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A HYPERSPECTRAL IMAGE CLASSIFIERS WITHIN WIRELESS SENSOR NETWORK IN EXTREME ENVIRONMENTS

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Abstract
Progress in the field of computer networks has produced many areas of researches which paved the way for studying many new applications. One of the most popular applications that has shifted from the research level to the application level is wireless sensor networks (WSNs), based on which other advanced fields such as the Internet of Things are built.
These wireless sensor networks have been applied in many applications, and has proven to be an effective tool in collecting information in different environments, but with the expansion of the range of places that humans are interested in and trying to explore, the need has become urgent to apply wireless sensor networks to environments that are difficult to deal with by humans. This imposes new obstacles on the implementation and the performance of wireless sensor networks such as space, or applications that impose immersion of sensors in water, or industrial environments with high noise or medical environments, and perhaps toxic environments or those characterized by very high or very low temperatures. All these mentioned before prompted us to open new horizons of researches for wireless sensor networks to collect data from those environments.
Many studies have appeared to deal with these types of environments, and we will add to them the use of edge computing to deal with data at the place of gathering, especially in the space environment and aerial photography, where the data will be processed at the end of data collection and transmission since the transmission consumes the major part of energy, we will decrease by processing the date at the edge of the network. Classified information is sent only to the ground station to reduce bandwidth usage and perform real-time calculations.
Keywords: hyperspectral images; classification; edge commuting; wireless sensor network; extreme environments
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КЛАССИФИКАТОРЫ ГИПЕРСПЕКТРАЛЬНЫХ ИЗОБРАЖЕНИЙ В БЕСПРОВОДНЫХ СЕНСОРНЫХ СЕТЯХ В ЭКСТРЕМАЛЬНЫХ УСЛОВИЯХ

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Аннотация
Прогресс в области компьютерных сетей породил множество областей исследований, которые проложили путь для изучения множества новых приложений. Одним из самых популярных приложений, перешедших с исследовательского уровня на уровень приложений, являются беспроводные сенсорные сети (WSN), на основе которых строятся другие передовые области, такие как Интернет вещей.
Эти беспроводные сенсорные сети применялись во многих приложениях и зарекомендовали себя как эффективный инструмент для сбора информации в различных средах. С расширением круга мест, которые интересуют людей и исследуются, возникла острая необходимость в применении беспроводных сенсорных сетей в средах, с которыми людям трудно иметь дело. Это вызывает новые препятствия для реализации и работы беспроводных

сенсорных сетей, таких сферах как космос, или приложения, требующие погружения датчиков в воду, промышленные среды с высоким уровнем шума или медицинские среды, а также, возможно, токсичные среды или среды, характеризующиеся очень высоким или очень низким уровнем шума, температуры. Все это, упомянутое ранее, побудило нас открыть новые горизонты исследований беспроводных сенсорных сетей для сбора данных из этих сред.

Появилось много исследований, посвященных этим типам сред, и мы добавим к ним использование граничных вычислений для обработки данных в месте их сбора, особенно в космической среде и аэрофотосъемке, где данные будут обрабатываться в конце сбора и передачи данных, так как передача потребляет большую часть энергии, основную часть энергии мы уменьшим объем за счет обработки данных на границе сети. Закрытая информация отправляется только на наземную станцию, чтобы уменьшить использование полосы пропускания и выполнять вычисления в реальном времени.

Ключевые слова: гиперспектральные изображения; классификация; пограничная коммутация; беспроводная сенсорная сеть; экстремальные условия

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1 INTRODUCTION

Wireless sensor Network (WSN) is a group of sensors that are used to transmit or follow a specific physical or chemical phenomenon (such as temperature, humidity, vibration, light... etc.) and then transfer information about the phenomenon wirelessly to the data processing center to benefit from it without the need for a human presence in the place of the physical phenomenon.

Wireless sensor Network, as one of the best emerging technologies of the 21st century, has started to develop at an accelerated pace in the past ten years. A lot of researches worked to improve it in various aspects, including its architecture, node operating systems, routing protocols, data collection and integration, positioning mechanism, time synchronization, and so on [1]. Moreover, large numbers of promising applications have emerged and been deployed in different geographical areas such as infrastructure protection, scientific exploration, military monitoring, traffic monitoring and control, mining and maritime security, environmental protection, object tracking, military affairs, etc. With the conveniences provided by the WSN, our lives have been greatly influenced and changed in many ways. However, there are still many problems affecting implementation of WSN. These include unreliability of wireless communication systems, limited available power, failure of nodes, etc. [2].

The world has seen a number of significant changes as a result of the last 40 years of economic and political upheaval. As new innovations took control, several technical trends came to an abrupt stop, stunning the experts. Smart sensing is one of the successful ones, blooming as a result of hopes for a better quality of life. Even though there have been several successful civic and industrial applications and projects all over the world, a true paradigm shift has yet to materialize [3]. Too many research papers have somehow failed to show the impressive industrial applications necessary to justify the resources being used as research activity has risen and resources have increased. So, we must evaluate the performance of sensors during the past 20 years on a worldwide scale and study the financial viability of the initiatives mentioned.

A new technology must satisfy four fundamental criteria in order to be successfully implemented: confidence, objectivity, security, and sustainability. Objectivity in this context refers to the requirement for a good service, which in our case means overcoming unusual working conditions so that system can enable new services, whether in the vacuum of space, the oceans, below ground, or in locations with extremely high, extremely low, and highly variable temperature, humidity, winds, and pressure [4].

The necessity for technological gadgets that can be linked to the wider world, gather data from it, and transfer it for analysis and processing has risen as a result of today's greater dependence on technology. This is also a result of the bandwidth's limitations. We found that many aspects have been covered by researchers, but some of the aspects still require further work, such as using artificial intelligence on the edge (smart edge) and security challenges. Many advantages, like overcoming bandwidth restrictions, scalability, real-time response, and mobility, deployment of a WSN.

Due to the slower development of communication technology compared to the growth of processing technology, there is interest in having processing occur at a node rather than a central server or in the cloud. As a result, the cost of the bandwidth package is still high compared to the cost of data processing at the network's edge. Long-lasting battery development has opened up new possibilities for utilizing WSNs more effectively and in a wider range of applications. With the need to save local storage and computation expenses growing, cloud computing is gaining popularity. However, cloud computing cannot be used easily due to the significant energy consumption and challenging internet connectivity for many resource-constrained machines. The aforementioned problems may be resolved through edge computing. When edge computing compared to cloud computing, it offers consumers a variety of services in a place that is closer to them, including easier access to processing power, storage, and communication bandwidth. Its benefits include a quicker reaction time, less demand on the main network's bandwidth, and better data security and privacy protection.

