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ENHANCED TECHNIQUE FOR LANDUSE CLASSIFICATION IN AGRICULTURE WITH SATELLITE DATA USING DEEP LEARNING

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ABSTRACT

This research explores the augmentation of agriculture land use classification leveraging satellite datasets and advanced deep learning methodologies. With the escalating demand for precise and timely information in the agricultural sector, the study aims to optimize the accuracy and efficiency of land use classification processes through the integration of cutting-edge technologies. The methodology involves the utilization of diverse satellite datasets, encompassing spectral, temporal, and spatial information. These datasets serve as the foundation for training deep learning models, enabling them to discern intricate patterns and variations in agricultural land use. The application of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) facilitates the extraction of nuanced features from the satellite imagery, enhancing the model's ability to discriminate between different land use categories. The research not only delves into the technical aspects of deep learning but also considers the practical implications for agricultural stakeholders. By refining land use classification models, this study contributes to optimizing resource allocation, crop monitoring, and overall decision-making processes in agriculture. Additionally, it explores the scalability and transferability of the developed models, providing insights into their adaptability across diverse geographical regions and varying agricultural practices. The outcomes of this research bear significance for precision agriculture, environmental monitoring, and sustainable land management. The integration of satellite datasets with sophisticated deep learning techniques offers a promising avenue for advancing agriculture land use classification, fostering informed and data-driven practices in the dynamic landscape of modern agriculture.

***Keywords**:- Agriculture, Land use classification, Satellite datasets, Precision agriculture, Environmental monitoring, Sustainable land management, Spectral information, Geospatial analysis , Data-driven practices.*

1. INTRODUCTION

The agricultural sector is currently in the midst of a profound transformation, compelled by the increasing demand for highly accurate and timely information to address the ever-growing challenges posed by the rapidly evolving global food demand. This shift is underscored by a crucial recognition of the need for precision in navigating the intricacies of the agricultural landscape. A pivotal aspect of this transformation lies in the strategic integration of cutting-edge technologies, notably deep learning, harmonized with the wealth of data provided by satellite datasets. This amalgamation not only signifies a technological leap but also holds the potential to revolutionize and optimize the intricate processes involved in agriculture land use classification. Delving into the realm of advanced machine learning techniques, this research is on a quest to explore the intricate synergies with high-resolution satellite imagery. The overarching objective is to elevate the accuracy and efficiency of land use classification in agriculture, positioning it as a key driver for informed decision-making in resource allocation, crop monitoring, and sustainable land management**[1].**

Accurate land use classification stands as a linchpin in the realm of informed decision-making, playing a pivotal role in resource allocation, crop monitoring, and the establishment of sustainable land management practices. The bedrock of agricultural decision-making relies heavily on the precision and timeliness of such classifications. However, traditional methods grapple with inherent limitations when it comes to capturing the nuanced variations that characterize agricultural landscapes. The advent of deep learning methodologies, spearheaded by the application of convolutional neural networks (CNNs) and recurrent neural networks (RNNs), introduces a transformative opportunity to surmount these limitations. These sophisticated algorithms provide the means to delve into the intricate complexities inherent in satellite imagery, enabling the unraveling of previously undecipherable patterns. This not only enhances the accuracy of land use classification but also opens new avenues for a more nuanced and comprehensive understanding of the dynamics shaping agricultural landscapes. The integration of CNNs and RNNs signifies a quantum leap in our capacity to extract meaningful insights from vast and intricate datasets, ultimately empowering decision-makers with unprecedented precision in navigating the challenges of modern agriculture.

This comprehensive study places a central emphasis on harnessing a wide array of satellite datasets that encapsulate crucial spectral, temporal, and spatial information. Through the adept application of advanced deep learning algorithms, these datasets transform into invaluable tools for discerning intricate features that serve as indicators for various land use categories. The convolutional layers within Convolutional Neural Networks (CNNs) demonstrate exceptional proficiency in capturing spatial dependencies within the satellite imagery, enabling a nuanced understanding of the complex interplay of features on the agricultural landscape. Simultaneously, Recurrent Neural Networks (RNNs) play a vital role by proving instrumental in modeling temporal aspects, enabling the study to adopt a holistic approach towards land use classification. This dual utilization of CNNs and RNNs not only enhances the accuracy of classifying different land use categories but also ensures a more nuanced and comprehensive analysis of the dynamic changes occurring in both spatial and temporal dimensions**[2].** The synergy between diverse satellite datasets and state-of-the-art deep learning methodologies thus forms the backbone of an innovative and robust approach to optimizing land use classification processes in agriculture.

Beyond the technical advancements, this research extends its scope to meticulously assess the practical implications for a wide array of agricultural stakeholders. The anticipated outcomes of the study hold the potential to not only refine precision agriculture practices but also to empower comprehensive environmental monitoring initiatives. Moreover, the research is poised to contribute significantly to the development of innovative and sustainable land management strategies that align with the evolving needs of the agricultural sector**[3].** Delving deeper into its objectives, the study places a strong emphasis on exploring the scalability and transferability of the developed models. This involves a comprehensive examination of their adaptability across diverse geographical regions and varying agricultural practices, providing invaluable insights that can inform and guide real-world decision-making processes. The holistic approach of this research positions it as a pivotal driver in bridging the gap between technical advancements and practical applications, contributing to a more resilient, efficient, and sustainable future for agriculture on a global scale.

As we venture into the realms where deep learning intersects with satellite data, the anticipated outcomes of this exploration carry the transformative potential to reshape our entire approach to perceiving, comprehending, and managing agricultural landscapes. This integration of cutting-edge technologies signifies more than a mere technical advancement; it embodies a profound and fundamental shift towards a paradigm of data-driven, informed practices within the dynamic and crucial sphere of modern agriculture. By leveraging the insights derived from advanced machine learning techniques and high-resolution satellite imagery, we are not only on the brink of revolutionizing traditional methodologies but also laying the groundwork for a new era characterized by unprecedented precision, efficiency, and sustainability in agricultural land use classification. This shift has the capacity to not only enhance the accuracy of decision-making processes in resource allocation and crop monitoring but also to foster more resilient and environmentally conscious land management strategies. In essence, the fusion of deep learning and satellite data transcends its role as a technological evolution; it emerges as a catalyst for a holistic redefinition of how we interact with and optimize the agricultural landscapes that are integral to our global food systems.

1.1. REMOTE SENSING IN AGRICULTURE

The integration of remotely sensed data into agricultural practices boasts a robust history that spans several decades. In the realm of agriculture, the implementation of suitable methodologies is imperative for accurate land cover classifications, considering the myriad phenological factors in play. Various crops showcase distinct planting and harvesting times, diverse leaf structures, and specific biophysical and biochemical characteristics. Additionally, factors such as soil moisture, organic matter content, and soil signatures contribute to the variability observed in remote sensing spectra**[4].** Agricultural remote sensing applications commonly leverage the measurement of reflected radiation from both soil and plant materials. Notably, plant pigments, such as chlorophyll, exhibit strong absorption of radiation in the visible spectrum, especially in the blue and red wavelengths, while the near-infrared experiences significant reflection due to leaf density and canopy structure.

