Project Based Learning Report

on

"Study on Different Scene Classification of Remote Sensing Images"

A Project Report submitted in partial fulfilment of requirements for the degree of Master of Technology in Computer Science and Engineering
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Content :

ABSTRACT

Remote sensing scene classification plays a crucial role in various applications such as environmental monitoring, urban planning, and disaster management. In recent years, deep learning methods have demonstrated remarkable performance in scene classification tasks, particularly through discriminative, generative, and hybrid approaches. This study investigates the efficacy of these methods in classifying remote sensing images across diverse scenes. The discriminative approach, represented by convolutional neural networks (CNNs), focuses on learning discriminative features directly from the input data. CNNs have excelled in capturing intricate patterns and structures in images, leading to high classification accuracy. However, they may struggle with limited data or classes that exhibit substantial intra-class variation. It combine the strengths of discriminative and generative approaches to enhance scene classification. By leveraging both discriminative feature learning and generative data modeling, hybrid models can achieve robustness against data variations, improve generalization, and mitigate overfitting. However, designing effective hybrid architectures requires careful consideration of feature extraction, data representation, and model integration. This study conducts comprehensive experiments using benchmark remote sensing datasets to evaluate the performance of discriminative, generative, and hybrid deep learning methods for scene classification. We analyze the strengths and limitations of each approach, highlighting their impact on classification accuracy, robustness to environmental changes, and scalability to large-scale datasets. The findings provide valuable insights for researchers and practitioners in leveraging deep learning techniques for remote sensing image analysis and classification.

Introduction

Remote sensing technology, leveraging advancements in satellite and aerial imaging, has emerged as a cornerstone in the observation and analysis of Earth's surface. Its applications span a wide range of fields, including environmental monitoring, agriculture, urban planning, and disaster management. One of the fundamental challenges in remote sensing lies in the accurate classification of imagery to extract meaningful information about land cover and land use. The classification process involves categorizing pixels within an image into distinct classes, allowing for the identification and mapping of different features(1).satellite images are considered the main source of acquiring geographic information. The data obtained from satellite sources are huge and are growing exponentially; to handle these large data, there is a need to have efficient techniques for data extraction purpose. Through image classification, these large number of satellite images can be arranged in semantic orders.(9). mage classification is a step-wise process that starts with designing scheme for classification of desired images. After that, the images are preprocessed which include image clustering, image enhancement, scaling, and so on. At third step, the desired areas of those images are selected and initial clusters are generated. After that, the algorithm is applied on the images to get the desired classification, and corrective actions are made after that algorithm phase which is also called postprocessing. Like example from the given figures as below.

FIGURE 1-

Dataset: Remote Sensing Image Scene Classification Based on Global Self-Attention Module Paper (7) which contains a huge accuracy value of

FIGURE 2 -

Dataset – The most common Dataset On 20 papers which was use in the paper in Literature survey That was given below in table was UC MERGED DATASET

METHODS OF REMOTE SENSING CLASSIFICATION:-

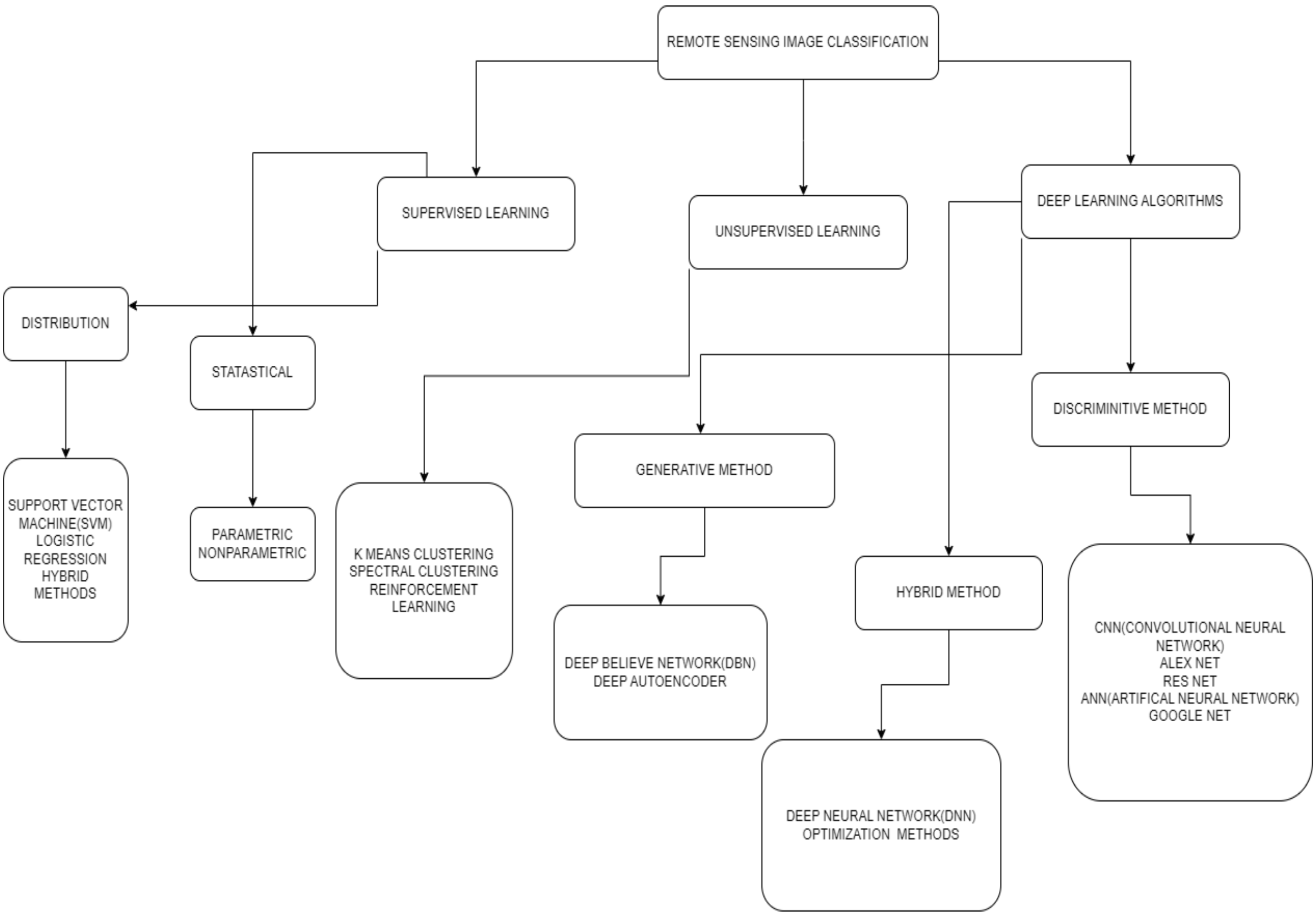

FIGURE -1 .