The benefit of edge computing is evident in sensor types that acquire a large amount of data, such as cameras, and especially in hyperspectral cameras that acquire a larger amount of data that is very difficult to send in their raw form to the data center. Hyperspectral imaging is a novel analytical method built on spectroscopy. For the same geographical region, it gathers hundreds of pictures at various wavelengths, while the human eye only has three color receptors—blue, green, and red—hyperspectral imaging analyzes the continuous spectrum of light for each pixel of the image with precise wavelength precision, both in the visible and near-infrared ranges. A so-called hyperspectral cube is created from the gathered data, and it has three dimensions: two of which indicate the scene's geographic extent and the third its spectral content.

In the late 1980s, Goetz et al. [5] developed hyperspectral imaging, which is today a potent remote sensing technique that gives access to more precise data on the Earth's surface and atmosphere among many applications. This technology, which entails the acquisition of numerous images in a number of closely spaced narrow spectral bands and the reconstruction of the reflectance spectrum for each pixel of the image [6], has the capacity to provide both spatial and spectral information that is crucial in the study of Earth's surface as well as of the properties of the atmosphere at various levels of scientific investigation.

A new age of precise, data-driven research into the Earth and the outer atmosphere has begun as a result of the development of hyperspectral imaging systems technology and data processing approaches during the past several decades. Land cover classification (vegetation studies: vegetation biophysical and biochemical properties characterization, species identification, plant stress assessment, leaf water content determination, development of spectral vegetation indices [7]; soil studies: soil mapping and classification, assessment of soil degradation [8], mapping of soil contamination [9].

Management of water resources, including monitoring of water quality parameters (chlorophyll-a, turbidity, and total suspended particles) and bathymetric measurements (evaluation of water depth and bottom type and mapping of shallow water benthic habitat) [7]. Observations of atmospheric composition (greenhouse gas studies: detection, identification, quantification, and visualization of sulfur dioxide (SO_2), methane (CH_4), ammonia (NH_3), nitrogen dioxide (NO_2), and carbon dioxide (CO_2) in the atmosphere. Aerosol and cloud studies: aerosol optical thickness and water content retrieval; cloud detection; cloud thermodynamic phase estimation; cloud microphysical parameters (optical thickness and effective radius).

We need to use a network for classifying hyperspectral images, characterized by speed and accuracy in classifying data, and its parameters are clear and easy to control. The scattering transform is a deep representation [10], defined as a cascade of wavelet transforms followed by the application of a complex modulus. On a more theoretical level, the scattering transform has the interest of modelling in a simple, yet realistic manner, the deep learned convolutional representations that have allowed, in the past five years, impressive progresses on a wide range of machine learning tasks, or at least the first layers of these representations. Indeed, it has the architecture of a deep convolutional representation. On various tasks, it performs essentially as well as learned convolutional representations [11, 12]. On other tasks, it can replace the first layers of a deep representation while retaining or improving the classification accuracy [13]. But compared to learned representations, the scattering transform has an entirely explicit expression. It is thus more amenable to mathematical analysis, and offers some insight into the behavior of deep learned representations, notably in terms of their invariance properties.

2 LITERATURE REVIEW

2.1 EDGE COMPUTING ENABLED WSN

Some requirements must be met in order to design a reliable Edge computing enabled WSN, including system security, real-time application support, efficient resource management, energy consumption, system cost, heterogeneous handling of hardware, ability to support mobility, system scalability, system support for artificial intelligence, system availability, and ability to avoid malfunctions. Researches are studied and classified into 10 classes, with one researcher in each class.

2.1.1 SYSTEM SECURITY

Any trustworthy system has to be protected. In the case of edge computing enabled WSN, the lake of sufficient resources, processing speed, or memory, and the fact that data is distributed makes it vulnerable to hackers. In the case of cloud computing enabled, the cloud has sufficient capabilities to run the most sophisticated security algorithm. The secure system requirements of availability, dependability, secrecy, and data integrity must be satisfied.

2.1.2 REAL-TIME APPLICATION SUPPORT

When it comes to real-time applications, reaction time is crucial for soft real-time systems and deadly for hard real-time ones. Using a cloud-enabled WSN would significantly decrease system performance by introducing latency and congestion issues [14]. Due to the neglection of the transit time from the data source to the processing of the data for the decision, edge computing's dispersed nature made it suited for real-time applications [15, 16].

The application trial approach is used to offer an edge computing platform that supports transit network systems by physically deploying mobile edge nodes devices aboard a transit bus [17]. Current issues with power transmission efficiency and reliability need the optimization of the framework and the proposal of an effective heuristic method based on the simulated annealing technique. In the simulation of the proposed system, many edge computing servers were employed to determine efficiency [18]. Applications for virtual reality (VR) and augmented reality (AR) need to be researched. Analyzing the interplay of head mounted displays with AR/VR networks requires discussion of the networking challenges faced by the AR/VR community in a practical situation [19] to satisfy the demands of 5G apps that need a lot of resources and suffer from delays. The use of a price system for photos while taking into account their freshness, resolution, and data size is proposed in an edge computing-based photo crowdsourcing (EC-PCS) framework [20]. An algorithm is proposed to locate the position of a robot precisely Extended Kalman Filter (EKF) and realize it using Edge computing instead of cloud computing to achieve real-time position control and to reduce bandwidth usage [21].

2.1.3 EFFICIENT RESOURCE MANAGEMENT

Due to the processor and memory limitations of high-end devices, resources in edge computing are substantially more constrained than those used in cloud computing. These devices can also vary in terms of their structural make-up and the tasks that are assigned to them. Since there are only so many resources available, it is crucial that they are used in an efficient manner to get the most out of them [22]. To address the issues with Edge computing implementation in WSN, few research were conducted in order to optimize the pseudorandom resource allocation, optimizing the placement of edge nodes in the physical environment utilizing a multitiered mobile edge computing system is investigated. Hardware resource allocation is accomplished using the Bayesian optimizer energy consumption.

2.1.4 SYSTEM COST

The cost of using the data transmission network may be high; thus, to improve the system, more resources must be added. Since costs may be constant or variable, a trade-off between the new costs and improvements must be made to determine whether the addition is essential [23, 24]. Due to initial hardware expenses, edge computing for stationary systems can, in the long term, lower the cost of data transmission and processing. The cost may be higher in systems with mobile peripherals since it becomes one of the difficulties in doing a feasibility study in these systems [24, 25].

2.1.5 HETEROGENEOUS HANDLING OF HARDWARE

Due to the diverse nature of WSN resources, including the kind of data representation, storage and processing capacities, and peripheral devices like wearables and sensors that are part of the Internet of Things. When building Edge computing, this variety must be taken into consideration since Edge nodes may find it difficult to manage this diversity WSN [26].