The Normalized Difference Vegetation Index (NDVI) is a crucial metric that leverages the absorption features of pigments in the red (~660 nm) and the reflectance in the near-infrared (~860 nm) regions of the electromagnetic spectrum. This index serves as a valuable tool for gaining insights into vegetation biomass, allowing estimation of properties such as leaf mass, chlorophyll concentration, water content, and absorbed photosynthetic radiation. When analyzing reflectance data, it is essential to account for bare soils and their associated moisture and organic matter content, as these factors contribute to distinct spectral reflectance signatures**[5].** The presence of both bare soil and crop canopy in remotely sensed images often complicates the interpretation of reflectance data, as the mixture of these two different spectral signatures poses challenges in distinguishing and interpreting the information accurately.

2. LITERATURE SURVEY

A growing body of research is focused on advancing agriculture land use classification through the integration of satellite datasets and deep learning techniques. This literature survey provides a comprehensive overview of key studies in this domain, highlighting the methods employed, datasets utilized, overall accuracy achieved, and key insights gained**[6].**

Year	Reference	Method	Dataset	Overall Accuracy (OA)	Key Points	Parameters	Pros	Cons
2023	**[7]**	CAR tree, RF, GTB	Google Earth Engine, Sentinal-2	95%	Valuable for local decision makers	PA, UA, K	Useful for planning, monitoring, and evaluating agricultural activities	Challenges in obtaining multi-year sample points
2023	**[8]**	LULC	Landsat TM/OLI	Not specified	Highlighted importance of agricultural land conservation, water resource management, etc.	Not specified	Valuable insights for land management	Specific dataset and limitations not specified
2021	**[9]**	CART, RF, gmoMax Ent	Google Earth Engine, Landsat-8 OLI	90%	Integrated greenhouse identification	-	Efficient and accurate greenhouse monitoring	Improvement needed for cloud cover, data accuracy, and geophysical

								mechanisms
2022	**[10]**	UNetDL, ENVINet 5, RF	Sentinal-2	97.8%	U-Net-based DL performed well	RT, CT, NC, PA, UA, K	Effective in identifying land-use features	Potential for improvement with additional features
2023	**[11]**	LULC	Landsat-8 OLI/TRIS	89.6%	Effective for spatial and temporal measurements	PA, UA, Kappa Coefficient	Valuable for measuring spatial and temporal phenomena	Limited resolution for detailed investigations
2022	**[12]**	PCC-MLC, PCC-ANN	Sentinal-2, USGS	93.4%	ANN for seasonal changes in agriculture classification	RGB, HSV	Provides new perspectives for crop yield estimation	Not specified
2023	**[13]**	MMLA	NBR, USGS, Google Earth Pro	92.6%	LULC Classification	PA, UA, K	Accurate mapping of NBR's LULC classes	Data accuracy depends on equipment and environment; Challenges in detecting small-scale land-use changes
2022	**[14]**	SPLC, SVM	Sentinal-2, MSI	94%	Efficiently identifies fragmented land covers	PA, UA, OCA	Useful for mapping crop classification	Challenges in distinguishing natural lands with high soil salinity; Some narrow features not well identified
2021	**[15]**	LUCC, SVM Classification	USGS, OLI	90%	Detecting potential land-use changes	-	Insights for impact assessments and urban	Improved land-use classifications could be

							planning	facilitated
2017	**[16]**	KCRC, SPM, SVM	UC_MERCED dataset	85%	Excellent classification performance	PA, UA, K	Lower computational cost with higher accuracy	Potential for improved characterization of local and global features
2023	**[17]**	ANPC, SAMPC, KNNPC	Hyperion EO-1	92.6%	Potential applications in plant disease detection, crop monitoring, etc.	RT, CT, NC, PA, UA, K	Versatile use in different applications	Limited availability of free datasets; Suggests exploring larger-scale computational methods with DL techniques
2020	**[18]**	LULC, SIC	Landsat, USGS	90.36%	Identifying LULC changes in Tana basin	PA, UA, K	Supports sustainable land management planning	Specific limitations not specified
2016	**[19]**	SVM, MLR, RF, DTC	Landsat-7, EOD (Sentinal -1)	97%	Important variables in classification	PA, UA, K	Effective separation between grazing land and cropping	Challenges with gaps in image archive and data volume

Table 1 . Literature review

Various studies in the field of remote sensing up to the year 2023. Let's break down the table and its components:

1. **Year**: This column specifies the year in which the study was conducted or published.
2. **Reference**: The reference number or citation for each study, which can be used to locate the original source for further details.
3. **Method**: This column describes the methodology or technique used in the study for remote sensing and land use/land cover classification.
4. **Dataset**: It mentions the data sources and datasets used for the study. These datasets often include satellite imagery or remote sensing data.
5. **Overall Accuracy (OA)**: This is a percentage value that represents the overall accuracy of the classification achieved in the study. It measures how accurately the method categorized land use and land cover.
6. **Key Points**: A brief summary of the main findings or key takeaways from each study. This column provides a quick overview of what the research revealed.

7. **Parameters**: It lists specific parameters or settings used in the study, which are often critical in remote sensing analysis.
8. **Pros**: The advantages or positive aspects of the study's methodology or findings. This column highlights the strengths and benefits of each research approach.
9. **Cons**: The limitations or drawbacks of the study's methodology or findings. This column discusses challenges or areas where improvement is needed.

The table serves as a convenient reference to grasp the variety of methods and discoveries within the realm of remote sensing. Professionals and researchers in this domain can leverage this resource to acquire a nuanced understanding of the capabilities and constraints associated with various techniques, datasets, and approaches for classifying land use and land cover. This compilation proves invaluable for gaining insights into the latest developments in remote sensing research, offering a snapshot of the field's current state as of 2023.

LAND USE AND LAND COVER CLASSIFICATION

Land use and land cover classification form the bedrock of our understanding and effective management of the intricate landscapes, gaining heightened significance in the continually evolving realm of agriculture. This complex classification process involves the meticulous delineation and categorization of diverse land features, surpassing mere observation to provide profound insights into the current state of land use**[20].** Yet, its importance extends far beyond observational value, serving as a crucial foundation for informed decision-making across various sectors, with agriculture standing out as a primary beneficiary. Through systematic categorization and comprehension of different land use facets, stakeholders in agriculture can make judicious decisions concerning resource allocation, crop selection, and the implementation of sustainable land management practices. Essentially, land use and land cover classification emerge as indispensable tools, not only shedding light on the present landscape but also establishing a robust foundation for strategic decision-making that reverberates across the multifaceted realms of modern agriculture and beyond, influencing broader aspects of environmental management and planning[**21**].

1st Level	Primarily Vegetated Areas				Primarily Non-Vegetated Areas			
2nd level	Terrestrial Primarily Non-Vegetated Areas		Terrestrial Primarily Vegetated Areas		Aquatic or regularly Flooded Primarily Non-Vegetated Areas		Aquatic or regularly Flooded Primarily Vegetated Areas	
3rd level	Cultivated Aquatic or Regularly Flooded Areas	Natural and Semi-Natural Aquatic or Regularly Flooded Vegetation	Cultivated and managed Terrestrial Areas	Cultivated and managed Terrestrial Areas	Artificial Waterbodies, Snow and ice	Natural Waterboodies, Snow and ice	Artificial Surfaces and Associated Areas	Bare Areas
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Table **2.** The three upper level categories in the land cover classification system (LCCS) hierarchy.

