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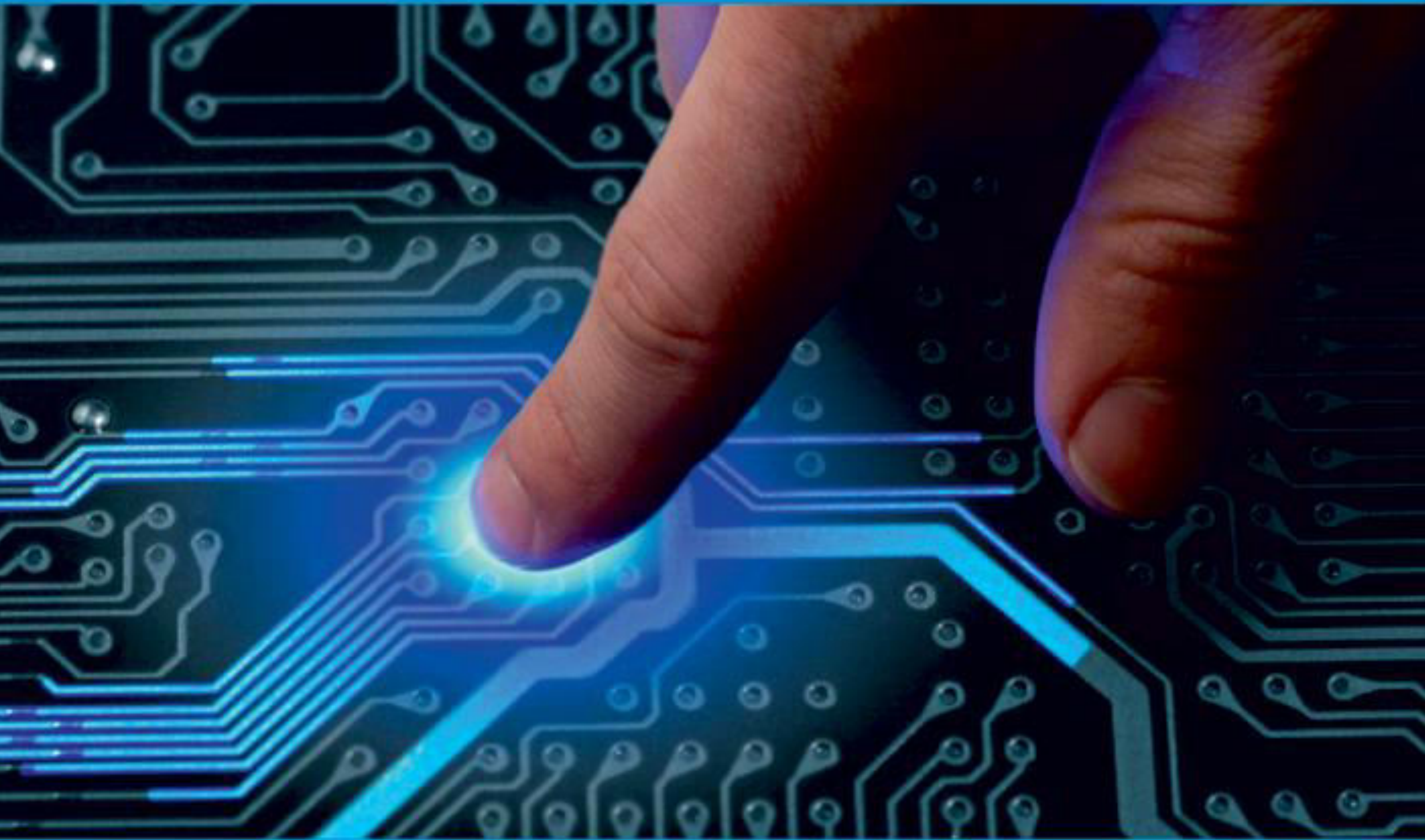

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A Review of Crop Classification Techniques UsingSatellite Image Processing

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ABSTRACT: The purpose of this research is to explore the application of deep learning (DL) concepts in satellite image processing for effective crop monitoring. The conventional meth-ods of crop analysis often face challenges in handling large- scale, high-dimensional satellite imagery. In response, this study leverages DL techniques to extract meaningful information from agricultural satellite data.The proposed methodology involves the use of convolutional neural networks (CNNs) to automatically identify and classify various crop types based on spectral and spatial features present in satellite imagery. The DL model is trained on a diverse dataset encompassing different crops, growth stages, and environmental conditions, ensuring robust generalization. Transfer learning techniques are employed to enhance the model's adaptability across different geographic regions. Additionally, the research explores the integration of DL- based object detection algorithms to identify and quantify specific agricultural features such as crop rows, irrigation systems, and anomalies.