2.1.6 ABILITY TO SUPPORT MOBILITY

One of the difficulties is delivering computing capacity utilizing mobile nodes [23]. But mobile edge computing may be used to do this (MEC). MEC can be used for a wide range of applications, including the temporary storing of certain data as well as the potential for processing that data. Mobile edge computing technology may be used in 4G mobile network systems, and 5G and 6G systems are anticipated to significantly support it [27]. It is now possible to migrate containers between hosts with various ISAs thanks to the integration of H-Container into Docker, which migrates natively generated containerized apps between compute nodes with CPUs of different ISAs. Integrate H-Container into Docker to enable container migration between hosts with various Instruction Set Architectures (ISAs), since Server programs originally developed for one ISA cannot do so when a client changes its physical location [28].

2.1.7 SYSTEM SCALABILITY

The scalability of the network is one of the key advantages of employing computers [29]. Edge computing enabled WSN is the ideal option owing to the ability to add many edge computing nodes as needed and at any location, which is made possible by the rapid development of applications employing WSN [30].

In order to provide location-based services in the context of smart cities, a Design and experimental assessment of a scalable two-tier Edge Computing architecture is built. The object-recognition service is powered by the Google-powered TensorFlow framework [31].

2.1.8 SYSTEM SUPPORT FOR ARTIFICIAL INTELLIGENCE

It is now a reality that any WSN should contain some type of intelligence algorithms to process and analyze the data gathered as the primary job of WSNs is to collect data. This data should then be processed and evaluated, which is mostly done using artificial intelligence (AI). The most complex algorithms can be handled by processing power in a cloud scenario, but there will be a significant delay owing to network and congestion latency. A smart edge may be defined as an edge node that can manage AI algorithms with edge resources that have the capacity to satisfy artificial intelligence service requests for edge devices connected to it [32, 33].

2.1.9 SYSTEM AVAILABILITY

Edge computing, in contrast to cloud computing, is less dependable since errors might arise; thus, alternate working plans must be prepared in the event of a mistake to prevent system collapse [34].

A solution is developed in Python 3 and tested on a set of edge devices to address the problem of reliable edge computing on dynamic, high-churn edge systems. A deviceless pipeline-based approach (DPA) is then developed to establish workflows in which stages of the analysis pipeline are finished on edge devices [34]. A Krill-based method is created to handle the dependable workflow scheduling problem across mobile edge computing environments by framing the problem as an optimization problem that takes the dependability of resources into account [35].

In the figure below the percentage density of research efforts in each of the edge computing requirement.

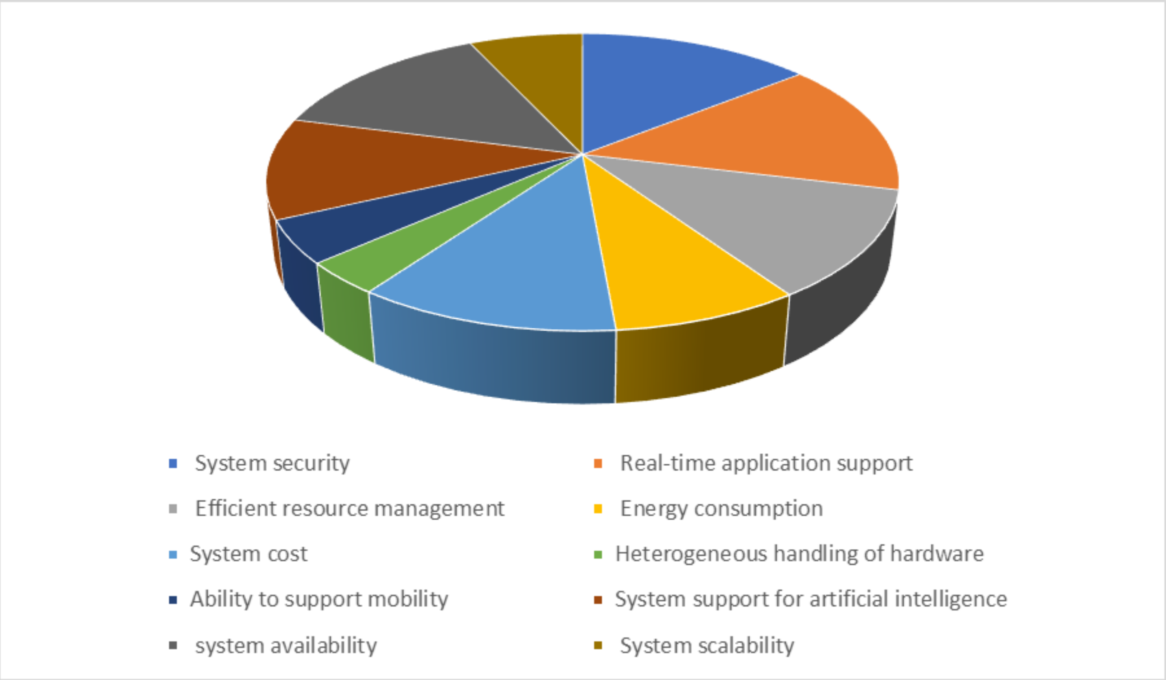

Fig. 1. Percentage of research efforts for each of the requirements
Рис. 1. Процент исследовательских усилий по каждому из требований

2.2 EXTREME ENVIRONMENTS

One of the key findings is that too many researchers focus more on publishing potential than on making their work helpful and applicable to real-world problems that might enhance quality of life. We observe many patterns of common networking manipulation, such as routing, scheduling, node replacement, mobility, and coverage under oversimplified working conditions, where simple computer simulations can produce enormous volumes of inaccurate data, in addition to the few useful research activities, such as energy conservation, optimized performance, cross layering, efficient sampling, and data management; They are only producing a giant black hole that will devour computer resources. We have decided that we need to focus research on the environments that need sensors the most “space and other harsh”.

All complicated sensing and actuating systems can benefit from the design characteristics offered by Wireless Sensor System (WSS) platforms for homogeneous Sensor wireless systems. Although generally helpful, this function might to operate under Space and Extreme Environments (SSE) restrictions, the system must be made robust. Given that some SEE applications require further leveraging of the WSS to function in harsh environments, we must implement a few crucially important refinements under the WSS-SEE flagship by adopting the extra stringent requirements of an unconventional environment in the design process for a "unconventional wireless sensing" (UWS) solution.

In other words, a further revitalizing that findings move us in a better position to reactivate more fruitful research and development as needed, which is crucial to injecting flagship breakthrough applications where both academics and industries can visualize the true potentials of wireless sensor platforms that can only happen under new unconventional application. We need to redefine SEE, or more properly EE in its condensed version, in order to find a good spot to support the Convolutional Sensos System approach for a new application paradigm. We further investigate the term "environment" in order to do this. One is for living circumstances; "human living environments" are often divided into three categories: acidic, alkaline, and astrobiology. Because of its unexpected properties, space is considered an EE.