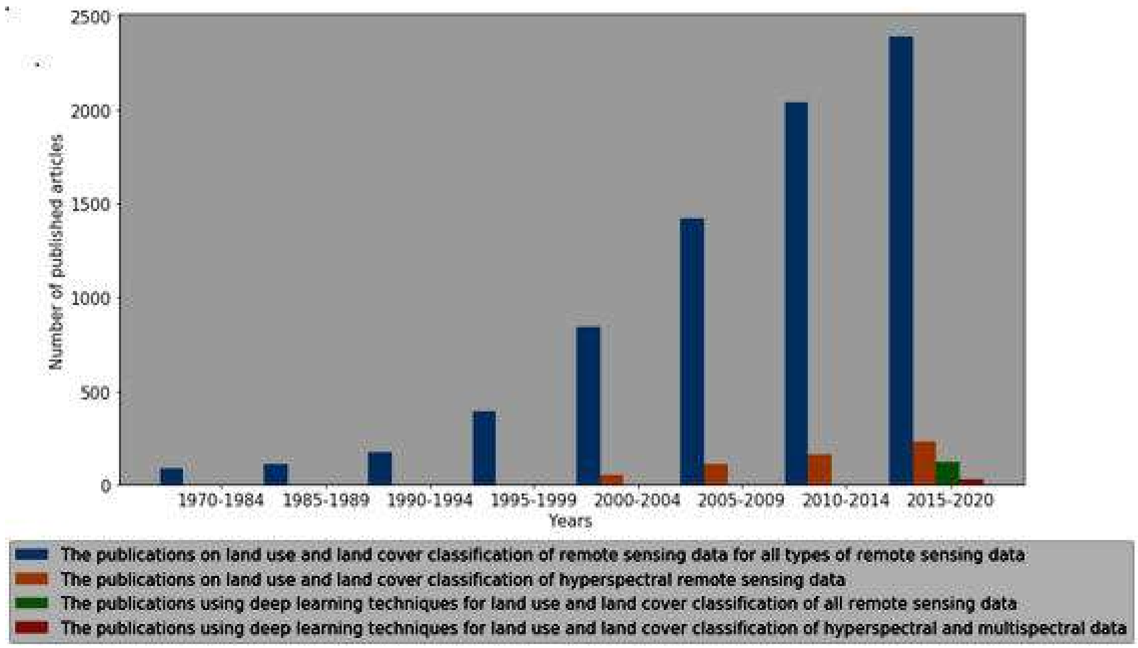

Figure **1.** The publication trends over LULC classification of remot sensing data. The graph shows consistent increase in the number of public actions. The graph also shows the portion of publications dedicated to hyper spectral images classification and the use of deep learning techniques (data were retrieved in May 2020).

3.1. Land Use vs. Land Cover

Land use encompasses the diverse array of human activities that shape and utilize a given piece of land for different purposes. This involves the allocation of land for residential, commercial, agricultural, industrial, recreational, or conservation activities. By classifying land use, we gain valuable insights into the intricate ways in which human actions impact the environment. This exploration of land use is crucial for urban planning, effective resource management, and the formulation of informed strategies for sustainable development. It provides a framework for understanding the dynamic interaction between society and the land, emphasizing the need to balance development goals with environmental considerations.

Land Cover: In contrast to land use, which emphasizes human activities on the land, land cover directs attention to the physical attributes and natural features of the Earth's surface. It encompasses the classification and depiction of vegetation types, water bodies, bare soil, constructed structures, and other elements that constitute the land's appearance. The categorization of land cover plays a crucial role in evaluating the ecological well-being of an area, tracking variations in vegetation, and investigating the repercussions of natural phenomena or human interventions on the environment. Unlike land use, land cover is concerned with the inherent physical characteristics of the surface, irrespective of the specific human activities occurring in the area**[22].**

3.2. Role of Satellite Data

Satellite data stands as a transformative force in modern environmental analysis, providing a panoramic view of the Earth's surface and revolutionizing our capacity to understand, monitor, and manage the environment. This section elucidates the pivotal role of satellite data, unveiling its multifaceted contributions to environmental sciences, resource management, climate studies, and beyond.

1. **Earth Observation at Scale:** Satellite data serves as the vantage point from which we observe our planet on a global scale. Orbiting satellites capture high-resolution imagery, offering a comprehensive and real-time perspective on various environmental features, including land cover, vegetation, water bodies, and atmospheric conditions.

2. **Monitoring Land Use and Land Cover Changes:** Satellite data plays a crucial role in monitoring and analyzing changes in land use and land cover. The continuous stream of imagery provided by satellites allows for the timely detection of variations in urban expansion, deforestation, agricultural practices, and other dynamic land-use patterns. This information is invaluable for making informed decisions regarding sustainable land management. The ability to observe and track these changes over time enhances our understanding of environmental trends, supporting efforts to address challenges such as urbanization, biodiversity loss, and the impact of human activities on the landscape.
3. **Precision Agriculture and Crop Monitoring:** In agriculture, satellite data plays a pivotal role in precision farming and crop monitoring. High-resolution imagery aids in assessing crop health, identifying areas of stress, optimizing irrigation, and predicting yields. This data-driven approach enhances agricultural productivity and resource efficiency**[23].**
4. **Climate Studies and Environmental Monitoring:** Satellite data plays a crucial role in advancing climate studies and environmental monitoring. It offers vital insights into temperature fluctuations, sea surface temperatures, concentrations of greenhouse gases, and the rate of deforestation. This wealth of information not only fuels climate modeling but also enables the development of early warning systems for natural disasters. Additionally, satellite data guides the formulation of effective strategies for both mitigating and adapting to climate change.
5. **Biodiversity and Ecosystem Health:** Satellite data assists in monitoring biodiversity and ecosystem health. By capturing information on vegetation types, habitat changes, and land surface temperatures, satellites contribute to the assessment of ecological conditions. This aids conservation efforts, biodiversity mapping, and the preservation of critical ecosystems.
6. **Disaster Response and Management:** In times of natural disasters, satellite data emerges as a crucial tool for rapid response and management. From assessing the extent of damage caused by hurricanes, earthquakes, or floods to guiding rescue operations, satellite imagery facilitates timely and informed decision-making in disaster-stricken regions.
7. **Remote Sensing Technologies:** The incorporation of remote sensing technologies, including multispectral and hyperspectral imaging, significantly amplifies the potential of satellite data. By extending the range beyond the visible spectrum, these advanced technologies facilitate the acquisition of comprehensive information for in-depth analyses of various aspects such as vegetation health, mineral composition, and other environmental parameters[24].

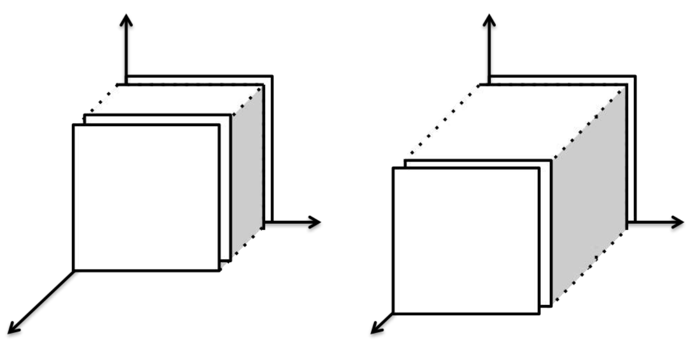

Figure **2** :- A representation of multispectral and hyperspectral images within the spatial-spectral domain.

A representation of multispectral and hyperspectral images within the spatial-spectral domain.