KEYWORDS: Deep learning, Convolutional neural networks, Satellite image processing, Crop classification.

I. INTRODUCTION

Satellite imagery has become a valuable tool in agriculture for monitoring crop health, estimating yields, and identifying potential issues affecting productivity. Deep learning (DL) has emerged as a powerful paradigm in computer vision, demonstrating remarkable capabilities in image recognition and analysis. Applying DL concepts to satellite image pro- cessing presents an opportunity to overcome the limitations of conventional methods and enhance the accuracy and efficiency of crop monitoring. Conventional crop analysis methods are hindered by their inability to effectively handle the vast amounts of data generated by contemporary agricultural satel- lites. These methods often struggle to adapt to the diverse range of crops, growth stages, and environmental conditions encountered in real-world scenarios. As a result, there is agap in the existing research, necessitating the exploration of innovative approaches to improve the scalability, adaptability,and automation of crop monitoring processes.

The motivation for this research stems from the inherent limitations and challenges faced by conventional methods in analyzing large-scale, high-dimensional satellite imagery for crop monitoring. The adoption of deep learning (DL) techniques provides a compelling solution to overcome these challenges. DL models, particularly convolutional neural net- works (CNNs), have demonstrated a remarkable ability to automatically extract meaningful information from complex data sets, making them well-suited for the intricate task ofcrop identification based on spectral and spatial features in satellite imagery.

II. LITERATURE SURVEY

[1] This paper deals with the need for effective tools to monitor crops from a distance, coupled with the availability of free satellite imagery, has led to the creation of new methods for classifying crops. This classification is often time-sensitive, so performance is crucial. In this study, a novel method is proposed, involving the generation of synthetic images by extracting pixel-level satellite data, considering various bands and data from multiple dates. The method employs a deep convolutional network system trained on Sentinel-2 satellite images to classify different crop types throughout the year. This approach allows for cost-effective crop classification. The developed software, applied in Extremadura (Spain), serves as a monitoring tool for Common Agricultural Policy subsidies of the European

Union.Traditionally, assessing land status involved manual sampling and studying changes over time. Recent technological advancements, such as the Sentinel-2 missions, have greatly improved the classification algorithms, providing updated multispectral samples automatically.

[2] This research paper focuses on using satellite-based re-mote sensing for monitoring agricultural ecosystems. In the agricultural context, understanding variations in soil fertility and crop growth across time and space is crucial. The study emphasizes the increasing role of remote sensing, particularly through satellites and unmanned aerial vehicles, in obtaining real-time farmland information. This technology allows for continuous monitoring of the agricultural environment, aiding in the identification of crop growth, pests, diseases, and water supply.The paper discusses the methods and features of remote sensing images, outlining how they can be employed to analyze targets in the agricultural ecosystem. Utilizing object- oriented classification technology, the researchers preprocess and analyze farmland images, transforming crop observations into effective discrimination between crops and non-crops in remote sensing data.The study demonstrates that processing remote sensing images of crop field maps can effectively ac- quire information about crop areas and enable the monitoring of crop farmland.

[3] This paper deals with the global challenges of population
growth and food scarcity, emerging technologies play a crucial role. This paper explores the application of remote sensing, particularly satellite imagery, in monitoring and classifying crops. The increasing spatial-temporal resolution and free availability of these services have contributed to their growing use. Typically, time series data is combined with supervised learning for crop type identification, but the scarcity of la- beled datasets hinders model training. This study proposestesting and analyzing the performance of various unsupervisedclustering algorithms for crop type identification in remote images.The world's population continues to rise, posing asignificant food security challenge. To meet the increasing demand, smart farming practices must be adopted. This in- cludes achieving the ambitious goal of zero hunger by 2030, as outlined in the United Nations' Sustainable Development Goal No. 2. Smart agricultural practices, facilitated by technologies like remote sensing, not only enhance production but alsobenefit the environment. Crop type mapping is a crucial aspectof smart agriculture.

