can open up a new possibility for better healthcare planning, disease management, and environmental health assessment based on the study area's population. This paper deals healthcare assets mapping based on the population and the study area of the Tirupati district hyperspectral image by applying the Deep Ensemble method.**

Keywords*—Geographical information system; hyperspectral image; remote sensing images; big data analytics; deep ensemble methods; healthcare asset

I. Introduction

Deep Learning is the ongoing innovation in reaction to emerging threats and possibilities, healthcare is an ever-changing industry. Modern healthcare delivery, public health administration, and resource allocation cannot be improved without incorporating state-of-the-art technology. Notable between these technologies are GIS and RS [14], both of which have become potent instruments with far-reaching consequences in healthcare. Exploring and clarifying the numerous claims of Remote Sensing (RS) and Geographic Information Systems (GIS) is vital for properly understanding their revolutionary potential in healthcare [1]. The field of RS, which includes gathering information about Earth's surface from sensors attached on aircraft or spacecraft, is playing an increasingly important role in medical research and practice. Its applications range from ecological monitoring to public health calculation, illness scrutiny and disaster organization. By gathering information remotely [15], RS provides a vantage point that allows medical personnel to keep tabs on expansive regions with unmatched precision and speed [2]. This GIS & RS data will have the numerous quantity of data so big data analytics is used for keeping and retrieving of info [14]. In contrast, GIS allows the visualisation and understanding of health-related data within a geographical context by making GIS as an ideal tool for spatial data analysis [18]. As a result, healthcare providers are better in allocating healthcare resources, conducting epidemiological studies and ensure that all citizens have access for necessary medical treatments. Improving the quality of healthcare and reducing healthcare inequities depends on GIS-based geospatial approach [19, 21].

This paper deals with the available and need of healthcare facilities in the study area of Tirupati district GIS and hyperspectral image based on the population by applying the Deep Ensemble method.

II. Related Work

A. Imaging Techniques Using Hyperspectral Rays

One method that merges the two regions is hyperspectral imaging. It often encompasses a long stretch of the electromagnetic spectrum and offers real-time scanning imaging throughout dozens or even hundreds of spectral series, including the UV, infrared, VIS and mid-infrared [3]. In Fig. 1, for example, you can see a combination of two-dimensional spatial data with one-dimensional spectral data can see it as a stack of many two-dimensional images [4]. Utilising this method, one can acquire the absorption, reflectance, fluorescence spectra of each individual pixel inside picture [24]. Compared to standard images of RGB and maps in grayscale offers a more robust spectral band and better spectral resolution [16]. It records subtle spectrum subtleties in reaction to various clinical conditions and can detect alterations in things that are invisible with traditional imaging techniques [23,25]. The usual push broom hyperspectral system principle [5] explains HSI system mechanism, as depicted in Fig. 2. The spatial information is initially illuminated by a light source, which travels via front lens into slit, where light of varied wavelengths is fixed to different degrees. Then, the detector is illuminated with light from every pixel point in that dimension using dispersion devices like prisms and gratings, which divide the light into tiny spectral bands [20].

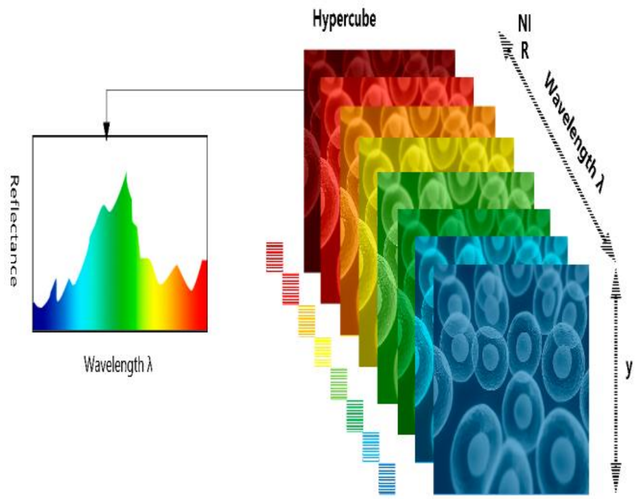


Fig. 1. Spectral data cube (Google courtesy).

The detector array is photographed with each row of sample space info as a 2-D picture. A hypercube with two spatial dimensions and one spectral dimension is created when HSI camera moves via plane using mechanical push sweep and captures adjacent two-dimensional images.