As from the figure 1 we can see there are three methods Supervised,Unsupervised, Deep learning algorithms. As every method has its own classification . so by generally we have taken a part of learning from that is Deep learning which is a main topic in it so, we have decided to show the methods of classification in it which are of three parts

.Discriminitive Method

.Generative Method

.Hybrid Method

2.Discriminitive Method -

Discriminative methods aim to learn the decision boundary that separates different classes directly from the training data. That don't attempt to model the distribution of each class explicitly but focus on finding the best boundary that distinguishes between classes. It typically involve the use of machine learning algorithms such as Support Vector Machines (SVM), Random Forests, Neural Networks, or other classifiers. These algorithms are trained using labeled data, where each sample is associated with a class label, and they learn to differentiate between classes based on the features extracted from remote sensing images.
It often rely on feature engineering to represent remote sensing images effectively. Features could include spectral information from different bands, texture features, shape features, or any other relevant characteristics of the imagery. These features are used as input to the machine learning algorithm to learn the decision boundary.It often rely on feature engineering to represent remote sensing images effectively. Features could include spectral information from different bands, texture features, shape features, or any other relevant characteristics of the imagery. These features are used as input to the machine learning algorithm to learn the decision boundary. The performance of discriminative methods is typically evaluated using metrics such as accuracy, precision, recall, F1-score, or confusion matrices. These metrics assess how well the classifier can correctly classify pixels or regions within remote sensing images. Itoften rely on feature engineering to represent remote sensing images effectively. Features could include spectral information from different bands, texture features, shape features, or any other relevant characteristics of the imagery. These features are used as input to the machine learning algorithm to learn the decision boundary.

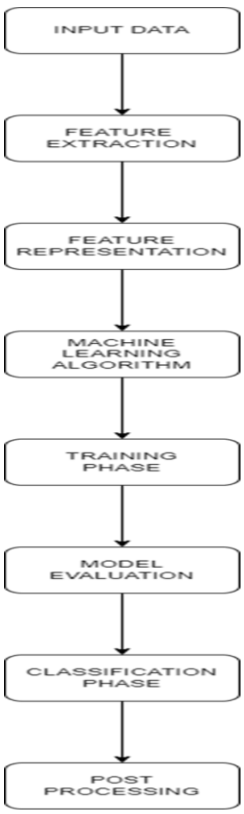

Figure 2: It is a step by step figure signifies how the Discriminitive method works

3. GENERATIVE METHOD –

Generative methods aim to model the probability distribution of each class in the remote sensing data. This involves estimating the statistical properties of the data for each class, such as the mean, variance, and covariance of different spectral bands or features. It calculate the class-conditional probability density functions, which describe the likelihood of observing a particular set of features given each class. These probability density functions represent how each class manifests in the feature space. Like discriminative methods, generative methods are also supervised learning approaches that require labeled training data. The difference lies in how they utilize this training data to model the probability distributions of each class. The performance of generative methods is evaluated using metrics such as accuracy, precision, recall, F1-score, or confusion matrices, similar to discriminative methods. However, the interpretation of these metrics may differ slightly due to the probabilistic nature of the classification process. It also may face challenges such as the curse of dimensionality when dealing with high-dimensional feature spaces, as well as the assumption of distributional similarity between training and test data. It offer a different perspective compared to discriminative methods and can be useful in certain scenarios, particularly when the statistical properties of the data are of interest.

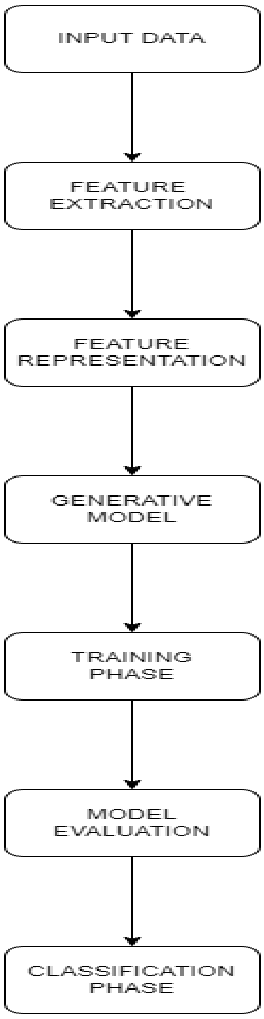

FIGURE 3:- It is a step by step phase of Generative method how it works

4.HYBRID METHOD -

A Hybrid method in remote sensing image classification refers to an approach that combines multiple techniques or algorithms to improve the accuracy and robustness of the classification process. These methods often integrate both traditional techniques, such as spectral analysis and feature engineering, with modern machine learning or deep learning approaches. use of a hybrid approach classification which combines pixels and objects, has been shown to be suitable for the identification of Landscape Units that contain a variety of land cover objects using VHSR images. However, the pixel-based classification of remote sensing im-ages performed with different classifiers usually produces different results. With the combination of the outputs of a set of classifiers it is possible to obtain a classification that is often more accurate than the individual classifications. It may employ ensemble learning techniques to combine multiple classifiers, including both generative and discriminative models. This could involve techniques like bagging, boosting, or stacking, where multiple classifiers are trained independently and their predictions are combined to make the final classification decision.It are often highly adaptable and can be customized to suit specific classification tasks and datasets. Researchers and practitioners can experiment with different combinations of generative and discriminative models, feature extraction techniques, and ensemble learning strategies to optimize classification performance. hybrid methods in remote sensing image classification leverage the strengths of both generative and discriminative approaches to improve classification accuracy, robustness, and adaptability. By combining multiple techniques, hybrid methods can effectively handle the complexities and challenges of remote sensing data classification tasks.