[4] In this paper, accurately predicting crop types in high-resolution satellite images is challenging due to the lack of ground truth labels. This work introduces a novel approach employing a hybrid deep capsule autoencoder for enhanced crop prediction in remote sensing images. The methodology involves preprocessing input images using Refined Lee Filter-ing to remove noise, extracting spectral–spatial features with Extended Morphological Profile (EMP), Extended Attribute Profiles (EAP), and hybrid wavelet features. A modified bi- nary equilibrium optimizer (MBE) is employed for feature selection to reduce dimensionality, and a hybrid deep capsule autoencoder is used for mapping different crops. The approach is evaluated using Sentinel-2 and Optical Radar datasets, demonstrating superior performance in terms of accuracy, sensitivity, F-score, precision, False Positive Rate (FPR), False Negative Rate (FNR), kappa coefficient, and ROC curve with AUC compared to existing methods.

[5] In this paper we deal with the fact that agriculture is a crucial aspect of livelihood, contributing significantly to a country's GDP. Precision agriculture requires accurate crop classification, aiding in decision-making for crop production. This paper focuses on leveraging machine learning algorithms for crop classification using multitemporal satellite images. The study explores various models and analyzes their per- formance, emphasizing their effectiveness in achieving high accuracy for crop identification. The use of remote sensing, specifically satellite images, helps assess crop yield, health, and other parameters. The paper delves into the integra- tion of time series and multitemporal properties of satellite images, utilizing machine learning techniques for improved crop classification. Key terms include remote sensing, satelliteimage data, multi-temporal data, crop classification, machine learning, and algorithms like k-means and random forest.

[6] This paper presents a transfer learning approach to the crop classification problem based on time series of images from the Sentinel-2 dataset labeled for two regions: Brittany (France) and Vojvodina (Serbia). The problem tackled in this paper is related to the nature of geospatial data. In both regression and classification tasks, unsatisfactory results are often obtained when the training data used to build the model is collected from one image or geographic region and then applied to another region. the transfer learning (TL) approach, in which a model developed for one learning task is adapted asa starting point for building a model for another learning task, provides some strategies to overcome this challenge. Cropclassification is a good example of a problem that, because of its scale and complexity, is solved almost exclusively through the use of (geospatial) remote sensing data.

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[7]The goal here was to design a CNN to perform semantic segmentation and output crop classification maps using high- resolution remote sensing satellite images. The data were obtained from GF-1 multi-spectral remote sensing image data, the first satellite in China's Gaofen satellite series. The spectral range of multi-spectral remote sensing images in the datasetis blue (0.45–0.52 micrometre), green (0.52–0.59 microme- tre), red (0.63–0.69 micrometre) and near-infrared (0.77–0.89 micrometre). Two datasets were constructed using the same data source. In the first dataset, the near-infrared bands of the GF-1 remote sensing images are removed, and the remaining three bands (RGB) are normalized, which can accelerate the convergence speed of the model. The Normalized Difference Vegetation Index (NDVI) was extracted from the second dataset and combined with the first dataset to generate 4- channel samples. methods. They used support vector machines (SVM) and random forest (RF) as benchmark models to compare performance with deep learning algorithms.

[8]The aim of this paper is to map agricultural crops by classifying satellite image time series. In this work, they propose a deep learning network architecture for crop mapping that is hierarchical, to exploit a tree-structured label hierarchy built by domain experts; convolutional to encode image data; and recursive to represent time series. In order to test themodel, they introduce a new dataset called ZueriCrop. This dataset is based on farm census data from the Swiss Federal Office for Agriculture (FOAG). ZueriCrop covers a 50 km × 48 km area in the Swiss cantons of Zurich and Thurgau. It contains 28,000 Sentinel-2 image patches of size 24 pixels × 24 pixels, each observed 71 times over a period of 52 weeks; 48 agricultural land cover classes; and 116,000 individual agricultural fields.

[9]In this work, we propose a new object-oriented deep learning framework that leverages residual networks with different depths to learn adjacent feature representations by embedding a multibranch architecture in the deep learning pipeline. The proposed approach mainly consists of three steps: (i) clustering pixels into objects for multiscale input,

(ii) training a multiscale residual neural network (ResNet)for classification and then (iii) optimizing the boundaries of the classification results. In this paper, we propose a network called a multiscale object-based network (MONet). MONet first utilizes superpixel neighborhoods at three scales as inputs. Then, it combines the feature maps obtained from three residual networks and loads them into the fully connected layerfor classification.