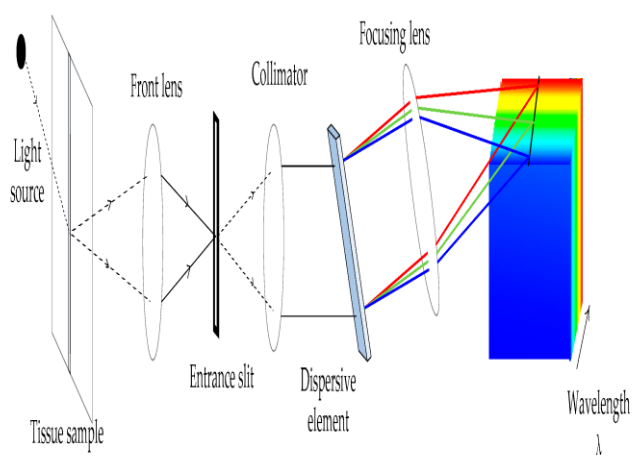


Fig. 2. Hyperspectral imaging system schematic using push-scan technology (Google courtesy).

The smallest discernible object within a picture is called its spatial resolution, and it is the smallest visible detail in the image [26]. There is a practical reason for the sensor's design and the altitude at which it operates above the surface. It is not the number of pixels but the spatial resolution that defines how sharp a picture is. The image sensor's architecture, particularly its height and field of view, determine the spatial properties of an image [27]. The energy received from a specific area of the ground surface is quantified by the remote sensor detector. There is an inverse relationship between spatial resolution and patch size. It is possible to extract more precise spatial information from the picture with smaller individual patches. Only when the cell dimensions are substantially lower than the object dimensions can shape be discerned, which is a common factor. The average brightness of the picture cell is affected by the item's brightness or darkness in relation to its surroundings; hence, this cell will seem brighter than neighboring cells. Linear features, like farm-fresh fruit, may be distinguished with more accuracy than cell dimensions thanks to the high spatial resolution.

A sensor's spectral resolution is defined by the number of spectral bands it can detect and the breadth of the electromagnetic spectrum. Even while an image sensor covers a lot of ground in terms of frequency, its spectral resolution could be inadequate if it only manages to get a few bands. A sensor can differentiate between scenes with identical or almost identical spectral fingerprints if it is accurate in the low-frequency range and catches a large number of spectral bands; this property is known as high spectral resolution [28]. The multispectral images can't pick up on faint spectral signals because of their poor spectral resolution. In the visible, near-infrared, and mid-infrared parts of the electromagnetic spectrum, HSI sensors capture images in numerous neighbouring and incredibly narrow spectral bands. Material identification using their unique spectral fingerprints is a promising area for this advanced imaging technique. One-pixel spectral image from HSI could reveal a lot more about the surface material than a regular range image.

Hyperspectral imaging's temporal resolution is sensor-specific and depends on its orbital properties. The time it takes for a sensor to go back to the same location and take readings is a common definition [29]. This period is also known as return time or revisit. When the sensor platform doesn't return to the same location very often, we say that the temporal resolution is low; when it returns frequently, we say that it has high temporal resolution. Common units of measurement for time resolution are days.

Benefits and drawbacks of hyperspectral scanners. The following are some of the benefits of adopting HSI in many fields, such agriculture [8] and food quality assessment:

1) The technology guarantees the eminence and security of food supplies without invasiveness, contact, or destruction.

2) Since no chemicals are used in the studies, they are safe for the environment.

3) There is a significant time savings compared to chemical and conventional methods when processing for quality valuation and food regulator/storing.

4) Chemical imaging provides a better thoughtful of chemical components of food goods.

5) It offers suitable region selection for crucial picture analysis.

6) It integrates spectral and geographical data to give better information about chemical samples. From relevant platforms, improve the likelihood of data refinement, and accomplish further experiments.

Hyperspectral imaging offers both benefits and drawbacks [30].

1) When compared to other methods of image processing, the price of a hyperspectral imaging system is quite high.

2) High-speed computers and solid-state drives with enormous storage capacities are in high demand due to the massive data sizes generated by hyperspectral imaging.

3) The signal-to-noise ratio may be low because environmental factors like scattering and lighting can affect the signal while collecting the photos.

4) It is typically challenging to detect and identify dissimilar items inside the similar image consuming spectral data except the individual objects consume distinct immersion properties.

B. Health Care Utilisation of RS and GIS

One new technology that the healthcare industry has found a wealth of uses for is remote sensing. The term "remote sensing" describes a method of retrieving data about Earth's surface that does not need physical contact. In most situations, data is gathered remotely via sensors attached to spacecraft or satellites [10]. Incorporating various types of electromagnetic radiation, such as visible light, infrared, and microwave, into the collected data can provide light on the Earth's surface and its characteristics [17]. When it comes to healthcare, RS is also useful for assessing environmental health issues. Environmental changes may influence public health, land use, and water and air quality can all be evaluated with its help [11]. Air pollution levels can be monitored via satellite-based remote sensing, which helps detect areas with poor air quality. This information can then be used to improve public health policies and actions. Further, RS data can be used to investigate environmental factors that may be influencing the incidence of respiratory diseases and other health problems.