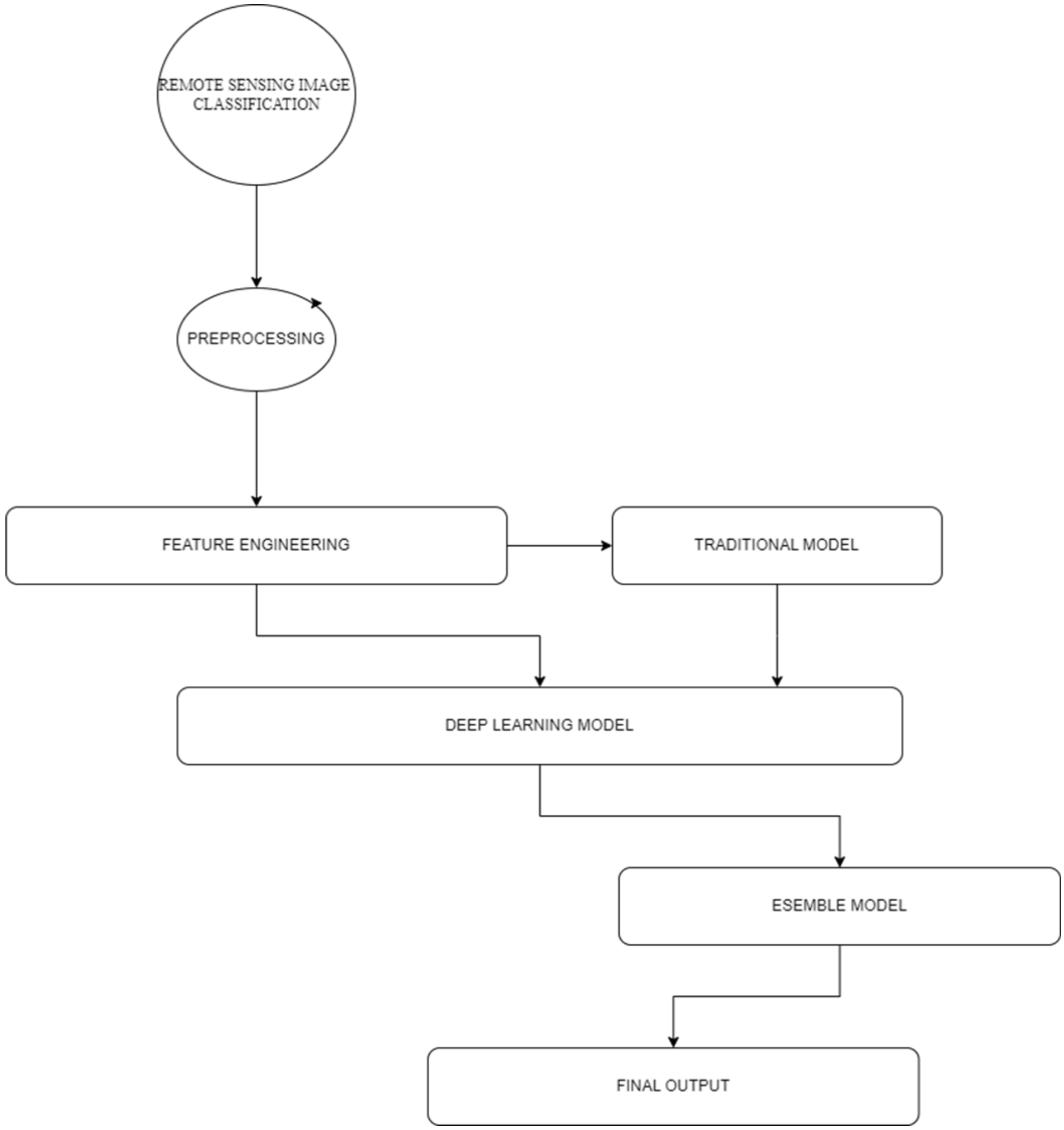

FIGURE 4 – It is a combination of different types of neural network as it is shown in figure how it works in hybrid method

Table 1. Literature Survey

Sl no	Author	Paper and publication details	Inference	Relevance to the Project	Research Gap
1.	Aakash Thapa Teerayut Horanot Jaganaath Aryal Bipul Neupane	Deep Learning for Remote Sensing Image Scene Classification: A Review and Meta-Analysis (2023) *Remote Sens.* 2023, *15*, 4804[1]	The paper provides a comprehensive review and meta-analysis of deep learning applications in remote sensing image scene classification, offering insights into the current state-of-the-art methodologies and their effectiveness, thereby contributing to the advancement of remote sensing technologies	The paper is relevant for synthesizing and analyzing the latest advancements in deep learning techniques applied to remote sensing image scene classification, providing valuable insights for researchers, practitioners, and decision-makers in the field of Earth observation and geospatial analysis.	A potential research gap could be the lack of focus on the scalability and generalizability of these techniques across different remote sensing datasets and conditions.
2.	Sultan daud khan Saleh Basalamah	Multi-BranchDeep Learning Framework for Land Scene Classification in Satellite Imagery (2023)	The paper introduces a multi-branch deep learning framework for robust land scene classification in satellite imagery, optimizing accuracy and interpretability for applications in land cover analysis and resource management. a multi-branch deep learning framework was designed to identify different land scenes in complex remote sensing images	The paper is relevant for advancing satellite image analysis by introducing a multi-branch deep learning framework, enhancing the precision of land scene classification for applications in environmental monitoring, urban planning, and	The research gap could be the limited exploration of incorporating domain knowledge or physical constraints into the deep learning framework to enhance the interpretability and robustness of land scene classification. The paper may not thoroughly

				land-use management.	investigate the transferability of the proposed multi-branch framework to different types of land cover and satellite imagery datasets, potentially leaving out scenarios where the model performance could be suboptimal.
3.	Xinglu cheng Yonghua sun Wangkaun Zhang Yihan wang	Application of Deep Learning in Multitemporal Remote Sensing Image Classification(2023)	The,paper characteristics of various models were summarized and generalized. Based on the summary of typical models, the application of deep learning algorithms in different fields was discussed	The paper leverages deep learning techniques to enhance the accuracy of multitemporal remote sensing image classification, enabling improved monitoring of temporal changes for applications in agriculture, land cover mapping, and environmental assessment.	A research gap might be the insufficient exploration of uncertainty quantification and propagation in deep learning models for multitemporal remote sensing image classification, especially in dynamic environmental conditions. The paper may not adequately address the challenges related to data scarcity and imbalance across different temporal stages, which could affect the generalizability of the proposed deep learning approach.