[10]The multi-scale remote sensing data of a new generation of Chinese high-spatial-resolution earth observation satellites Gaofen-1 (GF-1), Gaofen-2 (GF-2), Ziyuan-3 (ZY-3), and in- ternational earth observation satellites Sentinel-2A and Land- sat 8 OLI were selected as sources. Based on the DeepLabV3 Plus deep learning model, 12 intelligent marsh vegetation classification models were constructed. The research objectivesof this study are focused on the following four aspects: (1)The ability of DeepLabV3 Plus to identify marsh vegetation was explored. (2) Under the same spectral band, the impactof remote sensing image data with different spatial resolutions (0.8 m, 2 m, 4 m, 5.8 m, 8 m, 10 m, 15 m, and 30 m) on the accuracy of marsh vegetation identification was studied.

[11]The literature surrounding vegetation land cover classifi- cation has witnessed a paradigm shift with the integration of deep learning methods, particularly semantic segmentation ap-proaches. This work contributes to this evolving landscape by employing DeepLabV3+, a state-of-the-art semantic segmenta- tion model, for classifying three critical vegetation types—tree, shrub, and grass—solely based on RGB images. The study delves into the complexities posed by imbalanced datasets, where shrub pixels are notably fewer than tree and grass pixels. To address this issue, a median frequency weighting strategy is incorporated into DeepLabV3+, mitigating data imbalance and enhancing classification accuracy, particularly for underrepresented classes like shrub. The research under- scores the significance of accurate vegetation classification in diverse applications, such as agricultural management, change monitoring, and emergency landing site identification for un- manned aerial vehicles (UAVs). Unlike traditional methods relying on NIR and LiDAR data, the proposed approach demonstrates effectiveness using cost-efficient RGB images. The study compares DeepLabV3+ against other pixel-based classification methods, emphasizing its superior accuracy at the expense of longer training times.

[12]The increasing popularity of remote sensing data, par- ticularly from satellite and unmanned aerial vehicle (UAV) imagery, has propelled the use of artificial intelligence, specif-ically deep learning (DL), for crop classification tasks. This systematic review explores the effectiveness of DL techniques in crop classification using aerial imagery, focusing on various DL architectures, including convolutional neural networks (CNNs), long short-term memory networks, transformers, and hybrid models. The papers reviewed employ techniques such as data augmentation, transfer learning, and multimodal fusionto enhance model performance.

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The study evaluates the im- pact of factors such as spatial and spectral resolution, image annotation, and sample quality on crop classification accuracy.

[13]Crop classification is a critical aspect of agricultural management for ensuring food security, and Deep Learning (DL) has emerged as a significant decision-support tool in this domain. This review paper focuses on the application of DL and machine learning (ML) techniques for crop classification, with a specific emphasis on Synthetic Aperture Radar (SAR) remote sensing. The characteristics of SAR, such as cloud- free operation, all-weather functionality, and adaptability to various light conditions, make it a powerful tool for crop classification. The study reviews approximately 50 relevant studies from various databases, highlighting key algorithms and geographies employed in SAR-based crop classification.

[14]Hyperspectral imaging (HSI) has become increasingly crucial in agricultural remote sensing, offering a 3D hy- perspectral cube containing spatial and spectral data. This study focuses on advancing crop classification in precision agriculture through the integration of deep learning (DL) and computer vision (CV) techniques applied to HSI. The research introduces a novel approach called Dandelion Optimizer with Deep Transfer Learning-based Crop Type Detection and Clas-sification (DODTL-CTDC). The method employs the Xception model for feature extraction from HSI, utilizing a Dandelion Optimizer for hyperparameter tuning. Additionally, a Convo- lutional Autoencoder (CAE) model is implemented for crop classification, with hyperparameter optimization facilitated by an Arithmetic Optimization Algorithm (AOA). The study emphasizes the significance of optimal feature extraction from hyperspectral data and demonstrates the effectiveness of the proposed DODTL-CTDC technique in crop classification. The methodology involves a unique combination of DL models, optimization algorithms, and hyperparameter tuning, showcas- ing its potential for automated and accurate crop classification in HSI. Further improvement in classification accuracy is suggested through future work on feature fusion processes.