Rapid surveying allows for the quick assessment of damage, localization of impacted regions, and population movement tracking. Timely deployment of healthcare resources and planning for healthcare infrastructure rehabilitation following a disaster both rely on this knowledge.

We can gain a more comprehensive and insightful understanding of healthcare-related topics by combining Geographic Information Systems (GIS) with Remote Sensing (RS). This methodology takes advantage of both technologies. This section explores the ways in which Geographic Information Systems (GIS) and Remote Sensing (RS) work together, and it contains real-life examples to show how these two tools can be used together. When combined, the complementary technologies of remote sensing and geographic information systems (GIS) can improve healthcare applications. One way to get environmental data and pictures in real-time is through remote sensing, which can be easily integrated into GIS systems. By placing RS data in a geographical context, GIS allows medical professionals to analyze, understand, and display data in a spatially-based manner.

Remote sensing can furnish imagery depicting variables such as pollution levels, land utilization, or temperature fluctuations. When incorporated into a GIS, this data can facilitate the identification of regions with elevated health risks and support targeted actions. The integration of remote sensing data, including satellite imagery of vegetation and land cover, with geographic information systems can facilitate the comprehension of disease vector habitats and the forecasting of disease outbreaks. This is essential for the management of vector-borne diseases. In the event of natural catastrophes or public health [6] emergencies, remote sensing data can furnish real-time information regarding impacted regions. This data, when incorporated into a GIS, facilitates the effective allocation of healthcare resources. Here we may see how RS and GIS have been put to use in real-world healthcare situations through empirical case studies. Consider the following: Temperature and precipitation are two of the most important environmental factors for mosquito breeding and malaria transmission; a study conducted in a malaria-endemic zone used RS to track these variables. Using GIS, we were able to create models that could predict when malaria epidemics would occur. With the use of early warning systems made possible by RS and GIS integration, hospital authorities were able to distribute resources for management and prevention. Data on urbanization and population growth were gathered using remote sensing (RS) within the context of urban planning. The availability of telehealth services in rapidly expanding urban areas was assessed using Geographic Information Systems (GIS). The study integrated RS and GIS to elucidate the equitable distribution of telehealth services, assisting policymakers in guaranteeing citizens' access to remote healthcare resources [9].

By allowing the geographical analysis of health-related data, Geographic Information Systems (GIS) have completely transformed the healthcare sector. Here takes a look at the big picture of GIS in healthcare and examine their many uses. Capturing, organising, analysing, and visualising spatial data is made easier by a GIS. Analysis best probable localities for healthcare services is one of the main usages of GIS in this commerce. GIS tools examine demographics, convenience, population solidity, and other criteria to determine whether locations have a high need for healthcare services. As a result, people will be able to get the medical treatment they need regardless of where their healthcare facility is located. In addition, GIS helps with healthcare facility management by minimising response times in emergency circumstances by optimising ways for healthcare specialists and ambulances. Healthcare admission and disparities assessments greatly benefit from GIS. By GIS places can be pinpoint wherever persons lack contact to healthcare by healthcare institutions mapping, patient demographics, and socioeconomic data. In order to reduce dissimilarities and assurance a fair dissemination of healthcare possessions, planners and policymakers must have this data.

In spatial epidemiology study GIS is vital for time and space in healthcare. In order to improve understand of geographical outlines of healthcare and their possible reasons, epidemiologists can utilise GIS to map and identify hotspots. In order to focus resources on areas most at danger, this data is priceless for prevention initiatives. These uses highlight the value of GIS in medical settings. When it derives to healthcare capability locations, resource distribution and disease control GIS will provide professional tools to create data-driven decisions. When trying to make sense of healthcare inequalities and find ways to improve service delivery, having a spatial context is crucial [12].

Combining the strengths of remote sensing and GIS can improve healthcare outcomes may gain more thorough and insightful understanding. RS allows for the direct integration of real-time environmental data and images into GIS systems. On the flip side, healthcare providers can analyse prototype and visualise data in geospatial framework by means of GIS, which provides a spatial context for RS records. Pollution levels, land use, and temperature fluctuations are just a few of the factors that RS photography may reveal. Incorporating this data into a GIS can aid in the identification of high-risk areas for health and the subsequent implementation of targeted interventions. Disease vector habitats and outbreak predictions can be improved with the use of GIS and RS data, which contains satellite imagery of vegetation and land cover. Controlling diseases spread by vectors relies heavily on this. In the result of a public health emergency or natural catastrophe, RS data can give up-to-the-minute details about the areas impacted. The effective allocation of healthcare resources can be aided by including this data into a GIS.