4.	Huiwei Jiang Min Peng Yuanjun Zhong Haofeng Xie Zemin Hao	A Survey on Deep Learning-Based Change Detection from High-Resolution Remote Sensing Images (2022)	The paper conducts a comprehensive survey on the application of deep learning for change detection in high-resolution remote sensing images, offering a systematic overview of current methodologies and insights into the advancements, challenges, and potential applications in monitoring dynamic environmental and urban changes	The project is relevant as it addresses the increasing importance of change detection in high-resolution remote sensing images, providing a comprehensive survey of deep learning methods. This work contributes to the understanding and advancement of techniques crucial for applications in environmental monitoring, land-use planning, and disaster management.	The paper discuss on the integration of temporal information and contextual dependencies into deep learning models for change detection, which are crucial for accurately capturing subtle changes in remote sensing images. The survey may not sufficiently cover the challenges associated with large-scale change detection tasks and the scalability of deep learning approaches to handle such tasks effectively.
5.	Purnachand Kollapudi Saleh Alghamdi Neenavath Veeraiah	A New Method for Scene Classification from the Remote Sensing Images (2022)	The Paper proposes the Pass Over network for remote sensing scene categorization, a novel Hybrid Feature learning and end-to-end learning model	The paper addresses the need for more accurate and efficient scene classification in remote sensing images, enhancing applications such as environmental monitoring	Despite being a survey, a research gap could be the limited discussion on the integration of temporal information and contextual dependencies into deep learning models for change detection, which are crucial for

					accurately capturing subtle changes in remote sensing images.
6.	Xiaowei Xu Yinrong Chen Junfeng Zhang Prathik Anandhan	A novel approach forscene classification from remote sensing images using deep learning methods (2020)	The paper refers totheconclusions or insights drawn from the study or research conducted in the paper. This could include the effectiveness of the proposed approach, comparison with existing methods, analysis of results, and implications for future research or practical applications in the field of scene classification from remote sensing images using deep learning methods.	This,paper provides background information on the existing approaches, methodologies, and challenges in scene classification from remote sensing images. For instance, it can aid in identifying land cover types, monitoring changes in urban areas, detecting environmental hazards, and assessing agricultural productivity.	The,survey maynot sufficiently cover,the challenges associated with large-scale change detection tasks and the scalability of deep learning approaches to handle such tasks effectively.

7.	Qingwen Li Dongmei Yan Wanrong Wu	Remote Sensing Image Scene Classification Based on Global Self-Attention Module(2021)	The paper would likely to discuss how the proposed global self-attention module contributes,to improving,the performance of scene classification in remote sensing images compared to existing methods.	The paper is crucial for various applications such as land cover mapping, environmental monitoring, and disaster management. By incorporating a global self-attention module, the project aims to improve classification accuracy, which is essential for reliable decision-making in these domains.	The study may focus on a specific dataset or scenario, potentially lacking diversity in terms of geographic regions, sensor modalities, or land cover types. This could limit the generalization capability of the proposed method to real-world
8.	Biserka Petrovska Eftim Zdravevski Petre Lameski	Deep Learning for Feature Extraction in Remote Sensing: A Case-Study of Aerial Scene Classification(2020)	The paper likely discusses the effectiveness of deep learning techniques for automatically extracting relevant features from aerial remote sensing images. This could include discussions on the ability of deep learning models to learn hierarchical representations of the data, capturing both low-level and high-level features useful for scene classification.	The, paper is used to feature the extraction have the potential to improve classification accuracy by automatically learning discriminative features from aerial imagery data. Aerial imagery often contains complex spatial relationships	The,paper addresses,this research gap by allowing the model to attend to,distant,spatial locations and capture long-range dependencies effectively. By incorporating self-attention mechanisms, the model can dynamically weigh the importance of different spatial locations based

				and patterns that may be challenging to capture using traditional feature extraction methods.	on their relevance to the classification task, enabling better contextual understanding and improved performance in scene classification.
9.	Maryam Mehmood Ahsan Shahzad Bushra Zafar	RemoteSensing Image Classification:A Comprehensive Review and Application(2022)	The paper likely provides an overview of various techniques and methods used for remote sensing image classification, including both traditional and modern approaches.It may evaluate different performance metrics commonly used to assess the accuracy and reliability of remote sensing image classification algorithms. This could involve comparisons of classification accuracy, precision, recall, F1-score, and other metrics across different methods and datasets.	This,paper consolidates existing knowledge, providing researchers, practitioners, and policymakers with a comprehensive overview of the state-of-the-art techniques, methodologies, and applications in the field. The paper discusses real-world applications andcase studies where remote sensing image classification techniques havebeen applied.	The paper may contribute to advancing the state-of-the-art in remote sensing feature extraction by leveraging the capabilities of deep learning models. It may provide insights into the effectiveness of different deep learning architectures, training strategies, and optimization techniques for feature extraction tasks in aerial scene classification.