[15]This study explores the application of Convolutional Neural Network (CNN) for crop classification using hy- perspectral remote sensing data, evaluating its performance against other methods. Hyperspectral data is effective for crop feature extraction, and CNN, known for its efficiency with unstructured data, is employed. The research compares the optimized CNN with two classification algorithms, namely Deep Neural Network (DNN) and Convolutional Autoencoder, using datasets from the AVIRIS and EO-1 Hyperion sensors. Results indicate that the optimized CNN outperforms the other methods, achieving 97 ± 0.58% overall accuracy for the Indian Pines dataset and 78 ± 2.43% for the study area dataset. The study discusses the significance of accurate crop classification for various applications, emphasizing the role of deep learning, specifically CNN, in handling unstructured remote sensing data. Additionally, the study proposes the development of a pre-trained model for crop classification, highlighting the potential for further enhancement in accuracy through future work on deep learning-based methods for remote sensing data classification.

The given figures depict a summary of the literature survey that explains the contrasting work conducted by different researchers.

SL NO.	TITLE OF THE PAPER	PROBLEM ADDRESSED	AUTHORS APPROACH	RESULTS
1	Crop classification of satellite imagery using synthetic multitemporal and multispectral images in convolutional neural networks, 2021.	The demand for mass remote sensing of crops, coupled with freely available satellite imagery	Using synthetic images by extracting satellite data at the pixel level by applying multi-spectral and multi-temporal synthetic for inputs	Results an accuracy of 96% on average
2	Remote Sensing Satellite Image-Based Monitoring of Agricultural Ecosystem, 2023.	Understanding variations in soil fertility and crop growth across time and space is crucial	A new method for remote sensing image classification is proposed, which mainly uses object model	Using this method we get accuracy of 95.8 %
3	Analysis of clustering methods for crop type mapping using satellite imagery, 2022.	Analyse the behaviour that clustering methods can offer towards the problem of crop type mapping based on satellite images	Clustering algorithms in combination with different distance measures	Spectral clustering method combined with the Manhattan distance shows the most robust and consistent behaviour
4	A new approach for crop type mapping in satellite images using hybrid deep capsule auto encode, 2022..	Utilizing many features to minimize the time consumption, low complexity operation and effectiveness in crop type prediction	Hybrid deep learning approach	Accuracy of 98.78%
5	Crop classification with multi-temporal satellite image data, 2020.	challenging to achieve that precision in this field	Multi temporal classification is been used	It compares 3 methods and gives 95.06% for this dataset using random forest approach.

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Fig. 1. Literature Survey Summary Table I

SL NO.	TITLE OF THE PAPER	PROBLEM ADDRESSED	AUTHORS APPROACH	RESULTS
6	Transfer learning approach based on satellite image time series for the crop classification problem, 2023.	Challenge of regional variability in geospatial datasets for crop classification	Transfer learning approach using time series data from Sentinel-2 imagery in distinct regions.	Model with 83% accuracy.
7	Fine crop classification in high resolution remote sensing based on deep learning, 2022.	Challenge of accurately classifying crops in high-resolution remote sensing satellite images through semantic segmentation	Using Convolutional Neural Network (CSNet) and comparing it with traditional machine learning algorithms	91.2% accuracy model
8	Crop mapping from image time series: Deep learning with multi-scale label hierarchies, 2021.	Challenge of accurate agricultural crop mapping using satellite image time series	Proposing a hierarchical deep learning network architecture, ms-convSTAR, designed to enhance classification performance	Increase in performance measures like f1 score, precision and recall.
9	Classification of very-high-spatial-resolution aerial images based on multiscale features with limited semantic information, 2021.	Challenge of accurate object-oriented classification in remote sensing imagery	Proposing a multiscale object-based network (MONet) for feature extraction	85.2% accuracy in one dataset and 92.5% in another.
10	Comparison of multi-source satellite images for classifying marsh vegetation using DeepLabV3 Plus deep learning algorithm, 2021.	Challenge of intelligent marsh vegetation classification	Connstructing and evaluating 12 models based on the DeepLabV3	Accuracy from 76.4% to 92.8%.

Fig. 2. Literature Survey Summary Table II

III. DATASET USED

Crop classification using satellite image processing relies on diverse datasets that capture various spectral, spatial, and temporal aspects of agricultural landscapes. Several commonly used datasets contribute to the success of crop classification models, providing valuable information for training and vali- dating algorithms.