For wireless sensor technologies used in flight, we may now add the possibility of out-of-scale distances between systems with severe propagation issues, LOS, low air pressure, and fluctuating gravity, all of which must function in an energy-scarce environment. Even though every system is tested in a lab setting and in a terrestrial environment, the mission environment's extremely low pressure, variable gravity, and lack of atmosphere may cause some systems to operate differently. NASA, for instance, employs Skylab in space and undersea facilities (NEEMO) for testing space parts, components, and systems before their deployment because of the high expense of any potential failure. Final assembly and other tasks. The potential for upgrading man-made satellites with improved wireless sensor utilization is significant. Now that there are thousands of them, many of which are underutilized, they might considerably enhance human existence on Earth if properly utilized and fitted with sensors. Really, most airplanes require improved wireless sensing.

The biggest obstacle to the functioning of wireless sensor systems for SEE is batteries. Implementing several modes of operation, such as off, sleep, or standby power states, decreasing the operating voltage, precise hardware control, and power-efficient utilization of the wireless spectrum may all help save on board battery power [36]. Scaled-down modulation techniques can also be utilized to reduce power consumption [37]. The restricted battery on board can also be solved by eliminating overhead in sensor data packets based on the characteristics of the sensor data [38].

The battery power conservation is the least of our worries in severe locations where it is debatable whether a battery is even necessary given the hostile environment. Due to this, adopting passive or battery-free wireless sensors in certain settings might be quite appealing. Another factor that makes passive sensors a desirable option for space applications is the weight and cost reductions. Monitoring the temperature at various locations on the space telescope's mirrors is one example of how battery-free sensors are used in space applications (Figure 2).

Fig. 2. Space telescope (Picture courtesy of NASA GSFC)
Рис. 2. Космический телескоп (Изображение предоставлено НАСА GSFC)

We need a collection of tiny mirrors to keep the picture focused and maintain the structural integrity necessary for fine-resolution imaging. The mirrors enlarge and contract due to the hostile space environment's high temperature dynamic range. Temperature adjustment can be achieved by remotely activating and deactivating localized heaters using battery-free wireless sensors. As the number of sensors increases, the issue of spectrum sharing arises.

Another illustration is the incorporation of sensors, such as inflatable decelerators, inside the heat shield of re-entry vehicles (Figure 3).

Fig. 3. Inflatable decelerator (Picture courtesy of NASA GSFC)
Рис. 3. Космический телескоп (Изображение предоставлено НАСА GSFC)

The wireless sensors must be able to withstand extremely high temperatures at the re-entry in order to function properly.

By delivering cooling liquid to those precise spots, any unusually high local temperatures outside of the regular window may be found and disastrous events can be prevented.

Numerous technological platforms, including semiconductor-based sensors, piezoelectric substrates, and inductive sensors, can be used to implement passive wireless sensors. One of the extensively utilized technologies that relies on the concentration of the traveling wave on the surface of the piezoelectric-based sensors are surface acoustic wave (SAW) based sensors [39]. One sensor operation at a time was the norm for SAW device implementations in the past.

Recently, a coded SAW sensor system was put out in [40], which used coded sensors to offer a multiple-access capability.

2.3 HYPER SPECTRAL IMAGING

Hyperspectral images and remote sensing have been taken into consideration in recent advances in imaging science and technology. The learning of the machines is often the foundation of the contemporary intelligent technologies, including support vector machines, sparse representations, active learning, extreme learning machines, transfer learning, and deep learning. With their accuracy and integrity, these approaches improve the processing of such three-dimensional, multiple band, and high-resolution pictures.

One of the most important scientific and technical developments in remote sensing imaging is hyperspectral imaging. The technique known as hyperspectral imaging (HSI) perfectly exemplifies how remote sensing and geographic information systems (GIS) may work together. Additionally, HSI benefits include ecological protection, security, applications in agriculture and horticulture, crop specification and monitoring, and medical diagnosis, identification, and quantification. [3]

RGB images are Three dimensions structure: width, height, and three-color bands or channels made up of red, green, and blue color information. A mixture of RGB intensities laid out on a color plane, they are recorded in a 3D byte array that expressly stores a color value for each pixel in the image. Contrarily, HSI is made up of thousands of hypercubes and has a huge quantity of embedded information, including spectral, spatial, and temporal data, as well as a high resolution. This data enables numerous applications to identify and classify land coverings, which are extensively investigated [41].

Digital RGB cameras can only identify things by their color and shape, hence they are only able to take RGB photos. Additionally, only three visible bands are present in the human sight range, which results in insufficient embedded information. Contrarily, specialized spectrometers mounted on artificial satellites, or airborne hyperspectral sensors, are used to record the HSI. Due to their extensive collection of bands that are not limited to the visible light spectrum and their larger spectral band-pass, they have a wide variety of scenarios. However, a hyperspectral sensor's channel width is significantly narrower than a digital sensor, which only absorbs light in three large channels. This results in a much greater spectral resolution and data volume, which makes it more difficult to store, mine, and manage the data [42].

Additionally, processing these data with such a large number of bands comes with a number of challenges, such as noisy labels, geometric distortion, limited or unbalanced labeled training samples, the Hughes phenomenon, and dimensionality reduction-related artifacts, such as overfitting, redundancy, spectral variability, and the loss of important features between the channels [43–46].

The classification of HSIs is thought to be an inherently nonlinear problem, and the initial strategy by linear-transformation-based statistical techniques such as principal component analytical methods, such as principal component analysis (PCA) [47] and independent component analysis (ICA) [48], the discriminant analytical methods, such as linear and fisher, wavelet transforms, composite, probabilistic, generalized, kernel methods [48–55], However, they were only interested in spatial information. They underlined that the feature extractor approaches, which are complicated in terms of cost, space, and time and supported by certain simple random classifiers, are insufficiently accurate. Following the success of these conventional systematic procedures used for HSI categorization, researchers developed a strong interest in using the most recent developing but not laborious computer-based technologies, which improved the process overall and brought it closer to perfection. The development of machine learning, according to recent research, makes the last decade the one in which computer-based technologies have advanced the most (ML). ML is an algorithmic, potent instrument with cognition similar to that of the human brain. By holding abstraction, it only portrays a complicated system. In order to extract the latent discriminative characteristics, both spectral and spatial, it may therefore simplify the problem and look deeper into the insights of the enormous amount of HS data [54]. In order to obtain the needed accuracy in classifying the objects of the target HSI data, it thus overcomes all obstacles. As a result, they function as all-inclusive strategies that can accomplish the goal on their own. In light of this, we carried out a thorough assessment based on the numerous HSI discriminative machine learning (ML, DL) models. AVIRIS Indian Pines (IP), Kennedy Space Center (KSC), Salinas Valley (SV), and ROSIS-03 University of Pavia (UP) are the HSI datasets that are frequently used for landcover classification in most literature studies. Less frequently used datasets include Pavia Center, Botswana, University of Houston (HU), etc. They have already been improved and are now freely downloadable and operational on.