10.	Wei Zhang Ping Tang Lijun Zhao	RemoteSensing ImageScene Classification UsingCNN CapsNet(2019)	The paper likely found that using a combination of Convolutional Neural Networks(CNNs) andCapsule Networks,the proposed,approach demonstrated robustness,to variations in remote sensing imagery, such as changes in lighting conditions, seasonal changes, or sensor noise, making it suitable forreal-world applications.capsNets resulted in improved accuracy in classifying remote sensing images compared to traditional methods.	The paper aims to improve classification accuracy,which Directly benefits the application. (CNNs) and Capsule Networks (CapsNets) are state-of-the-art deep learning architectures known for their effectiveness in feature extraction and representation. Applying these techniques to remote sensing image scene classification can lead to more robust and accurate classification results.	The paper may lack in the comprehensive evaluation metrics and benchmarking against existing state-of-the-art methods. Without thorough comparison with alternative approaches, it may be challenging to assess the relative performance and effectiveness of the proposed CNN-CapsNet method. There may be a gap in demonstrating the transferability and scalability of the CNN-CapsNet approach to real-world applications..
11.	Yazeed Yasin Ghadi Tamara al Shloul Suliman A. Alsuhibany Jeongmin Park	Robust Object Categorization and Scene Classification over Remote Sensing Images via Features Fusion and Fully Convolutional Network(2022)	The paper is likely to would include the findings related to robust object categorization and scene classification using a combination of feature fusion techniques and a fully convolutional network (FCN) applied to remote sensing images. It could involve discussing the	The paper aims to remote sensing data can be complex, with variations in lighting, weather conditions, and other factors. Robust methods ensure that the categorization and classification	The research gap states that Transfer learning from pre-trained models and generalization to unseen data are important aspects of robust object categorization and scene classification. Bridging the gap in transfer learning techniques and improving the model's ability to

			effectiveness of the proposed method, comparisons with existing approaches, insights into the performance metrics achieved, and potential applications or future research directions based on the results.	algorithms perform well under different environmental conditions, leading to more reliable results.	generalize across diverse remote sensing datasets are key research areas.
12.	Haozhe Huang Zhongfeng Mou Yunying Li Qiujun Li Jie Chen Haifeng Li	Spatial-Temporal Invariant Contrastive Learning for Remote Sensing Scene Classification(2022)	The paper emphasizes the importance of spatial and temporal invariance in remote sensing scene classification.It proposes using contrastive learning techniques to learn representations that capture meaningful spatial-temporal information. Contrastive learning involves training a model to distinguish between positive (similar) and negative (dissimilar) pairs of samples, thereby learning a representation space where similar samples are closer together and dissimilar samples are farther apart.	The methods proposed in the paper are expected to lead to improved classification performance compared to traditional approaches. By learning spatial-temporal invariant representations through contrastive learning, the model can better capture the underlying characteristics of different scenes and make more accurate classification decisions.	The paper potential research gap could be scalability. While the paper may propose effective techniques for spatial-temporal invariant contrastive learning, scalability to large-scale remote sensing datasets or real-time processing may still be a challenge.
13.	Cuiping Shi Xin Zhao Liguo Wang	A Multi-Branch Feature Fusion Strategy Based on an Attention Mechanism for Remote Sensing Image Scene Classification(2021)	IT demonstrates that a multi-branch feature fusion strategy can effectively integrate diverse spatial and spectral features from remote sensing images. This leads to a more comprehensive representation of the scene, enhancing the model's ability to	Thepaper Based on Attention Mechanism for Remote Sensing ImageScene Classification" lies in its contribution to improving the accuracy and effectiveness of scene	The research gap in remote sensing scene classification is the effective integration of multiple types of features, such as spatial, spectral, and contextual information. Traditional

			discriminate between different classes. The inclusion of an attention mechanism helps the model focus on relevant regions or features within the image, effectively reducing noise and improving classification accuracy. This mechanism enables the model to prioritize important information during the classification process.	classification in remote sensing imagery. The use of a multi-branch feature fusion strategy, combined with an attention mechanism, addresses key challenges such as capturing diverse spatial and spectral information, handling complex scenes with multiple classes, and enhancing the discriminative power of the classification model.	methods often struggle to combine these heterogeneous features in a seamless and effective manner, leading to suboptimal classification performance.
14.	Xiaoqiang Lu Hao Sun Xiangtao Zheng	A Feature Aggregation Convolutional Neural Network for Remote Sensing Scene Classification(2019)	The paper,demonstrate feature aggregation techniques within a convolutional neural network(CNN) framework,thatcan effectively combine multi-scale and multi-level features from remote sensing images. This aggregation helps in capturing both local details and global context, enhancing the discriminative power of the model.	The paper that represents a technological advancement in remote sensing image analysis by leveraging deep learning techniques, specifically CNNs, for scene classification tasks. It demonstrates the potential of modern machine learning approaches in extracting valuable information from remotely sensed data, paving the way for further innovations in	The paper in Remote sensing scenes often exhibit hierarchical structures, with features at different levels of abstraction. Existing methods may not fully capture these hierarchical relationships, resulting in limited understanding of complex scene semantics and suboptimal classification performance.

				the field.	
15.	Cuiping Shi Xinlei Zhang Jingwei Sun Liguo Wang	Remote Sensing Scene Image Classification Based on Dense Fusion of Multi-level Features(2021)	The paper is basically densely fusing multi-level features, the classification model gains a more comprehensive representation of remote sensing scenes. This comprehensive representation enables the model to capture diverse spatial, spectral, and contextual information, leading to improved classification accuracy.	The proposed approach enhances the robustness of classification models to variations commonly encountered in remote sensing imagery, such as changes in illumination, viewpoint, and environmental conditions. This robustness is crucial for ensuring the model's performance across different scenarios and datasets.	The research gap in Remote sensing scenes often exhibit hierarchical structures with features at different scales and levels of abstraction. Existing methods may not fully capture these hierarchical relationships, resulting in limited understanding of complex scene semantics and suboptimal classification performance.
16.	Gong Cheng Peicheng Zhou Junwei Han	Learning Rotation-Invariant Convolutional Neural Networks for Object Detection in VHR Optical Remote Sensing Images(2016)	The paper proposes a method based on Convolutional Neural Networks (CNNs) that can learn rotation-invariant features. This is crucial in remote sensing because objects can appear in various orientations due to satellite imaging perspectives.It focuses on learning features that are robust to rotation variations. This includes learning filters and representations that are invariant or less sensitive to object rotations, improving object detection accuracy.	The paper targets the issue of rotation variance in object detection within remote sensing images. This is a crucial problem because objects in satellite images can appear in various orientations due to satellite viewing angles and the Earth's rotation.	The paper may focus on rotation invariance but might not extensively address the generalization of the proposed method to complex scenes with multiple objects, occlusions, and varying backgrounds. Investigating how well the rotation-invariant CNNs perform in diverse and cluttered environments could be a research gap.