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SL NO.	TITLE OF THE PAPER	PROBLEM ADDRESSED	AUTHORS APPROACH	RESULTS
11	Tree, Shrub, and Grass Classification Using Only RGB Images, 2020.	Classifying tree, shrub, grass in RGB images with data imbalance.	Applied DeepLabV3+ with median frequency weighting for improved accuracy.	DeepLabV3 + outperforms pixel-based classifiers.
12	Deep Learning Models for the Classification of Crops in Aerial Imagery, 2023.	Remote sensing data for crop classification demands innovative deep learning.	Evaluated deep learning models in aerial imagery for crop classification.	CNN and LSTM commonly outperform, emphasizing data and model selection.
13	Deep Learning Techniques for Crop Classification Applied to SAR Imagery, 2021.	Crop classification challenges addressed using SAR and deep learning.	Reviewed 50 studies, emphasized CNN, and identified research gaps.	Temporal aspects affect crop maps; SAR's potential in classification explored.
14	Exploiting Hyperspectral Imaging and Optimal Deep Learning for Crop Type Detection and Classification, 2023.	Enhancing hyperspectral imaging (HSI) crop classification with deep learning.	Introduced DODTL-CTDC using Xception, DO, CAE, and AOA.	DODTL-CT DC technique reported better results with a maximum accuracy of 99.47%.
15	Evaluation of CNN model by comparing with convolutional autoencoder and deep neural network for crop classification on hyperspectral imagery, 2020.	Crop identification using hyperspectral data; CNN for efficient classification.	Optimized CNN outperforms DNN and Convolutional Autoencoder in crop classification.	CNN achieves 97% accuracy on Indian Pines dataset, improving overall.

Fig. 3. Literature Survey Summary Table III

Sentinel-2 Data: One of the primary sources for crop classification is the Sentinel-2 satellite mission, launched by the European Space Agency (ESA) as part of the Copernicus program. Sentinel-2 provides multi-spectral, high-resolution imagery at various spectral bands, including visible, near- infrared, and short-wave infrared. Its revisit frequency ensuresregular updates, allowing for temporal analysis of crop growthstages and changes in land cover. Sentinel-2 data are widely utilized due to their global coverage, open access policy, and suitability for tasks such as land cover classification and vegetation monitoring.

Landsat Data: The Landsat program, operated by the United States Geological Survey (USGS) and NASA, offers a series of Earth observation satellites providing moderate to high- resolution imagery. Landsat data, particularly Landsat 8, is instrumental in crop classification studies. With a range of spectral bands, Landsat imagery aids in capturing detailedinformation about crop types, health, and land use patterns. The long history of Landsat missions also facilitates historical analysis, essential for understanding changes in agricultural practices over time.
MODIS Data: The Moderate Resolution Imaging Spectrora- diometer (MODIS) onboard NASA's Terra and Aqua satellitesprovides global coverage at a lower spatial resolution com- pared to Sentinel-2 or Landsat. While not suitable for detailed crop classification, MODIS data are valuable for large-scale monitoring, offering information on vegetation indices, land surface temperature, and other metrics. MODIS datasets are often used in conjunction with higher-resolution imagery to provide a broader context for regional or global-scale crop assessments.
USDA National Agricultural Statistics Service (NASS) Data: In addition to satellite imagery, ground-truth data from authoritative sources like the USDA NASS contribute to crop classification accuracy. Field-level data, including crop type and acreage, are crucial for training machine learning mod-els. Integrating such ground-truth data with satellite imagery enhances the reliability of crop classification results, allowing for the validation and improvement of algorithms.
High-Resolution Imagery: Besides satellite missions, high- resolution aerial imagery obtained from drones or aircraft can be employed for detailed crop classification in smaller agricultural plots. These datasets offer finer spatial details, capturing nuances in crop structure and facilitating more accurate identification of specific crop types.
In conclusion, the combination of satellite imagery from missions like Sentinel-2 and Landsat, along with ancillary data sources like MODIS and ground-truth datasets, forms a com- prehensive approach for crop classification. The integrationof multiple datasets enables researchers to extract meaningful insights into crop dynamics, contributing to advancements in precision agriculture and sustainable land management prac- tices. Although since many countries

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have their own satellites monitoring their territories it is also common to obtain imagerydirectly from these satellites for the purpose of image analysis and processing.

IV. MATHEMATICAL EXPRESSIONS

Crop classification using satellite image processing involves various mathematical expressions and algorithms to analyze spectral information from remote sensing data. Here are some key mathematical expressions commonly used in this context:

Normalized Difference Vegetation Index (NDVI)

$NDVI = (NIR - Red)/(NIR + Red)$

NDVI is a widely used vegetation index that utilizes the contrast between near-infrared (NIR) and red wavelengths. Positive NDVI values indicate healthy vegetation, while neg- ative values often correspond to non-vegetated surfaces.