Data on population growth and urban development were captured using RS in an urban planning framework. In order to determine how easily accessible telehealth facilities are in cities that experiencing high population progress GIS is used. The study helped to make sure that people could use remote healthcare resources by combining RS and GIS, which shed light on the fair allocation of telehealth services [13].

Although RS and GIS provide significant advantages to healthcare sector, their implementation is accompanied by hurdles and limits. This delineates the principal challenges encountered in the application of RS and GIS to healthcare initiatives.RS info can be influenced by features like cloud shield, sensor correction and atmospheric situations, potentially resulting in variations in data excellence. Contact to high-resolution remote sensing data is frequently constrained, especially for healthcare applications in underdeveloped regions where satellite or data archive access may be restricted. Utilizing RS and GIS in healthcare effectively necessitates specified skills and information that are not universally possessed by healthcare workers. Training and capacity growth are essential. The incorporation of RS and geographic information system data can be intricate, as it necessitates consideration of varying formats, projections, and scales. This necessitates a resilient IT infrastructure. The integration of geospatial data with healthcare information generates privacy problems. It is imperative to guarantee the ethical and secure utilization of such data. Establishing data ownership and sharing protocols can be complex, as remote sensing and geographic information system data frequently engage several stakeholders, including governmental entities, private enterprises, and academic institutes. Validating remote sensing-derived information with ground-based data can be complex, as it frequently necessitates substantial fieldwork and resources. The precision of predictive models utilizing RS and GIS data may fluctuate and requires thorough validation against empirical data. Confronting these obstacles and constraints is essential for the effective implementation of RS and GIS in healthcare. Cooperative initiatives among researchers, healthcare practitioners, and policymakers are essential to address these challenges and fully exploit the possible of emerging machineries for public health. Table I shows detailed comparison with previous work.

TABLE I. DETAILED COMPARISON WITH PREVIOUS WORK

Aspect	Current Work	Previous Work
Scope	HSI advanced spectral-spatial data is combined with remote sensing and GIS for tracking healthcare and the environment.	Mostly looked at how RS or GIS can be used alone in environmental studies or healthcare, without spectral imaging tools being added.
Integration of Data	Adds real-time RS data to GIS platforms and combines it with HSI for health and environmental apps that use maps.	In the past, methods focused on either GIS for geographic analysis or RS for environmental data, but they didn't include high-resolution spectral imagery (HSI).
Applications in Healthcare	RS-GIS systems that are fully integrated can be used to map disease vectors, plan for public health emergencies, and keep an eye on pollution.	focused more on environmental health factors like the quality of the air or water without using GIS to plan or allocate resources for healthcare.
Environmental Applications	RS and GIS are used together to keep an eye on air pollution, changes in land use, and the health effects of the climate.	Mostly looked at certain environmental measures (like deforestation) without incorporating them into many healthcare-related uses.
Real-World Case Studies	RS-GIS is used to predict malaria outbreaks, make sure that telehealth services are distributed fairly in cities, and map pollutants for public health tactics.	A lot of research has been done on static disease mapping or watching changes in the environment without using predictive modeling or frameworks that combine healthcare and the environment.

Asset Mapping is the method of community strengthening. The next step in asset mapping is to identify the institutions, citizen groups, and individuals within communities that can help put good resources in place. There is a great vibe in the community when assets are mapped out, and those assets may be leveraged to solve any problem. The community's healthcare facilities, parks, libraries, schools, police stations, grocery stores, and so on are its assets.

The primary objective of asset mapping is:

- The goal is to assess the community's current resources and use them to build it stronger.
- Among other things, to use the funds to find community connections and satisfy community needs.
- The community's resources should be acknowledged and appreciated.

C. About Dataset

The Dataset has the latitude and longitude positioning of healthcare unit of Tirupati district study area which is gathered form government portal. The study area selection is shown in Fig. 3.

In the southeastern corner of Andhra Pradesh Tirupati is the ancient holy city. This place is known as the abode of God Venkateswara. Conveniently located near numerous important cities, including Bangalore, Vijayawada, Hyderabad, and Chennai, at the base of the Eastern Ghats. Tirupati is famous for the Tirumala Venkateswara Temple, which is a major pilgrimage site in India and sees a large number of visitors annually. The Tirumala Hills, home to the temple, are among the world's oldest rock formations. People think that the temple even had followers who were members of great dynasties, such as the Pallavas, Pandyas, Cholas, and Vijayanagara rulers. The town's coordinates are 13° 37 N and 79° 25 E. Roughly 22,18 lakh people call Tirupati home, according to the 2011 Census. The winters are mild, but the summers can be quite hot. The official language is Telugu, but Tamil is also widely used due to the region's closeness to Tamil Nadu.