Our work's inspiration may be broken down into three categories. First, a brand-new approach is suggested for the review job that is completely methodical and aids in generating ideas for embedded questions and research gaps after reading a significant number of research publications. Second, this paper focuses on the most recent developments in ML technologies for categorizing HSI. They are briefly and methodically described, and a thorough assessment of the relevant literature is provided. Finally, conclusions are reached that provide researchers more information for next studies. Our innovative effort's main contributions to the field of hyperspectral images study are as follows:

– the full reworking of the ML/DL-based analytical and classification work done on HS imagery to date.

– emphasis on the categorization approaches that have been studied and used often thus far. It also provides a quick explanation of the newest technological advancements and the emphasized hybrid approaches.

An open knowledge base that evaluates all research on each indicated strategy in terms of their methodology, convenience and restrictions, and future strategies works as a reservoir of pertinent information that is listed forth. This example may aid in selecting an appropriate research goal for more HSIs-related study explicit notion of the growth in interest in the relevant field that would entice researchers to dedicate themselves to providing a coherent, substantial specification (benefit and drawbacks) of each method that informs the researchers academically about their preferred outcome and the challenges for a particular technique.

The present technologies that have been adopted are hot spots, according to a temporary depiction of the most recent study on HSIs. Additionally, concentrate on the areas of study that are of interest and may be applicable to others, i.e., the hybridized approaches that are commonly used by researchers to solve problems and produce the necessary experimental outcomes.

A number of challenges have made it difficult to analyze and manipulate hyperspectral pictures. It first struggled with spectroscopic technology since the hyperspectral sensors were of low quality and there wasn't enough data. However, as applied science has developed, things have become more straightforward, but there are still certain well-known nondispersible obstacles to be overcome. The following are some of them:

Lack of high-resolution, noise-free Earth observation (EO) images: When spectrometers were first discovered, they were not particularly effective. Because of this, the signals arriving from the Earth's surface for Earth observations are altered by sounds brought on by water vapor, air pollution, and other atmospheric disturbances. The creation of high-quality hyperspectral data for Earth observation and the development of a variety of high-performance spectrometers that combine the strengths of digital imaging, spectroscopy, and the extraction of numerous embedded spatial-spectral features have both been the focus of numerous efforts over the past few decades [56]. obstacles to extracting features: Redundancy between adjacent spectral bands causes the availability of redundant information during data collection, preventing the best and most discriminative retrieval of spatial-spectral properties [44].

The high spatial variety and similarities across classes: Due to collection errors that cause information loss in terms of the unique identification, that is, the spectral signatures, and high intraclass variability, the hyperspectral dataset obtained comprises useless noise bands. Additionally, low resolution results in broad spatial regions being represented by each pixel on the Earth's surface. This produces spectral signature mixing, which increases interclass similarity in border regions, leading to inconsistencies and uncertainties for the employed classification algorithms [56].

Insufficient labeled data and a shortage of training samples: Aerial spectrometers can only gather a certain amount of hyperspectral data because of how much smaller the regions they cover. This causes the amount of training data for classification models to be limited [57]. Additionally, classes in HSIs often correlate to a single scene, and the learning processes for the classification models that are currently available demand labeled data. However, identifying each pixel by hand takes laborious and prolonged human talent [58].

Insufficient balance between interclass samples: Many existing methods are less beneficial in terms of improving minority class accuracy without affecting majority class accuracy because of the class imbalance concerns, which arise when each class sample has a large range of occurrences [59]. The increased dimensionality: Because such high-band images incorporate more information across several channels, estimate errors rise. For supervised classification methods, the curse of dimensionality poses a serious problem since it adversely affects both performance and accuracy [60].

Spectral unmixing and resolution enhancement for better feature extraction and distinguishing capability of the embedded objects are potential solutions to the aforementioned limitations, which also represent potential operations that can be performed to analyze and comprehend the HSIs. Other potential solutions include (3) image compression-restoration and dimensionality reduction, (4) spectral unmixing, and (5) image compression-restoration and resolution enhancement and (4) the use of strong classifiers that can address the aforementioned problems as well as encourage quick computing [44].

These difficulties were particularly noticeable for techniques that categorize HSI based on feature extraction from HSI. The operations on HSI got simple once ML/DL entered the picture since explicit feature extraction is not required. It also has several benefits including excellent noise handling and low time complexity. Despite having many advantages, ML/DL has a few downsides in some criteria [61], such as parameter adjustment, multiple local minima issues, and compression [57] overfitting, optimization, and convergence issues.

2.4 HYPER SPECTRAL CLASSIFICATION

Technology developments have made it possible for cameras to continuously gather hundreds of spectral data points for each pixel in an image, which has led to an increase in the analysis of hyperspectral images (HSI) to use it in many application as mentioned in figure 4-5.

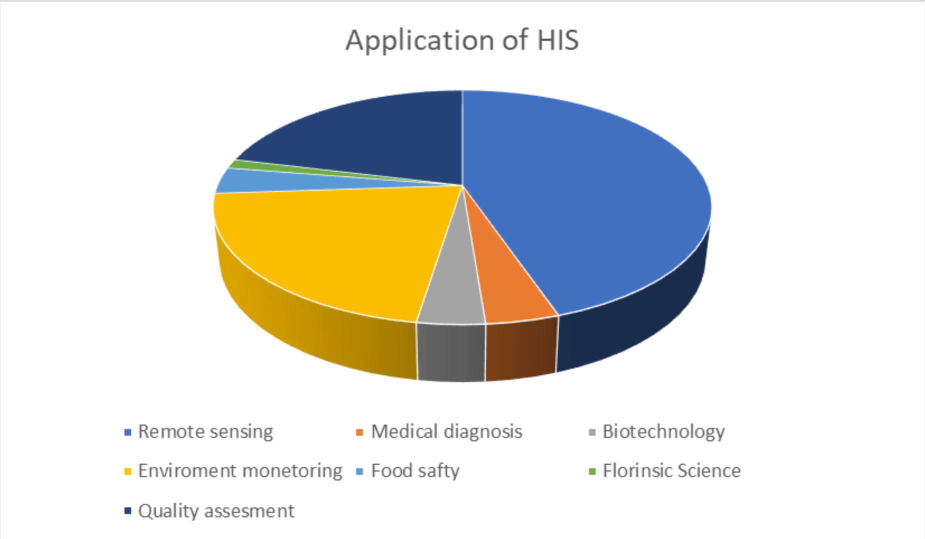

Fig. 4. Percentage of Research efforts HSI conducted researches
Рис. 4. Процент исследований, проведенных HSI

Due to the numerous redundant spectral bands, the small number of training samples, and the non-linear connection between the obtained spatial location and the spectral bands, HSI classification is difficult.