8. **Global Connectivity and Accessibility:** Satellite data's global coverage ensures connectivity to even the most remote regions. This accessibility proves invaluable for monitoring environmental changes in diverse landscapes, contributing to a more comprehensive understanding of Earth's interconnected systems.
9. **Future Frontiers:** As technology advances, the role of satellite data is poised to expand further. Innovations such as small satellite constellations, advanced sensors, and artificial intelligence-driven analysis promise to unlock new frontiers in environmental research, providing richer insights into the complex dynamics of our planet.

3.3. Deep Learning in Classification

Deep learning, a revolutionary subset of machine learning, has become a transformative paradigm in various classification tasks, demonstrating unparalleled capabilities in recognizing intricate patterns and achieving remarkable accuracy across diverse domains. Fundamentally grounded in artificial neural networks with multiple layers, known as deep neural networks, it draws inspiration from the intricate structure of the human brain. These networks, comprising input, hidden, and output layers, enable the extraction of hierarchical features from input data. Deep learning excels in feature learning, autonomously identifying relevant features through both forward and backward propagation, facilitating nuanced discrimination between different classes[25]. Specialized architectures like Convolutional Neural Networks (CNNs) are employed for image classification, utilizing convolutional layers to capture spatial hierarchies and detect patterns. Recurrent Neural Networks (RNNs), proficient in handling sequential data, enhance tasks such as natural language processing and time series analysis by retaining memory of past inputs. Transfer learning and model pre-training optimize performance by leveraging knowledge from one domain to enhance another, particularly when labeled data is scarce[26]. Unsupervised learning tasks, such as clustering, utilize techniques like autoencoders to discover underlying structures and patterns without explicit labels. Despite its successes, deep learning faces challenges such as overfitting, interpretability issues, and the demand for substantial labeled data. Ongoing research addresses these challenges through techniques like regularization, adversarial training, and transfer learning to enhance model robustness. Deep learning's impact spans industries, with applications in healthcare, finance, autonomous vehicles, cybersecurity, and more, highlighting its versatility and transformative potential. However, as deep learning systems become more prevalent, ethical considerations and responsible AI practices are crucial. Transparency, fairness, and accountability in the development and deployment of deep learning models are essential for building trust and mitigating potential biases. In conclusion, deep learning remains a formidable force, reshaping the landscape of artificial intelligence and holding far-reaching implications for the future of intelligent systems[27].

3.4. Applications in Agriculture

In the rapidly evolving realm of agriculture, technological advancements have ushered in a new era of innovation and efficiency. This comprehensive exploration delves into diverse applications of technology in agriculture, revealing how cutting-edge tools and methodologies are transforming traditional farming practices and contributing to sustainable agricultural development. Precision agriculture, utilizing satellite imagery, GPS technology, and sensors, allows farmers to tailor inputs precisely, optimizing resource efficiency and maximizing yields. Satellite-based remote sensing plays a pivotal role in monitoring crop health and growth patterns, enabling timely intervention to minimize potential crop losses. The integration of automated machinery and robotics streamlines various tasks, reducing labor costs and environmental impact. Technology supports climate-resilient agriculture through weather forecasting, climate modeling, and predictive analytics. Farm management software consolidates data, facilitating data-driven decisions on crop planning and pest control. The Internet of Things (IoT) in agriculture connects devices for real-time data collection, while digital mapping and GIS technologies offer spatial analysis tools. Biotechnology and genomic tools contribute to crop improvement, and block chain ensures supply chain transparency. The thriving ecosystem of AgTech startups and innovation hubs continuously advances agricultural technology, ranging from smart sensors to machine learning algorithms, shaping a more sustainable and technologically-driven future for agriculture**[28].**

4. PROBLEM FORMULATION

The primary objective of this research is to advance the development of a robust and highly precise classification model tailored specifically for categorizing agricultural land use into discrete segments using remote sensing data. These segments should comprehensively cover diverse crop types, various stages of land preparation, and an array of land cover types found within agricultural regions. To achieve this, the study aims to integrate state-of-the-art deep learning techniques, such as Convolutional Neural Networks (CNNs) and Transformer models, with a focus on optimizing the classification accuracy and capturing intricate patterns within the remote sensing imagery. The research will explore the utilization of multi-temporal datasets, including high-resolution satellite images, to enhance the temporal dimension of land use classification. Furthermore, an emphasis will be placed on addressing challenges related to class imbalance and small-scale land-use changes, contributing to the robustness and adaptability of the model in dynamic agricultural landscapes. The proposed model aims not only to excel in accurately classifying major crop types but also to provide detailed insights into specific growth stages, allowing for a more nuanced understanding of agricultural practices. The outcomes of this research are anticipated to significantly contribute to precision agriculture, resource allocation, and sustainable land management practices by providing reliable and detailed information about the agricultural landscape**[29].**

To achieve this ambitious goal, the research will leverage an extensive and diverse remote sensing dataset that includes ground truth labels for multiple agricultural land use categories, along with high-resolution multispectral and hyper spectral imagery. Ensuring the model's effectiveness in generalization, this dataset will be meticulously curated to span a diverse range of geographic regions, taking into account seasonal variations, soil characteristics, and climatic conditions. The inclusion of such comprehensive and nuanced information in the dataset will enhance the model's ability to capture the intricacies of agricultural land use patterns. Furthermore, the research will integrate cutting-edge data augmentation techniques to artificially expand the dataset, introducing variations in lighting conditions, perspectives, and atmospheric effects. This augmentation approach aims to improve the model's robustness by exposing it to a broader spectrum of possible real-world scenarios. Additionally, the research will incorporate temporal aspects by considering multi-temporal satellite imagery, enabling the model to grasp dynamic changes in land use over different seasons. By adopting a holistic approach that embraces both spatial and temporal dimensions, the study aspires to push the boundaries of accuracy and applicability in agriculture land use classification using deep learning techniques**[30].**

The refined problem formulation not only emphasizes the intricacies involved in agricultural land use but also highlights the critical importance of developing a classification model that possesses the capability to accurately differentiate and categorize these complexities. In addressing this challenge, the research aims to delve into the nuances of agricultural landscapes, acknowledging the multifaceted factors that influence land use patterns. By leveraging advanced deep learning methodologies, the study seeks to create a model that not only advances the understanding of agricultural landscapes but also holds significant implications for practical applications, contributing to informed decision-making in agriculture and related fields**[31].**

The model's training is grounded in a diverse and comprehensive dataset, surpassing the sole focus on accuracy and highlighting the significance of diversity to guarantee its versatility in diverse agricultural settings. By integrating an extensive array of agricultural scenarios, crop varieties, and environmental factors, the objective is to bolster the model's resilience and ability to generalize. This strategy not only validates the model's effectiveness across a spectrum of contexts but also equips it to offer insightful perspectives into the dynamic landscape of land use patterns across varied regions.

The research anticipates the advanced classification model to serve as more than just a conventional tool, aspiring to catalyze innovation in precision agriculture, sustainable land management, and environmental monitoring. Emphasizing practical applicability underscores the model's wider influence, aligning with the changing requirements of the agricultural sector. The ultimate goal of the research is to enhance our understanding of agricultural land use, promoting progress in technology-driven practices and encouraging sustainable approaches to land management.