Some of the factors in the dataset are Location Coordinates, which are the healthcare facility's latitude and longitude. with Type of Facility: Which type of healthcare center it is (e.g., hospital, clinic, primary health center), as well as the area, district, state, and name of the hospital or PUC. The type of file is (.CSV). It's about 1GB in size.

Whereas hyperspectral image is in band sequential (BSQ), band-interleaved-by-pixel (BIP), or band-interleaved-by-line (BIL) format downloaded from bhuvan portal based on mapping of areas.

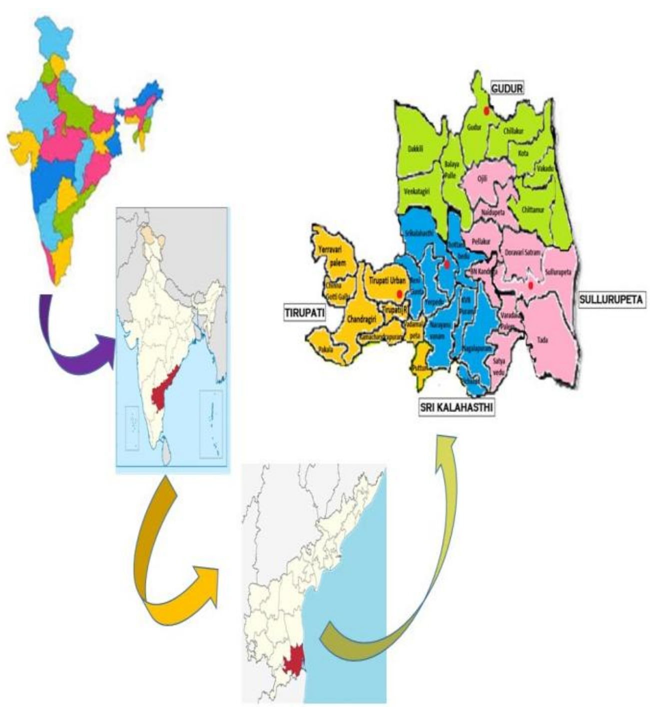


Fig. 3. Study area division (Image created by author).

III. PROPOSED METHODOLOGY

The key objective of our study is to map healthcare asset centred on the GIS and positions of healthcare asset in hyperspectral images to know the need of healthcare unit in the Tirupati District study area by using deep architectures base models. The methodology procedure is as shown in Fig. 4.

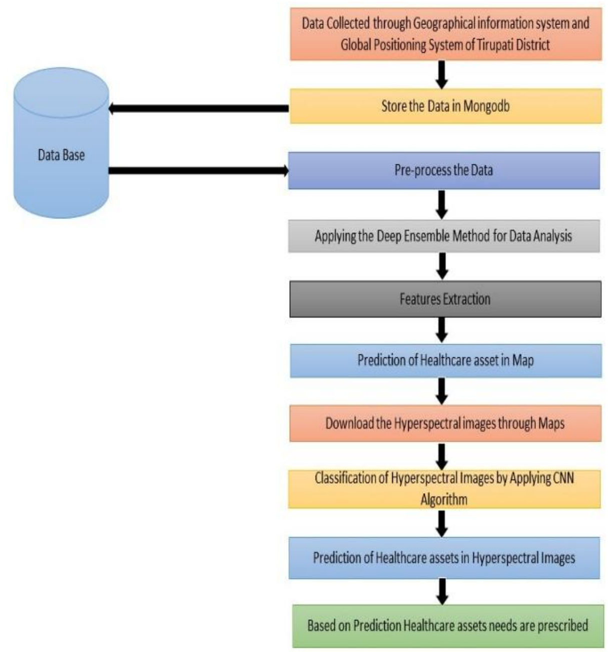


Fig. 4. Methodology procedure.