17.	Weijia L Haohuan Fu Le Yu Arthur Cracknell	Deep Learning Based Oil Palm Tree Detection and Counting for High-Resolution Remote Sensing Images(2016)	The paper most likely presents a methodology that involves deep learning algorithms, such as convolutional neural networks (CNNs), for detecting and counting oil palm trees. It may detail the preprocessing steps, network architecture, training process, and evaluation metrics used.	The paper showcases the application of deep learning techniques, specifically convolutional neural networks (CNNs), in the field of high-resolution remote sensing for detecting and counting oil palm trees. This represents a technological advancement as deep learning methods are known for their effectiveness in handling complex image analysis tasks.	While the paper focuses on oil palm tree detection and counting, there could be a research gap in distinguishing oil palm trees from other tree species present in the images. Improving the model's ability to differentiate between different tree types can enhance its utility in broader vegetation analysis tasks.
18.	Somenath Bera Vimal K. Shrivastava	Analysis of various optimizers on deep convolutional neural network model in the application of hyperspectral remote sensing image classification(2019)	The paper may discuss which optimizer (e.g., SGD, Adam, RMSprop) performs better in terms of convergence speed, model accuracy, and generalization ability for hyperspectral remote sensing image classification tasks. It may analyze how the choice of optimizer influences the final classification accuracy and the ability of the CNN model to generalize well on unseen hyperspectral images.	The paper addresses a crucial aspect of deep learning model development in remote sensing, which is the selection of the optimizer. Optimizers play a significant role in training neural networks by optimizing the model parameters during the learning process.	Hyperspectral remote sensing images have unique spectral characteristics and high-dimensional data, which may require specialized optimization techniques. The paper may not have explored optimization methods tailored specifically for handling the complexity of hyperspectral data, representing a potential research gap.

19.	Yiqing Guo Xiuping Jia David Paull	Effective Sequential Classifier Training for SVM-Based Multitemporal Remote Sensing Image Classification(2018)	Sequentially training the classifier, the paper may suggest that overfitting to specific temporal instances or features is mitigated, resulting in a more generalized and robust classification model.	The paper's focus on sequential classifier training for SVM-based models adds to the methodological advancements in remote sensing image classification. It provides a framework for incorporating temporal information effectively into machine learning models, which is valuable for researchers and practitioners in the remote sensing community.	One research gap could be the limited adaptability of traditional classifiers like SVMs to temporal changes in remote sensing images. The paper may bridge this gap by proposing a sequential training approach that improves the model's ability to handle temporal variability effectively.
20.	Wenmei Li Jiaqi Wu Qing Liu Yu Zhang	An Effective Multimodel Fusion Method for SAR and Optical Remote Sensing Images(2023)	The paper may demonstrate that the multimodel fusion method leads to higher classification accuracy compared to using SAR or optical images alone. This improvement could be attributed to the complementary information captured by each modality and the synergy achieved through fusion	The paper contributes to advancing remote sensing methodology by demonstrating an effective multimodel fusion technique. This is relevant for researchers, practitioners, and decision-makers involved in remote sensing applications, providing them with valuable tools and insights for data integration and analysis.	The paper may target a gap in the application of multimodal fusion methods to specific remote sensing tasks such as land cover mapping, disaster monitoring, or urban analysis. By demonstrating the effectiveness of their fusion method in these applications, the paper could contribute to filling this research gap.

PROBLEM STATEMENT

Remote sensing classification ,which have both supervised and unsupervised approaches, involves accurately categorizing or identifying objects, land cover types, or features within remote sensing imagery which is a limited labelled data which can be can be expensive, time-consuming, or infeasible for certain classes or regions.As it may lead to biased models or poor generalization to unseen data. Remote sensing imagery exhibits variability due to factors such as environmental conditions, sensor characteristics, and seasonal changes.As Variability poses challenges in developing classifiers that can accurately generalize across diverse conditions. Also it faces in feature extraction as it extract relevant features from remote sensing data is which crucial for effective classification.As feature extraction methods may not capture the full complexity of spatial and spectral information present in remote sensing imagery, leading to suboptimal classification performance.It also contains semantic gap. which comes between low-level image features and high-level semantic concepts. The primary challenge is to achieve high classification accuracy while ensuring the robustness of the classification model across different environmental conditions, sensor modalities, and geographic regions. Supervised learning algorithms may overfit to the training data or fail to generalize well to unseen data, leading to poor performance on new datasets. Unsupervised learning algorithms may produce ambiguous or inconsistent results, particularly in the presence of noise or data artifacts.

It faces a challenge i to develop classification algorithms that are scalable and computationally efficient, capable of processing large volumes of high-resolution remote sensing imagery in a timely manner. Both supervised and unsupervised learning methods may suffer from scalability issues when applied to big data scenarios, requiring innovative solutions for distributed computing, parallel processing, and algorithm optimization. Overall, the main problem in remote sensing image classification with both supervised and unsupervised learning involves developing robust, accurate, and scalable classification algorithms that effectively leverage labeled and unlabeled data to extract meaningful information from complex remote sensing imagery.