5. EXPERIMENT AND ANALYSIS

5.1. Experimental Environment

Creating a conducive and meticulously designed experimental environment is pivotal for extracting precise insights from remote sensing technologies in agriculture. This section delves into the intricacies of the experimental setup, outlining the physical and technological parameters that define the environment. From satellite orbits to ground-based sensor networks, the design of the experimental environment plays a central role in the success of agricultural investigations**[32].**

a. Satellite Orbits and Coverage: The choice of satellite orbits is a critical aspect of the experimental environment. Geostationary and polar orbits offer distinct advantages, influencing revisit times, spatial resolution, and the ability to capture dynamic changes in agricultural landscapes. The experiment meticulously selects satellites based on these parameters to ensure comprehensive coverage and timely acquisition of imagery.

b. Drone Surveys and Flexibility: Incorporating drone surveys introduces a layer of flexibility and precision to the experimental environment. Drones, equipped with multispectral and high-resolution cameras, navigate the agricultural landscape, capturing detailed imagery with a level of granularity unmatched by satellites. This flexibility allows researchers to target specific regions of interest and obtain localized data.

c. Ground-Based Sensor Networks: Ground-based sensor networks contribute real-time data on crucial agricultural parameters. Soil moisture sensors, weather stations, and spectroradiometers form a network that complements satellite and drone data. This holistic approach enhances the depth and accuracy of the experimental environment, providing insights into the immediate conditions impacting crop health**[33].**

d. Weather and Climate Monitoring: An integral component of the experimental environment is the monitoring of weather and climate conditions. Real-time weather data, including temperature, humidity, and precipitation, influences the interpretation of remote sensing imagery. Climatic variations are considered in the analysis, contributing to a nuanced understanding of crop responses to changing environmental factors.

e. GIS Integration for Spatial Analysis: Geographic Information System (GIS) integration forms the spatial backbone of the experimental environment. GIS enables the creation of detailed maps, spatial overlays, and analyses of terrain variations. This spatial dimension enhances the accuracy of resource allocation, precision farming practices, and the identification of specific zones for targeted interventions.

f. Controlled Experiments and Field Trials: In certain scenarios, controlled experiments and field trials are conducted to isolate variables and validate remote sensing findings. Experimental plots within agricultural fields are subjected to controlled interventions, allowing for a direct comparison between the remote sensing-derived insights and ground truth data.

g. Data Storage and Processing Infrastructure: The experimental environment requires a robust data storage and processing infrastructure. High-performance computing clusters and cloud-based solutions are employed for the efficient storage and analysis of large datasets generated by remote sensing technologies. This infrastructure ensures timely processing and interpretation of the wealth of information collected.

h. Calibration and Validation Protocols: Calibration and validation protocols are established to maintain the accuracy of remote sensing data. Radiometric and geometric calibration procedures are applied to satellite and drone imagery, and ground truth data is systematically collected for validation purposes. These protocols ensure that the experimental environment maintains a high level of data integrity.

The experimental environment is not merely a backdrop but a dynamic and interconnected system that shapes the success of agricultural investigations. By carefully orchestrating satellite orbits, integrating drone surveys, deploying ground-based sensor networks, and leveraging GIS capabilities, researchers create a comprehensive ecosystem. This environment serves as the canvas upon which the intricate patterns of agricultural dynamics are painted, guiding the way toward a more sustainable and informed future in agriculture**[34].**

Land Classification Result Map

The Land Classification Result Map stands as a visual testament to the transformative power of remote sensing technologies in deciphering the intricate tapestry of agricultural landscapes. This section explores the significance of the Land Classification Result Map, its creation process, and the wealth of information it provides to stakeholders, ranging from farmers to policymakers.

1. Mapping Agricultural Diversity: The Land Classification Result Map serves as a dynamic canvas that vividly portrays the diversity within agricultural landscapes. Through the integration of remote sensing data, the map categorizes land into distinct classes, capturing variations in land cover, land use, and cropping patterns. This visual representation becomes a cornerstone for understanding the spatial complexity of agriculture.

6. Remote Sensing Technologies at Play: The creation of the Land Classification Result Map hinges on the capabilities of advanced remote sensing technologies. Multispectral and hyper spectral imagery, captured by satellites and drones, unveil the spectral signatures of different land features. Machine learning algorithms, employed in the data analysis phase, categorize these features into classes, contributing to the creation of a nuanced and accurate map.

7. Precision Agriculture Insights: For farmers engaged in precision agriculture, the Land Classification Result Map becomes an invaluable tool. It delineates zones within fields based on specific land characteristics, allowing farmers to tailor interventions such as irrigation, fertilization, and pest control. By aligning farming practices with the map's insights, farmers optimize resource use and enhance overall efficiency.

8. Environmental Monitoring and Conservation: Beyond precision agriculture, the map contributes to environmental monitoring and conservation efforts. It highlights areas of natural vegetation, water bodies, and potential conservation zones. Policymakers and environmentalists leverage this information to assess the ecological health of agricultural regions, identify areas for conservation, and formulate strategies for sustainable land management**[35].**

9. Integration with Geographic Information Systems (GIS): The Land Classification Result Map seamlessly integrates with Geographic Information Systems (GIS), unlocking additional layers of spatial analysis. GIS tools enable overlays with topographic maps, soil information, and climatic data, providing a holistic understanding of the factors influencing land classification. This integration enhances the map's utility for decision-makers in agriculture and land management.

10. Monitoring Changes Over Time: As a dynamic tool, the Land Classification Result Map is not static. It serves as a time capsule, allowing stakeholders to monitor changes in land cover and land use over different seasons and years. This temporal dimension aids in tracking the impact of agricultural practices, climate variations, and land management strategies over time.

11. Communication and Decision Support: The map serves as a powerful communication tool, translating complex data into accessible visuals. Stakeholders across diverse domains, including farmers, researchers, and policymakers, find common ground through the map. Decision-making processes are informed by the clarity and precision offered by the Land Classification Result Map.

The Land Classification Result Map transcends its role as a visual representation. It becomes a cornerstone for informed decision-making, sustainable land management, and the harmonious integration of technology into agriculture. As it continues to evolve with advancements in remote sensing technologies, the map stands as a beacon, guiding the way toward a future where agriculture is not just productive but also ecologically mindful and socially inclusive.

7. METHODOLOGY

7.1. Preprocessing of the Input Data

The preprocessing of Sentinel-2 data is a crucial step, strategically employed to overcome atmospheric and radiometric errors inherent in the raw imagery. To address these challenges, the Sen2Cor v2.9 module has been specifically designed for Sentinel-2 Level 2A data and is compatible with the Sentinel application platform (SNAP) version. This module not only conducts precise atmospheric and radiometric corrections but also effectively mitigates variations in sun angles, daytime haze effects, and smaller haze effects, thereby enhancing the overall quality of the data. It is important to note, however, that Sen2Cor does not eliminate clouds. To ensure the accuracy and reliability of subsequent analyses, it is highly recommended to use cloud-free images when processing Sentinel-2 data with Sen2Cor[36].

After completing the crucial preprocessing steps, the enhanced Sentinel-2 dataset is optimally prepared for the implementation of state-of-the-art techniques, such as deep learning and machine learning. These advanced methodologies can then be employed to produce classified maps, providing invaluable information about land cover and usage patterns. The seamless integration of preprocessing techniques with sophisticated learning algorithms not only enhances the precision of classification but also unleashes the complete potential of Sentinel-2 data across various applications. These applications encompass environmental monitoring, land management, and agricultural assessments, underscoring the enhanced data's versatility and significance in facilitating well-informed decision-making and comprehensive analyses within these domains.