Enhanced Vegetation Index (EVI)

$EVI = 2.5 * ((NIR - Red)/(NIR + 6 * Red - 7.5 * Blue + 1)$

EVI is an improved version of NDVI, designed to minimize the influence of soil background and atmospheric conditions, providing a more accurate measure of vegetation health. In this expression: NIR represents the reflectance in the near- infrared band. Red represents the reflectance in the red band. Blue represents the reflectance in the blue band.

V. EXISTING SYSTEM

Google Earth Engine: Google Earth Engine is a cloud-based platform that provides access to a vast archive of satellite imagery and the tools to analyze it. It supports various remote sensing applications, including crop classification. Users can leverage the platform’s extensive data catalog, machine learn- ing algorithms, and scripting capabilities for crop mappingand monitoring. Sentinel Hub: Sentinel Hub is a cloud-based service that offers access to a range of satellite data, including Sentinel-1 and Sentinel-2 from the European Space Agency’s Copernicus program. It provides tools for the analysis of multispectral and radar data, allowing users to perform crop classification and monitoring. NASA Harvest: NASA Harvest is a joint initiative between NASA, the University of Maryland, and other partners. It aims to provide global agricultural monitoring and early warning through satellite data. NASA Harvest uses remote sensing data, machine learning, and other technologies to monitor crop conditions, yield predictions, andcrop type mapping.

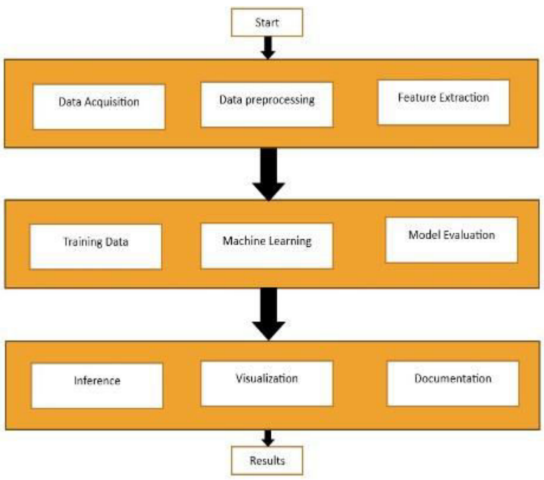

Fig. 4. Module Diagram

CropWatch: CropWatch is a system developed by the Uni- versity of Nebraska-Lincoln that utilizes satellite data for monitoring crop conditions. It provides information on crop health, water use, and other relevant agricultural parameters using satellite observations. USDA Crop Data Layer: The United States Department of Agriculture (USDA) releases an annual Crop Data Layer (CDL) that provides crop-specific land cover information for the entire United States. The CDL is created using satellite data and serves as a valuable resource for understanding crop distribution

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and land use patterns. European Space Agency's Sen2Agri: Sen2Agri is an operational system developed by the European Space Agency for agriculture monitoring using Sentinel-2 data. It includes tools for crop type classification, crop growth monitoring,and yield prediction as shown in Fig[4]. Planet Labs: Planet Labs operates a constellation of small satellites that capture high-frequency, high-resolution imagery of the Earth's surface. Users can access Planet Labs' data to monitor crop conditions,detect changes, and perform crop classification at a finer spatial resolution.

VI. PROPOSED SYSTEM

The proposed system for crop classification aims to ad- dress the drawbacks of existing methods and leverage recent advancements in technology. It integrates key features and methodologies to enhance the accuracy, scalability, and prac- ticality of crop classification using satellite image processing. Researchers can consider implementing the following compo- nents:

First is to implement advanced Deep Leanring architecturesand to develop a sophisticated convolutional neural network (CNN) architecture designed for hierarchical and temporalanalysis. Incorporate recent advancements in deep learning, such as attention mechanisms or transformer networks, to improve feature extraction and classification accuracy.

Second is to perform multi-source data fusion by Integrating data from multiple sources, including Sentinel-2 and Landsat imagery, to leverage the strengths of different sensors. Fusing high-resolution satellite data with temporal information to capture the dynamic nature of crop growth stages and changesin land cover over time.

Third is the Transfer Learning and Pre-training step which implements well-known transfer learning techniques to lever- age pre-trained models on diverse datasets. Pre-training the model on large-scale datasets to capture generic features before fine-tuning it on the specific crop classification task. This approach addresses the challenge of limited labeled data for certain crops.