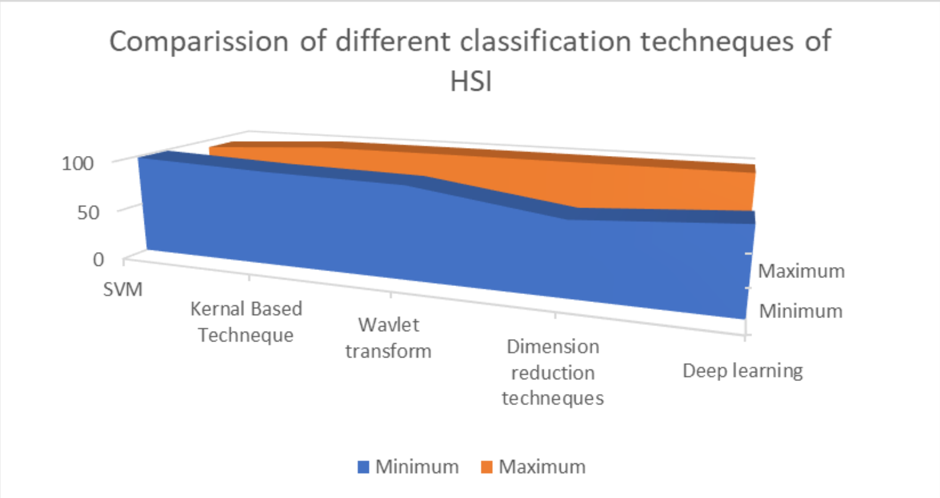

Fig. 5. Percentage of Research efforts in the accuracy of different classification algorithms
Рис. 5. Процент усилий по исследованию точности различных алгоритмов классификации

Figure 5 shows the approximated percentage of research efforts to use classification for hyperspectral images.

Our study emphasizes recent work in HSI classification utilizing conventional machine learning methods, such as transform-based methods, dimension reduction, support vector machines, and kernel-based methods. Our research also explores Deep Learning (DL) methods for classifying HSI, including the use of autoencoders and 1D, 2D, and 3D-Convolutional Neural Networks. The comparison shows that DL-based classification algorithms perform better than ML-based ones (Figure 6).

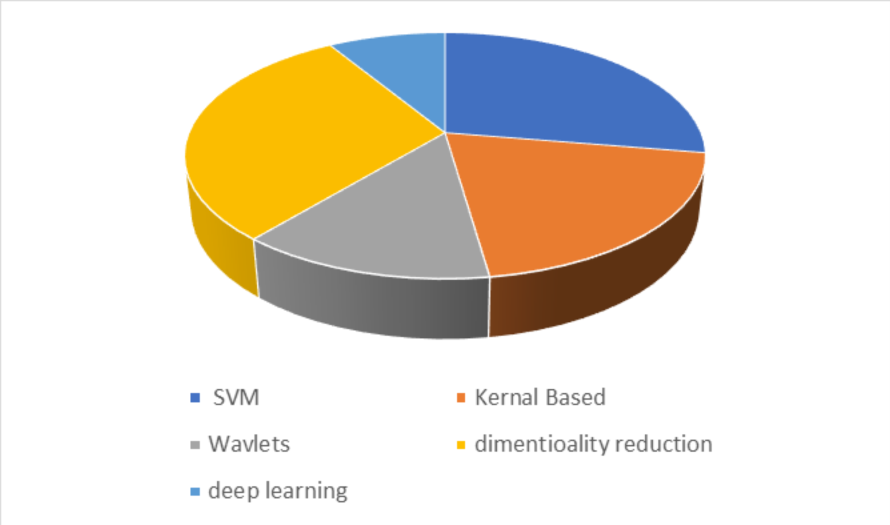

Fig. 6. Percentage of Research efforts in classification techniques
Рис. 6. Процент усилий по исследованию методов классификации

Additionally, it has been noted that spectral-spatial HSI classification surpasses pixel-by-pixel classification since it takes into account both spatial domain information and spectral characteristics. On widely used land cover datasets including Indian Pines, Salinas Valley, and Pavia University, the effectiveness of ML and DL-based classification approaches has been examined.

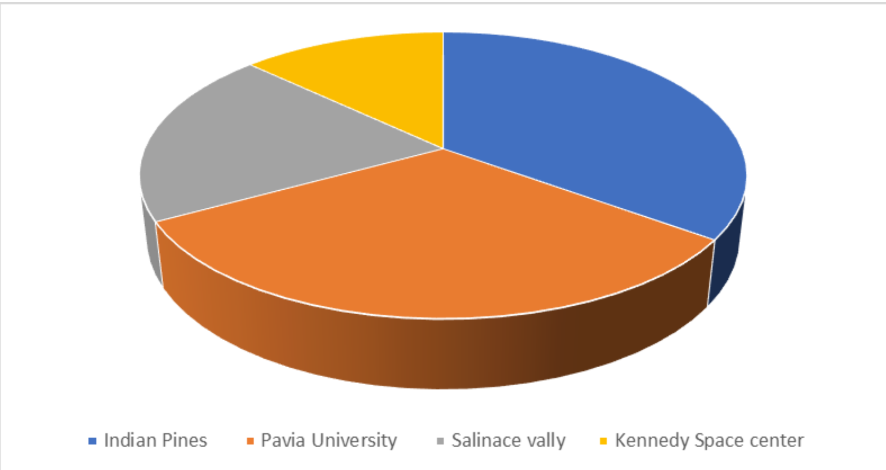

Fig. 7. Percentage of Research efforts of majorly used datasets in existing techniques
Рис. 7. Процентная доля исследований наиболее часто используемых наборов данных в существующих методах

CONCLUSION

Many methods and techniques have arisen to deal with the deployment of WSN within an extreme environment such as space, underwater, etc. in space most of the data are gathered using Hyperspectral images because they give more details, so the classification would be better. we reviewed many studies for such situations and found that Hyperer spectral classification fits the situation of using Hyperspectral classification as Wavelet-based classification algorithms because they ate light, fast learning, and accurate.

References

1. Kandris D., Nakas C., Vomvas D., Koulouras G. Applications of wireless sensor networks: an up-to-date survey. Applied System Innovation, vol. 3, no. 1, p. 14, 2020.
2. Sharma S., Bansal R.K., Bansal S. Issues and challenges in wireless sensor networks. 2013 international conference on machine intelligence and research advancement, 2013, pp. 58–62.

3. Abdulkarem M., Samsudin K., Rokhani F.Z., Rasid M.F.A. Wireless sensor network for structural health monitoring: A contemporary review of technologies, challenges, and future direction. Struct Health Monit, vol. 19, no. 3, pp. 693–735, 2020.