A. Deep Ensemble Method

The construct of heterogeneous ensembles with multiple base models and combine their results to make a more informed decision, taking advantage of recent architectural developments in GIS analysis. here makes use of both our fusing technique and classical fusers like XGBoost, AdaBoost. The method involves superimposing the model on top of the first ensemble. For an example of how it is trained on vectors of feature.

$$\mathcal{F} = [\boldsymbol{o}1; \boldsymbol{o}2;\cdots;\boldsymbol{o}N]^T$$

where $\boldsymbol{o}_i$ is vector output of i-th base model and considered feature vector consistent to ji. For each training sample, N base models are used to build a collective feature vector. This vector is sent to fusing learner. Consequently, larger values of N will result in feature vectors of greater dimension. For a classification assignment, for instance, the i-th base model would use the softmax layer to build c class probabilities, which would be represented by $\boldsymbol{o}_i$ (where $c{\cdot}N$ is the size of the concatenated feature selection). In contrast, a base boosting would provide more detail on HU's abundances, and all base models would use this same process to combine their abundance vectors. This would result in a final vector of profusions that is N times greater than the sum of the abundance vectors obtained from each vile model individually because it takes the outputs of N models and applies them all. In order to refine the ensemble's output, the fuser combines the initial projections.

B. Image Classification with Convolution Neural Network

Here for classification of hyperspectral images used three convolutional architectures for GIS analysis because it is the most efficient model to ensure that spectral and spectral-spatial generalise. In contrast to the spectral network [7], which is based on [22], two spectral-spatial CNNs are 3D-CNN [18] and 2.5D-CNN [17]. The former model does pixel-wise classification, while the latter performs patch-wise cataloguing of central pixel in each consistent area. The area sizes for 2.5D-CNN were determined according to the recommendations in [19]. While both the 3D-CNN and 2.5D-CNN models use spatial and spectral info to categorise the input patch's central pixel, the 3D-CNN model takes advantage of small (3×3×3) convolutional kernels to capture hyperspectral cube's fine-grained spectral interactions. It differs from 2.5D-CNN, which uses kernels that cover the complete spectrum, i.e., μ. categories in the initial convolutional layer.

C. Performance Metrics

Accuracy is defined as the number of right predictions out of all the instances.

$$Accuracy = \frac{True\ Positive + True\ Negatives}{Total\ Instances}$$

Precision is the number of successfully predicted positive cases out of all the predicted positive cases.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

Recall is the number of properly predicted positive cases to all actual positive cases.

$$Recall = \frac{True\ Positives}{True\ Positives + false\ Negatives}$$

The F1 Score is the harmonic mean of accuracy and memory, which makes it a fair measure.

$$F1\ Score = 2 * \frac{precision * recall}{precision + recall}$$

In multi-class classification problems, the Macro Average is a performance measure that gives an overall picture of a model's accuracy, recall, or F1 score by giving each class the same weight, no matter how big it is or how many times it appears in the dataset.

$$M_{macro\ avg} = \frac{1}{N}\sum_{i=1}^{N} M_i$$

N represents number of Class

$M_i\ represents\ Metric\ value\ for\ class\ i$

In multi-class classification, the Weighted Average is another way to measure success. It figures out the general metric (like F1 score, precision, or recall) by giving each class a weight based on how much data it has.

$$M_{weighted\ avg} = \frac{\sum_{i=1}^{N} M_i \,.\, n_i}{\sum_{i=1}^{N} n_i}$$

N represents number of Class

$M_i\ represents\ Metric\ value\ for\ class\ i$

$n_i$represents of samples in class i

IV. Experimental Analysis

To map the exact assets, execution is processed by using different classifiers and feature selection measures on two different datasets. Both trials included healthcare unit datasets from the Tirupati district and used hyperspectral image data for categorization and location analysis. This section presents the experimental setup and provides a detailed discussion of the outcomes. We used Python for model coding and QGIS for experimental validation.

At first healthcare facilities asset dataset is taken from Andhra Pradesh state government and it has created through GIS with the latitude and longitude as features. These are stored in mongodb for easy accessing and retrieving of data for the analysis. Applying ensemble classifiers on the data set the predictive model will be constructed. The deep ensemble method which is generated by using XGBoost, AdaBoost. From the data set, 28 features related to the healthcare assets are extracted. The Features are extracted to reduce the quantity of resources needed without losing valuable information. The feature extraction graph for the healthcare assets shown in Fig. 5.