SOLUTION STRATEGY

Remote sensing image classification in supervised learning of Discriminitive method aim to learn the decision boundary between different classes based on labeled training data. However, traditional discriminative classifiers may struggle with complex and high-dimensional remote sensing data, leading to challenges such as overfitting, class imbalance, and limited generalization capability.However in case of Deep learning techniques, such as Convolutional Neural Networks (CNNs), have shown remarkable success in remote sensing image classification by automatically learning hierarchical representations of features directly from the raw data. CNNs can effectively handle high-dimensional dataand capture complex spatial and spectral patterns, leading to improved classification accuracy and robustness compared to traditional classifiers. Remote sensing image classification in supervised learning of Hybrid Method rely on labeled training data, acquiring large-scale labeled datasets for remote sensingimagery can be costly and time-consuming. Additionally, supervised classifiers may struggle with class imbalance, noisy labels, and limited generalization to unseen data.And also in case of unsupervised learning aim to cluster pixels or regions within remote sensing imagery into meaningful groups without requiring labeled data. However, traditional unsupervised techniques may struggle with scalability, interpretability, and the curse of dimensionality.

However in case of Hybrid method combine supervised and unsupervised learning techniques to leverage the strengths of both approaches. For example, deep learning-based autoencoders can be used for unsupervised feature learning and dimensionality reduction, followed by supervised classification using labeled data. This integration enables more efficient use of labeled and unlabeled data, leading to improved classification performance and scalability.

Hybrid generative and discriminative methods in deep learning involves combining the strengths of both approaches to improve overall performance. It can leverage both labeled and unlabeled data more effectively, which is particularly useful in scenarios where labeled data is scarce but unlabeled data is abundant. The combination of generative and discriminative techniques can lead to models that generalize well across different datasets and domains, reducing overfitting.

Table 2: Summary of different Remote Sensing Scene Classification Algorithms

Sl.no	**Algorithm/ Technique**	**Dataset**	**Performance**	**Category**
Deep Learning for Remote Sensing Image Scene Classification [1]	Recurrent Neural Networks Convolutional Neural Networks Graph Neural Networks	AID NWPU-RESISC45	99.08% 97.40%	Discriminitiv Method
Multi-BranchDeep Learning Framework for Land Scene Classification in Satellite Imagery [2]	Deep belief network (DBN) ResNet-50	The UC-Merced Dataset EuroSAT Dataset BigEarthNet Dataset	95.00% 93.75% 90.34%	Generative Method

Application of Deep Learning,in Multitemporal RemoteSensing Image Classification [3]	Alex NET ResNET	3D U-Net Geo-3D CNN+Geo Conv1	92.5% 94.1%	Discriminitive Method
4 A Survey on Deep Learning-Based ChangeDetection fromHigh-Resoluti on Remote Sensing Images [4]	Recurrent Neural Network (RNN) U-NET	WHU-CD DATASET SYSU-CD	0.75% 0.5%	Discriminitive Method
ANew Methodfor Scene Classification fromthe Remote Sensing Images[5]	ConvontunialNeural Network(CNN) Res Net Network	UCM dataset NWPU-RESISC45 SpaceNet Dataset	98.96% 93.45%	Discriminitiv Method

A,novel approachfor scene classification from remote sensing images using deep learning methods.(6)	ConvolutionalNeural Networks (CNNs): RecurrentNeural Network(RNN):	UC Merced (UCM) dataset	90.26%	Discriminitiv Method
Remote Sensing Image Scene Classification Based on Global Self-Attentio n Module(7)	ConvolutionalNeural Networks (CNNs): Optimization	UCM UC Merced Dataset NWPU Dataset AID Dataset	99.50% 94.00% 97.10%	Hybrid Method

Deep Learning for Feature Extraction in Remote Sensing: A Case-Study of Aerial Scene Classification (8)	Google Net Res Net Xception Inception	UCM UC MERGED DATASET WHU-RS DATASET	94.31% 98.26%	Discriminitiv Method
RemoteSensing Image Classification:A Comprehensive Review and Application(2022) (9)	Greywolf optimization Reinformcent learning	UCM DATASET SAT4 DATASET SAT6 DATASET	98% 95.8% 94.1%	Hybrid Method
RemoteSensing ImageScene ClassificationUsing CNN CapsNet(2019) (10)	ConvolutionalNeural Networks (CNNs): Caps Net Google Net	UC MERCED LAND USE DATASET AID DATASET NWPU-RESISC45 DATASET	99.05% 86.39% 78.48%	Discriminitiv Method
Robust Object Categorization and Scene Classification over Remote Sensing Images via Features Fusion and Fully Convolutional Network(2022) (11)	Fully Convolutional Network (FCN) CNN Feature Extraction Spectral–Spatial Features (SSFs)	RESISC45 Dataset UCM Dataset Aerial Images Dataset	96.57% 98.75% 97.73%	Discriminitive Method
Spatial-Temporal Invariant Contrastive Learning for Remote Sensing Scene Classification(2022) (12)	Contrastive Learning Framework Temporal Modeling Feature Extraction with Convolutional Neural Networks (CNNs):	UC Merced Land Use Dataset, NWPU-RESISC45 AID dataset	99.9% 95.61% 97.43%	Discriminitive Method

A Multi-Branch Feature Fusion Strategy Based on an Attention Mechanism for Remote Sensing Image Scene Classification(2021) (13)	.ConvolutionalNeural Networks (CNNs): ResNet.	UC Merced Land-Use Dataset (UCM21) AID30 Dataset NWPU45 Dataset	99.52% 95.35% 92.42%	Discriminitive Method
A Feature Aggregation Convolutional Neural Network for Remote Sensing Scene Classification(2019) (14)	Convolutional Neural network(CNN) Optimization Algorithms	UC Merced Land Use Dataset EuroSAT Dataset: WHU-RS19 Dataset:	95.22% 90.64% 85.25%	Hybrid Method
Remote Sensing Scene Image Classification Based on Dense Fusion of Multi-level Features(2021) (15)	Convolutional Neural Networks (CNNs) Transfer Learning LCNN-BFF	AID dataset RSSCN Dataset . UC Merced Land Use Dataset	96.76% 97.86% 99.53%	Discriminitive Method
Learning Rotation-Invariant Convolutional Neural Networks for Object Detection in VHR Optical Remote Sensing Images(2016) (16)	convolutional neural network (CNN) normalization, AlexNet	UC Merced Land Use Dataset: DOTA Dataset WHU-RS19 Dataset	99.4% 88.15% 60%	Discriminitive Method
Deep Learning Based Oil Palm Tree Detection and Counting for High-Resolution Remote Sensing Images(2016) (17)	Optimization convolutional neural network (CNN)	Training Dataset Test Dataset Image Dataset	96.05% 96.34% 98.77%	Hybrid Method
Analysis of various optimizers on deep convolutional neural network model in the application of hyperspectral remote sensing image classification(2019) (18)	convolutional neural network (CNN) Optimization Spatial Feature Extraction	Indian Pines Dataset Hyperion Dataset Salinas Dataset	90.65% 95.00% 90.02%	Hybrid Method