4. Rashvand H.F., Abedi A. Wireless Sensor Systems for Extreme Environments. Wireless Sensor Systems for Extreme Environments, John Wiley & Sons, Ltd, 2017, pp. 1–19. doi: 10.1002/9781119126492.ch1.

5. Goetz A.F.H., Vane G., Solomon J.E., Rock B.N. Imaging spectrometry for earth remote sensing. Science (1979), vol. 228, no. 4704, pp. 1147–1153, 1985.

6. Goetz A.F.H. Three decades of hyperspectral remote sensing of the Earth: A personal view. Remote Sens Environ, vol. 113, pp. S5–S16, 2009.

7. Thenkabail P.S. Hyperspectral remote sensing of vegetation: knowledge gain and knowledge gap after 50 years of research (Conference Presentation). Hyperspectral Imaging Sensors: Innovative Applications and Sensor Standards 2017, vol. 10213, p. 16, 2017.

8. Ben-Dor E. et al. Using imaging spectroscopy to study soil properties. Remote Sens Environ, vol. 113, pp. S38–S55, 2009.

9. Van der Meer F.D. et al. Multi-and hyperspectral geologic remote sensing: A review. International Journal of Applied Earth Observation and Geoinformation, vol. 14, no. 1, pp. 112–128, 2012.

10. Mallat S. Group invariant scattering. Commun Pure Appl Math, vol. 65, no. 10, pp. 1331–1398, 2012.

11. Tschannen M., Kramer T., Marti G., Heinzmann M., Wiatowski T. Heart sound classification using deep structured features. 2016 Computing in Cardiology Conference (CinC), 2016, pp. 565–568.

12. Andén J., Lostanlen V., Mallat S. Joint time-frequency scattering for audio classification. 2015 IEEE 25th International Workshop on Machine Learning for Signal Processing (MLSP), 2015, pp. 1–6.

13. Oyallon E. A hybrid network: scattering and convnet. 2017.

14. Trinks S., Felden C. Edge computing architecture to support real time analytic applications: A state-of-the-art within the application area of smart factory and industry 4.0. 2018 IEEE International Conference on Big Data (Big Data), 2018, pp. 2930–2939.

15. Dustdar S. et al. Internet of Things, People, and Processes A Serverless Real-Time Data Analytics Platform for Edge Computing. 2017. [Online]. URL: http://aws.amazon.com/

16. Ananthanarayanan G. et al. Real-time video analytics: The killer app for edge computing," Computer (Long Beach Calif), vol. 50, no. 10, pp. 58–67, 2017.

17. Cao H., Wachowicz M., Cha S. Developing an edge computing platform for real-time descriptive analytics. 2017 IEEE International Conference on Big Data (Big Data), 2017, pp. 4546–4554.

18. Huang Y., Lu Y., Wang F., Fan X., Liu J., Leung V.C.M. An Edge Computing Framework for Real-Time Monitoring in Smart Grid. Proceedings – 2018 IEEE International Conference on Industrial Internet, ICII 2018, Nov. 2018, pp. 99–108. doi: 10.1109/ICII.2018.00019.

19. Shannigrahi S., Mastorakis S., Ortega F.R.Next-generation networking and edge computing for mixed reality real-time interactive systems. 2020 IEEE International Conference on Communications Workshops (ICC Workshops), 2020, pp. 1–6.

20. Yu S., Chen X., Wang S., Pu L., Wu D. An Edge Computing-Based Photo Crowdsourcing Framework for Real-Time 3D Reconstruction. IEEE Trans Mob Comput, vol. 21, no. 2, pp. 421–432, Feb. 2022, doi: 10.1109/TMC.2020.3007654.

21. Ullah I., Qian S., Deng Z., Lee J.-H. Extended Kalman filter-based localization algorithm by edge computing in wireless sensor networks. Digital Communications and Networks, vol. 7, no. 2, pp. 187–195, 2021.

22. Hong C.H., Varghese B. Resource management in fog/Edge computing: A survey on architectures, infrastructure, and algorithms. ACM Comput Surv, vol. 52, no. 5, Sep. 2019, doi: 10.1145/3326066.

23. Buyya R., Srirama S.N., Fog and edge computing: principles and paradigms. John Wiley & Sons, 2019.

24. Hassan N., Gillani S., Ahmed E., Yaqoob I., Imran M. The Role of Edge Computing in Internet of Things. IEEE Communications Magazine, vol. 56, no. 11, pp. 110–115, Nov. 2018, doi: 10.1109/MCOM.2018.1700906.

25. Shi W., Cao J., Zhang Q., Li Y., Xu L. Edge Computing: Vision and Challenges. IEEE Internet Things J, vol. 3, no. 5, pp. 637–646, Oct. 2016, doi: 10.1109/JIOT.2016.2579198.

26. Multi-Access Edge Computing in Action.

27. Al-Turjman F., Al-Turjman F., Edge computing. Springer, 2019.

28. Barbalace A., Karaoui M.L., Wang W., Xing T., Olivier P., Ravindran B. Edge computing: The case for heterogeneous-ISA container migration. VEE 2020 - Proceedings of the 16th ACM SIGPLAN/SIGOPS International Conference on Virtual Execution Environments, Mar. 2020, pp. 73–87. doi: 10.1145/3381052.3381321.

29. Aruna K., Pradeep G. Performance and Scalability Improvement Using IoT-Based Edge Computing Container Technologies. SN Comput Sci, vol. 1, no. 2, Mar. 2020, doi: 10.1007/s42979-020-0106-9.

30. Khan W.Z., Ahmed E., Hakak S., Yaqoob I., Ahmed A. Edge computing: A survey. Future Generation Computer Systems, vol. 97, pp. 219–235, 2019.

31. Spatharakis D. et al. A scalable Edge Computing architecture enabling smart offloading for Location Based Services. Pervasive Mob Comput, vol. 67, Sep. 2020, doi: 10.1016/j.pmcj.2020.101217.

32. Zhou Z., Chen X., Li E., Zeng L., Luo K., Zhang J. Edge Intelligence: Paving the Last Mile of Artificial Intelligence With Edge Computing. Proceedings of the IEEE, 2019, doi: 10.1109/JPROC.2019.2918951.

33. Wang X., Han Y., Leung V.C.M., Niyato D., Yan X., Chen X. Convergence of Edge Computing and Deep Learning: A Comprehensive Survey. IEEE Communications Surveys and Tutorials, vol. 22, no. 2. Institute of Electrical and Electronics Engineers Inc., pp. 869–904, Apr. 01, 2020. doi: 10.1109/COMST.2020.2970550.