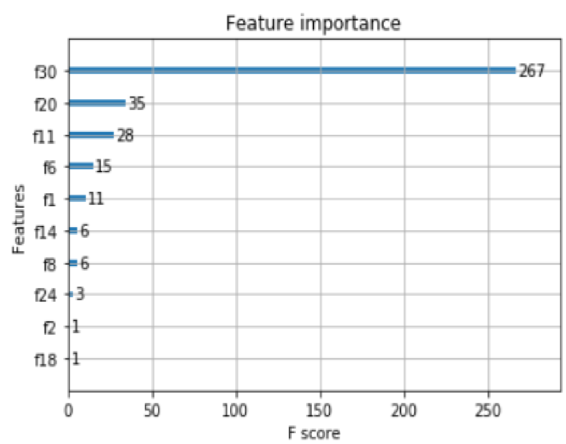


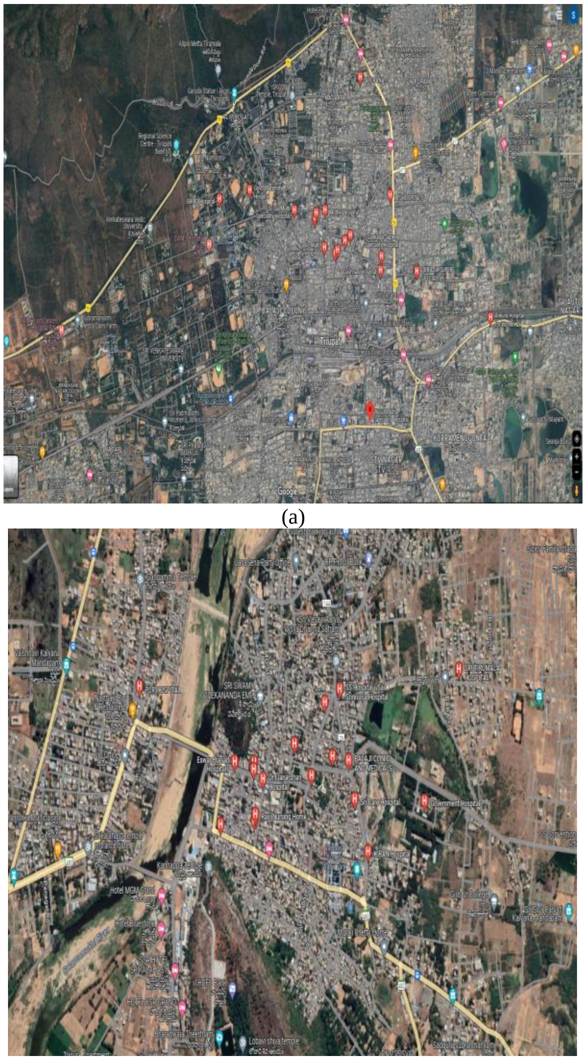
Fig. 5. Extracting the features from deep ensemble method.

TABLE II. Classification Report of Deep Ensemble Method for Healthcare Asset

	Precision	Recall	F1-Score	Support
Class 0	0.65	0.43	0.51	76
Class 1	0.82	0.92	0.89	194
Accuracy			0.84	256
Macro Avg	0.74	0.71	0.79	256
Weighted Avg	0.84	0.89	0.91	256

When deep learning algorithm is applied on healthcare asset data, classification report is generated with different parameters as shown in Table II like accuracy, weighted avg, macro avg, with precision, F1-Score, Recall by observing table deep ensemble algorithm has the highest accuracy of 84%.

Then after analysing deep ensemble algorithm with healthcare assets GIS data, the dataset is accessed into QGIS in python using interconnection and visualised the hospitals with their locations as shown in Fig. 6 (a) and (b).

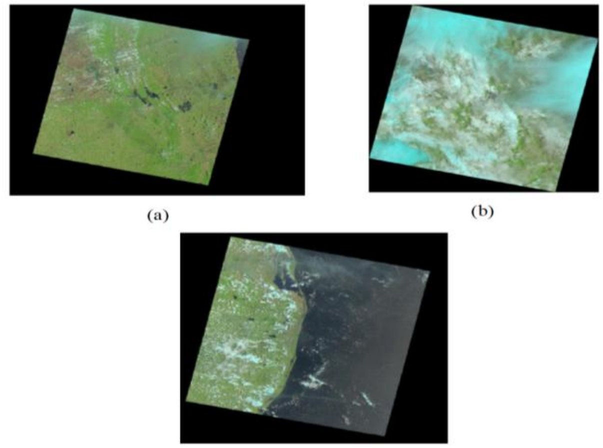


(a)

(b)

Fig. 6. (a): Visualization of Tirupati region healthcare assets. (b): Visualization of Srikalahasti region healthcare assets.

By observing Fig. 6(a) and 6(b) the red color pin with H letter indicates the healthcare assets. In Fig. 6(a) the healthcare assets are located either all the healthcare asset is nearer or for away from the village at tirupati city area. In Fig. 6(b) the healthcare assets are located for way from the village at Srikalalhasti. Then Hyperspectral images are acquired by integrating Python programming with QGIS. This study involves the collection of four distinct Landsat images of Tirupati district to facilitate the classification of healthcare facilities within the region. The hyperspectral images were collected and subsequently pre-processed through various techniques, including data cleaning, integration, transformation, and reduction. The images are subsequently divided into cubes by defining a region of interest (ROI), which is quantified using shapes such as polygons, circles, and rectangles. The subsequent step involves segmenting the images and employing a CNN algorithm to classify the healthcare facilities within the Tirupati district. The landsat input images of tirupati district are shown in Fig. 7 and the classified landsat image are shown in Fig. 8.