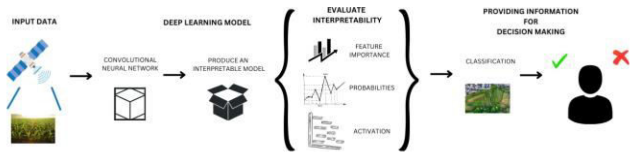

Fig. 5. System Architecture

Fourth is to pay attention to temporal dynamics to Enhance the model's ability to analyze temporal dynamics by consider- ing time-series data. Incorporate convolutional neural networks (CNNs) as showing in Fig[5] or attention mechanisms to capture sequential patterns in crop growth and phenology, enabling the model to recognize temporal variations.

Fifth is to utilise cloud-based platform for real-time pro- cessing. Implementing a cloud-based infrastructure for real-time processing, ensuring scalability and accessibility. Cloud computing enables researchers to handle large datasets, deploymodels efficiently, and provide on-demand processing for usersin diverse geographical locations.

Next is integration of ancillary data involving incorporation of additional datasets, such as climate data or soil information, to enhance the contextual understanding of crop classification. Integrating these ancillary data can improve the model's ro- bustness and accuracy under varying environmental conditions. It is also necessary to continuously monitor and update the model. Implement a system for continuous monitoring ofmodel performance. Introduce mechanisms for model updat- ing, allowing the system to adapt to changes in crop types, agricultural practices, or environmental conditions over time.

By considering these advancements and addressing the drawbacks of existing approaches, researchers can contribute to the development of a robust and effective crop classificationsystem, fostering advancements in precision agriculture and sustainable land management.

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VII. RESULTS

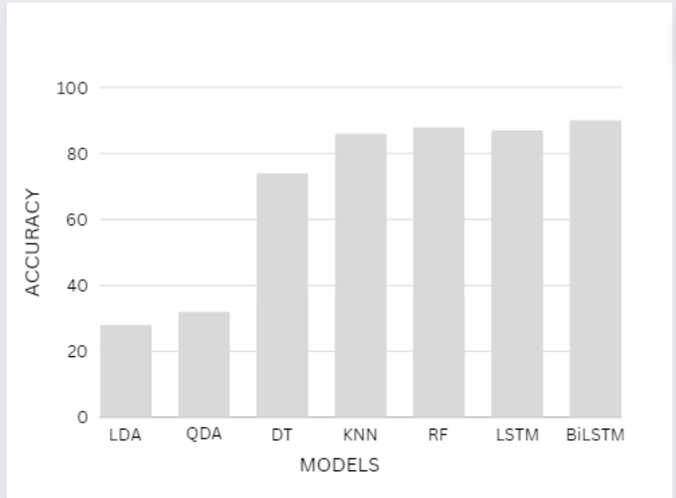

Fig. 6. Accuracies of different DL models

As technology continues to evolve, the proposed projectlays a foundation for continuous improvement, allowing for updates and refinements to the deep learning model to stayat the forefront of advancements in machine learning and satellite technology. With its holistic approach, the projectaspires to contribute significantly to the enhancement of crop management strategies, resource efficiency, and overall agricultural productivity. The problem of crop classification continues to remain relevant in pre-dominantly agricultural nations like China, USA, Russia, India and Brazil. The useof Machine Learning and Deep Learning technologies to help solve agriculture-related problems and to address key local issues is a field that is yet to reach its highest innovationpoint and breakthroughs. Therefore, in this review, we attempt to analyse the course of this application since its inception to the present-day, where newer technologies and better satellite positioning helps to fully understand the agricultural ecosys- tem. It also attempts to expose some flaws and drawbacks that researchers can aim to mitigate via further research and proposes the subsequent upgrades that can revolutionise both the deep learning and the agricultural worlds.

VIII. CONCLUSION

In conclusion, the proposed project for crop classification using advanced satellite image processing and deep learning presents a promising solution to the challenges faced in pre- cision agriculture. By integrating a hierarchical convolutional neural network with multi-scale satellite imagery, the system strives to significantly improve the accuracy and efficiencyof crop identification. The emphasis on real-time processing, resource optimization insights, and a user-friendly interface underscores its practical applicability for farmers and stake- holders in diverse agricultural settings. The project not only addresses the limitations of existing systems but also aligns with the global need for sustainable agricultural practices in the face of increasing food demand and changing environmen-tal conditions. The educational outreach component further enhances its impact by fostering awareness and facilitatingthe adoption of the system among farming communities.

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