34. Vance N., Tahmid Rashid M.D., Zhang D., Wang D. Towards reliability in online high-churn edge computing: A deviceless pipelining approach. Proceedings - 2019 IEEE International Conference on Smart Computing, SMARTCOMP 2019, Jun. 2019, pp. 301–308. doi: 10.1109/SMARTCOMP.2019.00066.

35. Peng Q., Jiang H., Chen M., Liang J., Xia Y. Reliability-aware and Deadline-constrained workflow scheduling in Mobile Edge Computing. 2019.

36. Rhee S., Seetharam D., Liu S. Techniques for minimizing power consumption in low data-rate wireless sensor networks. 2004 IEEE Wireless Communications and Networking Conference (IEEE Cat. No. 04TH8733), 2004, vol. 3, pp. 1727–1731.

37. Schurgers C., Aberthorne O., Srivastava M. Modulation scaling for energy aware communication systems. Proceedings of the 2001 international symposium on Low power electronics and design, 2001, pp. 96–99.

38. Mukhopadhyay S., Panigrahi D., Dey S. Data aware, low cost error correction for wireless sensor networks. 2004 IEEE Wireless Communications and Networking Conference (IEEE Cat. No. 04TH8733), 2004, vol. 4, pp. 2492–2497.

39. Pavlina J.M., Santos B., Kozlovski N., Malocha D.C. SAW wireless, passive sensor spread spectrum platforms. 2008 IEEE Ultrasonics Symposium, 2008, pp. 1112–1115.

40. Arora A. et al. Exscal: Elements of an extreme scale wireless sensor network. 11th IEEE International Conference on Embedded and Real-Time Computing Systems and Applications (RTCSA'05), 2005, pp. 102–108.

41. Falco N., Benediktsson J.A., L. Bruzzone Spectral and spatial classification of hyperspectral images based on ICA and reduced morphological attribute profiles. IEEE Transactions on Geoscience and Remote Sensing, vol. 53, no. 11, pp. 6223–6240, 2015.

42. Adão T. et al. Hyperspectral imaging: A review on UAV-based sensors, data processing and applications for agriculture and forestry. Remote Sens (Basel), vol. 9, no. 11, p. 1110, 2017.

43. Xu Z. et al. Noisy labels are treasure: mean-teacher-assisted confident learning for hepatic vessel segmentation. Medical Image Computing and Computer Assisted Intervention–MICCAI 2021: 24th International Conference, Strasbourg, France, September 27–October 1, 2021, Proceedings, Part I 24, 2021, pp. 3–13.

44. Ghamisi P., Yokoya N., Li J., Liao W., Liu S., Rasti B., Plaza A. Advances in hyperspectral image and signal processing: A comprehensive overview of the state of the art", IEEE Geoscience and Remote Sensing Magazine, vol. 5, no. 4, pp. 37–78, 2017.

45. Northcutt C., Jiang L., Chuang I. Confident learning: Estimating uncertainty in dataset labels", Journal of Artificial Intelligence Research, vol. 70, pp. 1373–1411, 2021.

46. Northcutt C.G., Wu T., Chuang I.L. Learning with confident examples: Rank pruning for robust classification with noisy labels. arXiv preprint arXiv:1705.01936, 2017.

47. Beirami B.A., Mokhtarzade M. Band grouping SuperPCA for feature extraction and extended morphological profile production from hyperspectral images. IEEE Geoscience and Remote Sensing Letters, vol. 17, no. 11, pp. 1953–1957, 2020.

48. Xia J., Bombrun L., Adalı T., Berthoumieu Y., Germain C. Spectral–spatial classification of hyperspectral images using ICA and edge-preserving filter via an ensemble strategy. IEEE Transactions on Geoscience and Remote Sensing, vol. 54, no. 8, pp. 4971–4982, 2016.

49. Imani M., Ghassemian H. Principal component discriminant analysis for feature extraction and classification of hyperspectral images. 2014 Iranian Conference on Intelligent Systems (ICIS), 2014, pp. 1–5.

50. Li W., Prasad S., Fowler J.E., Bruce L.M. Locality-preserving discriminant analysis in kernel-induced feature spaces for hyperspectral image classification. IEEE Geoscience and Remote Sensing Letters, vol. 8, no. 5, pp. 894–898, 2011.

51. Cao X., Yao J., Fu X., Bi H., Hong D. An enhanced 3-D discrete wavelet transform for hyperspectral image classification. IEEE Geoscience and Remote Sensing Letters, vol. 18, no. 6, pp. 1104–1108, 2020.

52. B.A. Beirami, M. Mokhtarzade Band grouping SuperPCA for feature extraction and extended morphological profile production from hyperspectral images. IEEE Geoscience and Remote Sensing Letters, vol. 17, no. 11, pp. 1953–1957, 2020.

53. Peng J., Chen H., Zhou Y., Li L. Ideal regularized composite kernel for hyperspectral image classification. IEEE J Sel Top Appl Earth Obs Remote Sens, vol. 10, no. 4, pp. 1563–1574, 2016.

54. Liu J., Wu Z., Li J., Plaza A., Yuan Y. Probabilistic-kernel collaborative representation for spatial–spectral hyperspectral image classification. IEEE Transactions on Geoscience and Remote Sensing, vol. 54, no. 4, pp. 2371–2384, 2015.

55. Li J., Marpu P.R., Plaza A., Bioucas-Dias J.M., Benediktsson J.A. Generalized composite kernel framework for hyperspectral image classification. IEEE transactions on geoscience and remote sensing, vol. 51, no. 9, pp. 4816–4829, 2013.

56. Paoletti M.E., Haut J.M., Plaza J., Plaza A. Deep learning classifiers for hyperspectral imaging: A review. ISPRS Journal of Photogrammetry and Remote Sensing, vol. 158, pp. 279–317, 2019.

57. Chowdhary C.L., Patel P.V., Kathrotia K.J., Attique M., Perumal K., Ijaz M.F. Analytical study of hybrid techniques for image encryption and decryption. Sensors, vol. 20, no. 18, p. 5162, 2020.

58. Jia S., Jiang S., Lin Z., Li N., Xu M., Yu S. A survey: Deep learning for hyperspectral image classification with few labeled samples. Neurocomputing, vol. 448, pp. 179–204, 2021.

59. Quan Y., Zhong X., Feng W., Chan J.C.-W., Li Q., Xing M. SMOTE-based weighted deep rotation forest for the imbalanced hyperspectral data classification. Remote Sens (Basel), vol. 13, no. 3, p. 464, 2021.

60. Hughes G. On the mean accuracy of statistical pattern recognizers. IEEE Trans Inf Theory, vol. 14, no. 1, pp. 55–63, 1968.

61. Paoletti M.E., J.M. Haut, J. Plaza, A. Plaza Deep learning classifiers for hyperspectral imaging: A review. ISPRS Journal of Photogrammetry and Remote Sensing, vol. 158, pp. 279–317, 2019.

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