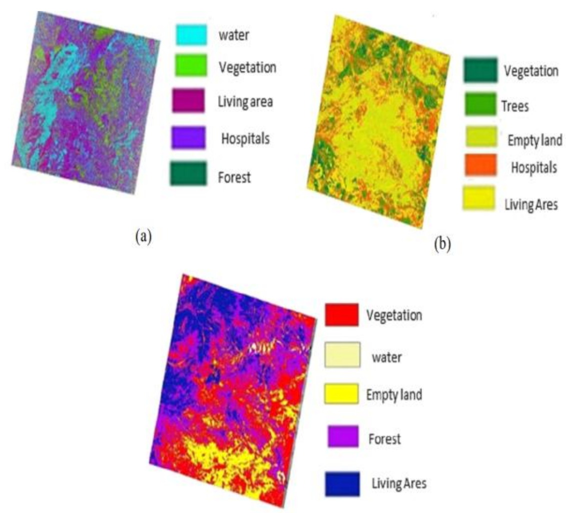


(a)

(b)

(c)

Fig. 7. Tirupati district hyperspectral images.



(a)

(b)

(c)

Fig. 8. Tirupati district classified hyperspectral images.

The classification of the healthcare asset in hyperspectral images from three distinct regions of the Tirupati district is presented in Fig. 8, specifically in Fig. 8 (a), Fig. 8 (b), and Fig. 8 (c). In this section, each figure illustrates the classified areas, depicted in various colors, with each color corresponding to a distinct area within that region, such as: In Fig. 8 (a), sky blue colour signifies water, green color indicates vegetation, Marron color represents Living area, Violet color represents Hospitals and Dark green color represents forest. In Fig. 8 (b), Dark green color represents vegetation, green color indicates trees, musted colour represents empty land, Orange color represents Hospitals and yellow color represents Living area. In Fig. 8 (c), Red color symbolizes vegetation, light yellow color indicates water, yellow colour represents empty land, Violet color represents forest and Blue color represents Living area. At last, explored how close healthcare services are to cities and rural areas. With spectral and geographic integration, it was possible to accurately identify and classify healthcare assets using their locations.

Here, in this work Two sets of healthcare facility data from the Tirupati district (Andhra Pradesh state government) were handled using GIS tools and hyperspectral imaging data to figure out where they are. The dataser took 28 traits from the healthcare dataset. Then, Deep ensemble algorithms (XGBoost, AdaBoost) were used to save resources while keeping important data. The results were shown as feature extraction graphs, and the Deep ensemble method (XGBoost and AdaBoost) got the best results with an 84% success rate. Some of the measures in the classification report are precision, recall, F1-score, weighted average, and macro average. Then Landsat pictures of the Tirupati district were edited and looked at. Steps like cleaning, integrating, transforming, and reducing that were part of the pre-processing are now complete. The data was then split into ROI cubes that were measured with circles, squares, and polygons. CNN used an algorithm to sort healthcare sites into groups. The classification results for three different areas in Tirupati district are shown. Based on the observation the need of healthcare facility is there in this study area.

Because, as per 2024 Censes, the population of tirupati distict is around 77,50,000 (approx.). so by observing our GIS and HSI analysis of healthcare assets it concludes that all the healthcare facilities are either in one place or it in different distance places which are outside the living area. So mainly for every village there is need to have healthcare facility centre for the population who is living there.

V. Conclusion

The deep learning techniques have proven useful for GIS and HSI data sorting and has some limits to use the large-capacity initiates and calls their generalizability into doubt in real-world scenarios. An exciting new paradigm is emerging in medical research and practice at the intersection of deep learning, Big data, GIS, HSI, and healthcare. This convergence has great promise for improving patient outcomes, streamlining healthcare delivery, and addressing public health issues. here presented deep ensembles for GIS analysis, which incorporate as effective base model fusers and other deep architectural advancements to capture and extract needful futures for location identification of healthcare facilities around the study area tirupati district. At last it concludes that there is a need of constructing the healthcare facilities in the tirupati district because as per 2024 censes, the population of tirupati distict is around 77,50,000 (approx.). so by observing our GIS and HSI analysis of healthcare facilities all the healthcare facilities are either in one place or it in different distance places which are outside the living area. So mainly for every village there is need to have healthcare facility centre for the population who is living there.

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