7.2. Data Pre-Processing

The Sentinel-2 L2A satellite images undergo atmospheric correction, requiring minimal pre-processing. Comprising 13 bands with resolutions spanning from 10m to 60m, these images are refined by selecting the optimal three bands using the Optimum Index Factor (OIF) statistic value. The Bands B4, B3, and B2 are chosen for further processing based on the highest OIF value, ensuring the selection of key spectral information for subsequent analyses.

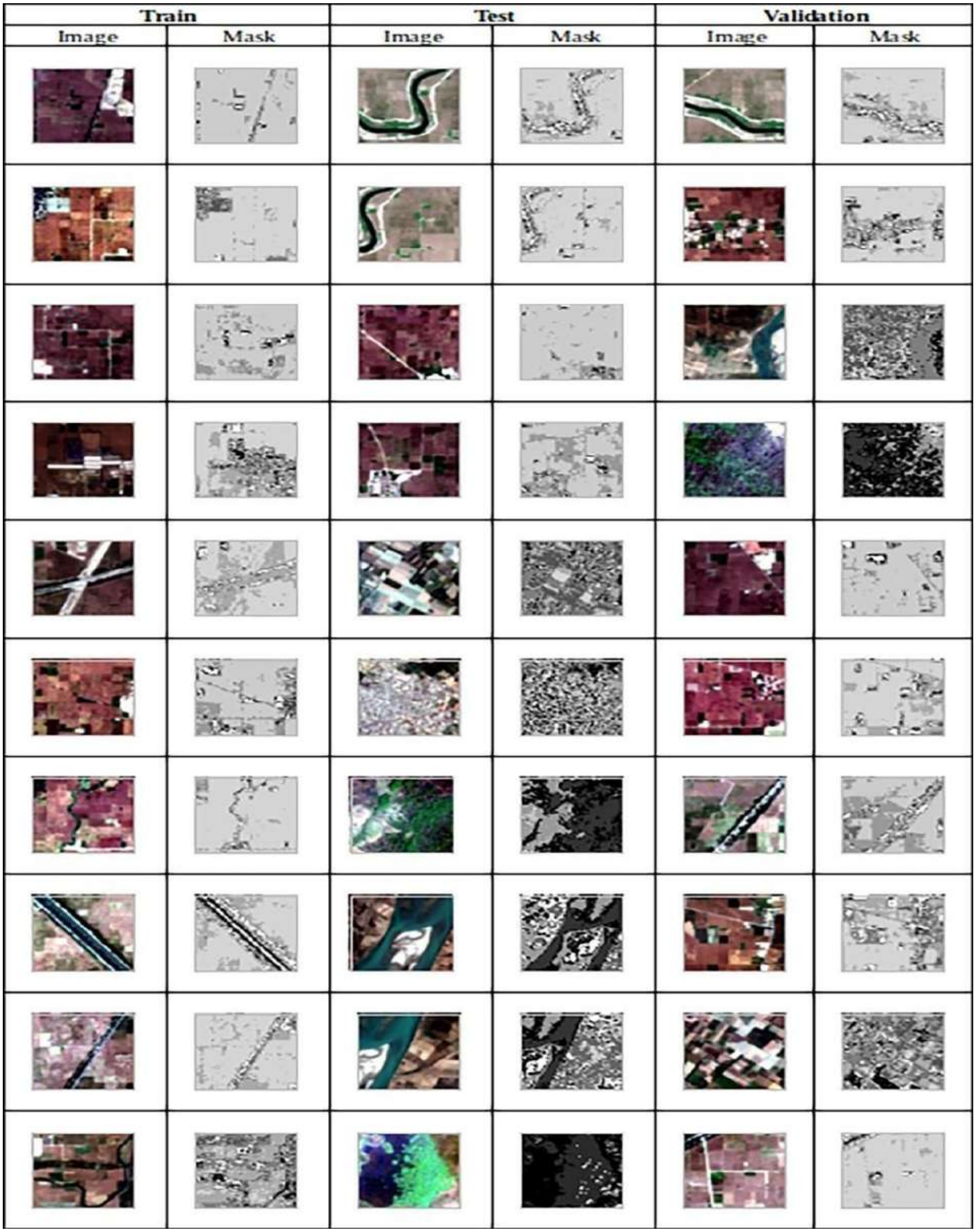

Fig.**3.** Sentinel-2 imagery on the left is paired with corresponding generated masks on the right, organized within the Training, Testing, and Validation folders.

The selected Sentinel-2 bands undergo various pre-processing techniques utilizing the Geospatial Data Abstraction Library (GDAL), an open-source Python library designed for managing geospatial data in both vector and raster formats. The pre-processing steps encompass tasks such as mosaic creation, layer stacking, and clipping to enhance the quality and usability of the data.

Class Label	Class denotation	Description
0	Water Bodies	Water from streams, rivers, lakes and reservoirs
1	Agriculture land	Area where crops are cultivated or planted vegetation.
2	Barren land	Land where crops or plants can not be cultivated due to infertility of the soil.
3	Dense Forest	Area where tree cover canopy density is in between 40 and 70 %
4	Unclassified	Pixel that is not classified is assigned unclassified name and zero label.
5	Fallow land	Land under agricultural cultivation but currently kept unclutivated
6	Sparse Forest	Area where tree cover canopy density is in between 10 and 40 %
7	Built up	Artificial / concrete surface

Table3. LULC classes denotation

1. **Mosaic king:** Individual tiles are merged for every single band, ensuring a seamless combination of data from multiple sources.
2. **Layer-stacking:** The bands are combined by stacking them on top of each other, creating a single satellite image with multiple bands. This process enhances the information available in the image.
3. **Clipping:** The final satellite image is cropped to generate the required study area. This step ensures that the image focuses on the specific region of interest, eliminating unnecessary data outside the study area.

The workflow involves selecting optimal bands based on the OIF statistic, using GDAL for various pre-processing tasks such as mosaic king and layer-stacking, and finally, clipping the satellite image to produce a refined image for the designated study area.

7.3. Patches Generation

To address the challenges posed by large dimensions of selected tiles and corresponding labeled masks, a process of creating smaller patches from the entire dataset was initiated. Initially, patches of size 256 × 256 were generated; however, this approach proved insufficient as the dataset remained small and the patches were non-overlapping, resulting in suboptimal model performance. To enhance diversity and increase the dataset size for training Convolutional Neural Networks (CNNs), the decision was made to generate smaller patches of size 64 × 64.

The generation of these compact patches was streamlined through the utilization of the Rasterio 19 and GDAL Python libraries. Geospatial data boundaries, crucial for delineating the satellite image limits, were acquired with the assistance of the Rasterio library. Following this, the GDAL translate function was employed to systematically navigate the satellite images both horizontally and vertically. This process resulted in the creation of individual patches, each measuring 64 × 64 pixels, based on the identified spatial extents. A total of 213,761 patches were generated, with 70% designated for training purposes, while the remaining 30% was evenly split between validation and testing sets.

The workflow diagram in Fig. 4 illustrates the step-by-step process of creating the dataset. This comprehensive approach ensures that the dataset is appropriately sized, diverse, and suitable for training CNNs, addressing the challenges posed by the original large dimensions of the selected tiles and masks.