Effective Sequential Classifier Training for SVM-Based Multitemporal Remote Sensing Image Classification(2018) (19)	Data Preprocessing Sequential Classifier Training Validation and Testing	Landsat Dataset Sentinel-2 Dataset Multispectral Datasets	91.81% 95.82% 83.6%	Discriminitive Method
An Effective Multimodel Fusion Method for SAR and Optical Remote Sensing Images(2023) (20)	Convolutional Neural Networks (CNNs) Transfer Learning Domain Adaptation	SEN1-2 Dataset UAVSAR Dataset WHU-RS19 Dataset	93.84% 85.00% 95.02%	Hybrid Method

Result and Discussion

In Remote sensing scene classification we get to know and analyze about the Three methods which is

1. Discriminitive Method
2. Generative Method
3. Hybrid Method

In these three methods we have mainly focuses on the Hybrid Method as because it is a combination of both Discriminitive and Generative Method . So by that we know that
Hybrid method in remote sensing image classification refers to an approach that combines multiple techniques or algorithms to improve the accuracy and robustness of the classification process. These methods often integrate both traditional techniques, such as spectral analysis and feature engineering, with modern machine learning or deep learning approaches.

Findings: Most Researchers have use Hybrid in their advantage with trained on the dataset like **UCM UC Merced Dataset** with the average accuracy of **99.50%**

Advantages of Hybrid methods:

Through the survey from different research papers, it has been observed that hybrid methods often achieve better performance by combining the strengths of discriminative and generative models. It can learn discriminative features while also capturing the underlying data distribution. Further the method is more robust to variations in data and environmental conditions because it leverages multiple perspectives and representations. Hybrid methods offer flexibility in model design, allowing for customization based on the specific task or dataset. They can combine discriminative and generative components as needed. It can learn more informative feature representations by integrating discriminative and generative feature learning techniques.It can adapt to changing environments or evolving datasets by adjusting the contributions of discriminative and generative components dynamically. Depending on the components used, hybrid methods can offer improved model interpretability compared to purely generative or discriminative models.

Disadvantages of Hybrid methods:

Through the survey from different research papers, it has been observed that Hybrid methods can be more complex to design and implement compared to purely discriminative or generative models. Integrating multiple components requires careful architecture design and training strategies. The computational cost of hybrid methods can be higher due to the need to train and maintain multiple components. This can lead to longer training times and higher resource requirements. : Combining multiple models or techniques in hybrid methods can increase the risk of overfitting, especially if not properly regularized or validated. Managing the balance between model complexity and generalization is crucial. Depending on the complexity of the hybrid model, interpretability can be challenging. Understanding the contributions of different components to the overall model decision may require additional analysis. Hybrid methods may have higher data requirements for training, especially if they involve pre-training multiple components separately before integration. This can be a limitation in domains with limited labeled data availability.

Application work

Hybrid models can enhance object detection tasks by leveraging generative models to extract meaningful features from images and discriminative models to accurately localize and classify objects within the images. This is particularly useful in applications like autonomous driving, surveillance systems, and medical imaging. or tasks requiring pixel-level segmentation, hybrid methods can integrate generative models to capture contextual information and discriminative models to delineate object boundaries accurately. This approach improves semantic segmentation accuracy, especially in scenes with overlapping or intricate objects. In image classification tasks, hybrid models can combine generative features for robust representation learning with discriminative components for precise class differentiation. This approach is beneficial in scenarios with complex image variations and fine-grained distinctions between classes. Hybrid generative-discriminative models are used in recommendation systems to understand user preferences (generative aspect) and predict user-item interactions (discriminative aspect) effectively. This approach enhances recommendation accuracy and user satisfaction in personalized recommendation scenarios. These applications demonstrate the versatility and effectiveness of hybrid generative and discriminative methods in addressing complex discriminative tasks across diverse domains.It is also used in NLP tasks such as named entity recognition, sentiment analysis, and text classification. Generative models help capture semantic relationships and generate meaningful representations, while discriminative models refine predictions based on specific task objectives.

CONCLUSION

The project aims to do a survey on different methods of Deep learning techniques in Remote scene classification problem such as discriminative ,generative and hybrid. Most of the researchers have used Hybrid methods and are able to achieve model performance of about 99.50%.In generative approach, the performance of remote scene classification .were on an average of 95.00% Also in discriminative approach, the performance of remote scene classification on an average of 99.00%The hybrid model were mostly implemented using datasets like UCMercedDataset,NWPU Dataset, AID Dataset. Despite of good accuracy , researchers have faces major drawbacks in Hybrid Method like Complexity which requires more computational resources for training and inference. Training Challenges Which may require specialized training techniques and careful tuning hyperparameters due to the combination of different components. Interpretability which is the combined nature of hybrid models can make them less interpretable compared to purely discriminative or generative models, making it challenging to understand the model's decision-making process. Domain Expertise which often requires deep domain expertise in both discriminative and generative modeling techniques, limiting their accessibility to a broader range of researchers. Though by this we can clearly see the both benefits and limitation of Hybrid model training model . In future, empirical analysis on different methods will be implemented to observed the performance of Remote scene classification using Large remote scene dataset.

Gantt Chart :

ACTIVITY	Sep 2023	Oct 2023	Nov 2023	DEC 2023	Jan 2024	Feb 2024	Mar 2024	Apr 2024
Literature Survey								
Problem Identification								
Design and Development								
Analysis								
Documentation								

Proposed Activity		Activity Achieved		Present Position	

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