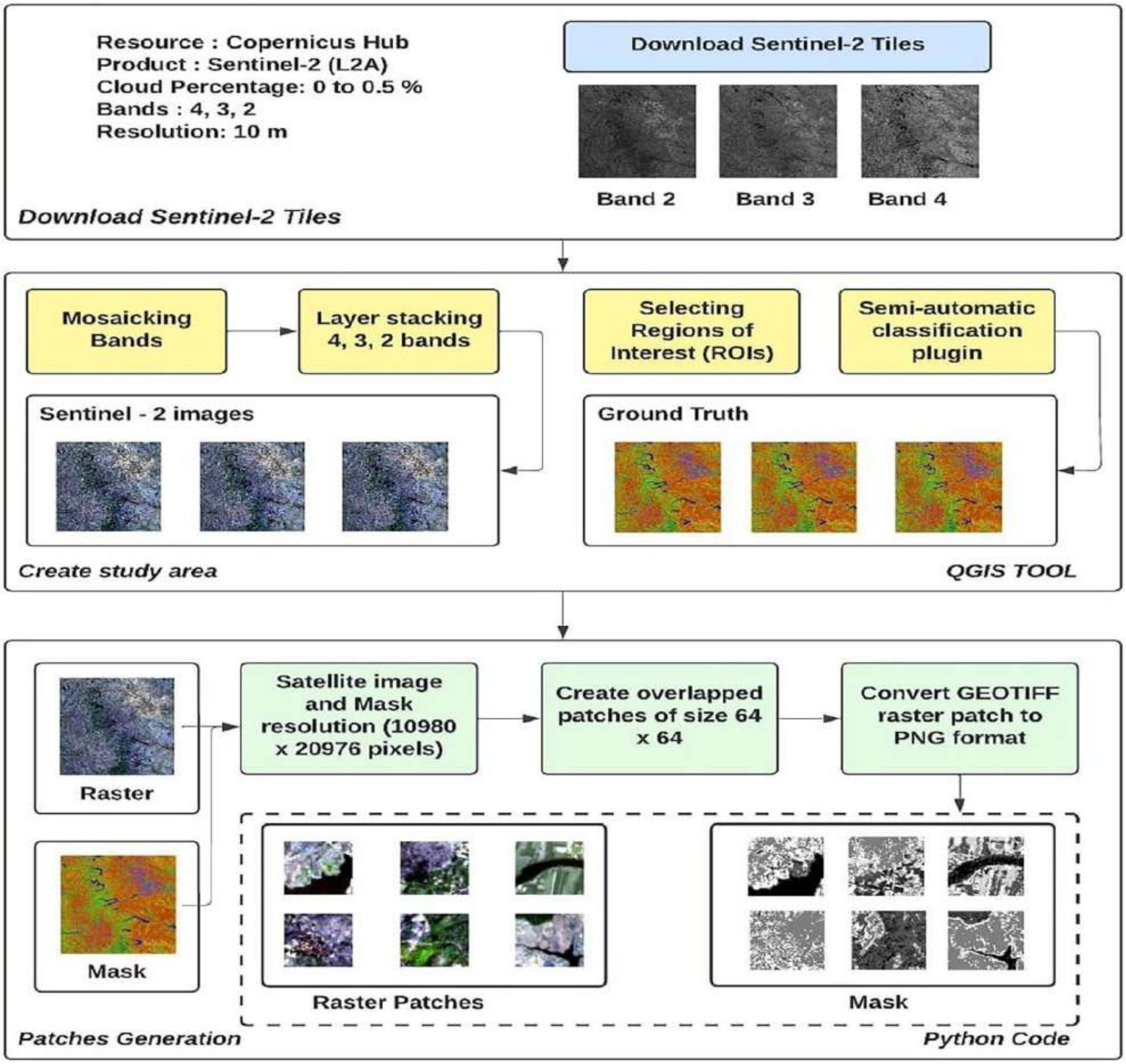

Fig.**4.** Data set generations teps.

The proposed dataset is subjected to thorough evaluation using three Deep Learning models, each with unique backbones. The primary model utilized is based on the Unet architecture, augmented by ResNet50, ResNet101, and ResNet152 as additional backbones. The results of these evaluations are detailed in Tables 4–5. The models undergo training over 100 epochs, employing a learning rate of 0.01. All computations are executed on an Nvidia DGX-1 Workstation, featuring a 32GB Graphics Processing Unit for enhanced processing capabilities.

The findings indicate that the majority of classes demonstrate satisfactory performance, underscoring the dataset's reliability and practicality. Nevertheless, challenges emerge when differentiating between dense and sparse forests, leading to interpretational complexities. This difficulty can be traced back to the inherent intricacies within these two specific classes, as highlighted by the results presented. Overcoming this challenge requires acquiring supplementary ground truth information to accurately delineate class definitions and improve discrimination along class boundaries.

Owing to the close structural resemblance and subtle distinctions between dense and sparse forest categories, the model faces challenges in achieving precise interpretation. A proposed solution involves integrating supplementary ground truth data and considering the introduction of additional indices to strengthen the structural constraints within the classification strategy. Detailed outcomes for each model are presented in Table 6, offering a thorough and comprehensive assessment of their respective performances.

	Sparse Forest	Water	Fallow Land	Built up	Barren land	Dense Forest	Agricultur e Land
Recall	0.63	0.46	0.65	0.81	0.73	0.51	0.96
F1- Score	0.69	0.5	0.7	0.83	0.73	0.56	0.91
MCC	0.67	0.5	0.68	0.76	0.7	0.55	0.85
Precision	0.75	0.56	0.74	0.85	0.74	0.61	0.87
Over all Accuraccy	0.96	0.98	0.97	0.9	0.94	0.99	0.92

Table 4. Results of proposed dataset on UNet-ResNet50.

	Built up	Fallow Land	Water	Barren land	Dense Forest	Agricultur e Land	Sparse Forest
Over all Accuraccy	0.89	0.96	0.98	0.93	0.99	0.92	0.96
MCC	0.73	0.57	0.52	0.66	0.52	0.83	0.65
Precision	0.84	0.63	0.54	0.69	0.50	0.87	0.73
Recall	0.79	0.56	0.52	0.70	0.56	0.94	0.61
F1- Score	0.81	0.59	0.53	0.70	0.53	0.90	0.67

Table 5. Results of proposed dataset on UNet-ResNet101.

	Fallow Land	Water	Built up	Sparse Forest	Barren land	Agricultur e Land	Dense Forest
Over all Accuraccy	0.97	0.98	0.88	0.95	0.94	0.92	0.99
MCC	0.70	0.48	0.72	0.62	0.68	0.84	0.62
Recall	0.67	0.46	0.81	0.56	0.74	0.93	0.57
Precision	0.77	0.51	0.79	0.73	0.70	0.90	0.69
F1- Score	0.72	0.49	0.80	0.64	0.72	0.92	0.62

Table 6. Results of proposed dataset on UNet-ResNet152.

	UNet-ResNet152	UNet-ResNet50	UNet-ResNet101
F1- Score	0.70	0.70	0.68
MCC	0.67	0.67	0.64
Precision	0.73	0.73	0.69
Recall	0.68	0.68	0.67
Overall Accuraccy	0.95	0.95	0.95

Table 7. Results of proposed dataset on deep learning models.

7.4. Deep Learning and Machine Learning

Deep learning, a pivotal component of machine learning, relies on neural networks to understand and identify patterns within data. It involves three main paradigms: supervised, unsupervised, and transfer learning. In supervised learning, the model learns to associate input data with predefined labels, while unsupervised learning discovers patterns and relationships within the data itself. Transfer learning enhances efficiency by leveraging knowledge gained from one task to improve performance on another, fostering a more generalized understanding.

The effectiveness of object-level detection in deep learning models often depends on the network's depth, as illustrated by architectures like Convolutional Neural Networks (CNN) and Graph Neural Networks (GNN). The U-Net, an advancement from CNN, has found diverse applications ranging from glacier research and biomedical imaging to sea-ice mapping, land boundaries, and big data remote sensing[**37**].

In this research, we leverage the U-Net architecture as a supervised semantic segmentation network to delineate agricultural land use types. The application of U-Net is carried out using deep learning techniques within the ENVI software version 5.6. This involves employing an encoder-decoder framework with a mask-based architecture to categorize satellite data into distinct land use types. The implementation incorporates Tensor Flow, an open-source software library that plays a crucial role in facilitating the deep learning process, offering advantages such as flexibility, portability, and performance optimization. The U-Net architecture is composed of downscaled components, enhancing resilience against imagery distortion, and upscaled components, aimed at restoring and decoding object features in the land use classification process.

Within the ENVI deep learning model, users can choose between two options: ENVINet5 for single-class classification and ENVI Net-Multi for categorizing multiple classes. The Tensor Flow model undergoes training with diverse samples from each class category, such as wheat, berseem, mustard, other vegetation, water, and buildup. Throughout the training process, the Tensor Flow model transforms spatial and spectral information from input imagery into a class activation or thematic map. After training, the model produces georeferenced activation and classified maps. These activation maps, depicting fractional information for each class, play a crucial role in refining the classified maps using either manual or automatic threshold methods. Additionally, for comparative analysis, a machine learning-based RF classifier is incorporated. This classifier utilizes a random decision forest approach, constructing multiple decision trees during training to classify datasets effectively.

8. RESULTS AND DISCUSSION

The Results and Discussion section serves as the culmination of the study's rigorous methodologies, data analyses, and experimentation, transforming theoretical groundwork into tangible insights for a comprehensive understanding of the agricultural landscape through remote sensing technologies. Here, key findings are presented, their implications unravelled, and a nuanced discussion ensues, advancing our comprehension of agriculture in the digital era. This section not only demonstrates the effectiveness of employed methodologies but also provides actionable intelligence for stakeholders, researchers, and policymakers in precision agriculture, sustainable land management, and environmental monitoring. Beyond interpretation, the discussion delves into practical implications, addressing challenges, proposing avenues for further research, and contemplating the integration of emerging technologies to enhance the efficacy of remote sensing in agriculture. In essence, the Results and Discussion section becomes a nexus where scientific rigor converges with real-world applications, breathing life into data points and contributing to both academic understanding and practical endeavors in shaping the future of agricultural landscapes in the digital age.

1. Land Classification Result Map: The centerpiece of the results is the Land Classification Result Map, a visual representation of the intricacies within agricultural landscapes. The map delineates different land classes, showcasing variations in land cover, land use, and crop types. It becomes a navigational tool for stakeholders, providing insights into spatial dynamics and laying the foundation for targeted interventions.

2. Precision Agriculture Insights: Results derived from remote sensing technologies offer a profound understanding of precision agriculture. Spatial variability maps, guided by the Land Classification Result Map, unveil zones with distinct characteristics. Farmers can leverage these insights to implement precision interventions, optimizing resource use and enhancing crop yield. The discussion explores how these findings translate into actionable strategies for precision agriculture.

3. Crop Health Assessment: The study's analysis of spectral data contributes to a comprehensive assessment of crop health. Spectral indices, such as NDVI, serve as indicators of chlorophyll content and overall plant vigor. The discussion interprets these indices in the context of ground truth data, shedding light on the health

dynamics of different crops. Insights gleaned from the analysis inform strategies for early disease detection and stress management.

4. Resource Optimization Strategies: Results pertaining to resource optimization strategies provide a roadmap for sustainable agriculture. The study evaluates the effectiveness of resource allocation based on the Land Classification Result Map. Discussion revolves around how these strategies minimize resource wastage, enhance water-use efficiency, and contribute to environmentally conscious farming practices.

5. Environmental Impact Assessment: The Land Classification Result Map contributes to an informed environmental impact assessment. By highlighting areas of natural vegetation, water bodies, and potential conservation zones, the study provides insights into the ecological footprint of agriculture. The discussion addresses the implications for biodiversity, conservation efforts, and the overall sustainability of agricultural practices.

6. Time-Resolved Agricultural Insights: The temporal dimension introduced through time-resolved agricultural insights offers a unique perspective on land dynamics. Results depicting changes in land cover and land use over different periods become a focal point for discussion. The study explores the factors influencing these temporal variations and discusses their implications for adaptive agricultural strategies.

7. Stakeholder Engagement and Decision-Making: The discussion extends beyond the technical aspects, addressing the role of stakeholder engagement and decision-making. How the study's findings empower farmers, policymakers, and communities becomes a central theme. Insights into collaborative efforts, knowledge dissemination, and the democratization of agricultural information are explored in the context of stakeholder engagement.

8. Validation and Reliability: An integral part of the discussion is the validation of results and the reliability of remote sensing insights. The study's calibration and validation protocols are scrutinized, and the discussion reflects on the alignment of remote sensing-derived data with ground truth information. This scrutiny enhances the credibility of the study's findings.

As the Results and Discussion section unfolds, it serves as a nexus where data-driven insights converge with the complexities of agricultural systems. The discussion not only interprets the findings but also explores their implications for transformative agricultural practices. Stakeholders are invited to navigate this intersection of data and interpretation, contributing to a shared understanding that propels agriculture into a realm of precision, resilience, and sustainability.

9. CONCLUSIONS

This comprehensive study serves as a pivotal milestone in reshaping the agricultural paradigm through the integration of cutting-edge remote sensing technologies. The intricate details encapsulated in the Land Classification Result Map stand as a testament to the transformative potential of precise data analysis. The spatial variability maps, enriched with spectral analyses, not only provide farmers with unprecedented accuracy in resource allocation but also usher in a new era of precision agriculture. Our findings highlight the resilience achievable through proactive crop health management, offering not only increased yield protection but also contributing to the long-term sustainability of agricultural practices. The strategies identified for sustainable resource allocation hold promise for minimizing waste, optimizing water use, and fostering environmentally conscious farming methods. The study's environmental impact assessment, particularly in delineating conservation zones and areas of natural vegetation, provides valuable insights for policymakers and environmentalists striving for a delicate balance between productivity and ecological preservation.

The temporal dynamics unraveled through time-resolved insights offer a dynamic perspective on the agricultural landscape's evolution. This temporal dimension equips stakeholders with the foresight needed for adaptive strategies, climate resilience, and informed decision-making over varying seasons and years. Beyond the scientific realm, this study champions stakeholder empowerment by democratizing agricultural insights. Farmers, policymakers, and communities are now armed with accessible and interpretable information, fostering collaboration, knowledge dissemination, and shared responsibility for steering agriculture towards a sustainable future. As we draw conclusions from this study, we do so with a commitment to ongoing advancements and future directions. The continued exploration of emerging technologies, refinement of analytical models, and interdisciplinary approaches promises to further illuminate the path toward a resilient, sustainable, and technologically empowered agricultural landscape. In the synthesis of data, innovation, and stakeholder collaboration lies the key to unlocking a future where precision and sustainability converge harmoniously in agriculture.

DATA AVAILABILITY

Sen-2 LULC (**https://data.mendeley.com/datasets/f4ky6ks248/2**) (**Mendeley Data).**

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