A project report on

DEEP LEARNING AND NDVI BASED MULTISPECTRAL AND HYPERSPECTRAL ANALYSIS FOR PANICLE AND WATER STRESS DETECTION IN CROPS

Submitted in partial fulfillment for the award of the degree of

Bachelor of Technology in Computer Science and Engineering with Specialization in Cyber Physical Systems

by

SHETTY VIDHEE SHRIDHAR (21BPS1526)

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Vellore Institute of Technology

(Deemed to be University under section 3 of UGC Act, 1956)

CHENNAI

SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

April, 2025

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DECLARATION

I hereby declare that the thesis entitled "DEEP LEARNING AND NDVI BASED MULTISPECTRAL AND HYPERSPECTRAL ANALYSIS FOR PANICLE AND WATER STRESS DETECTION IN CROPS" submitted by SHETTY VIDHEE SHRIDHAR (21BPS1526), for the award of the degree of Bachelor of Technology in Computer Science and Engineering, Vellore Institute of Technology, Chennai is a record of Bonafide work carried out by me under the supervision of Dr. Balasundaram A.

I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

Place: Chennai

Date: 02/04/25

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CERTIFICATE

This is to certify that the report entitled **"Deep Learning and NDVI based Multispectral and Hyperspectral analysis for Panicle and Water stress Detection in crops"** is prepared and submitted by **Shetty Vidhee Shridhar (21BPS1526)** to Vellore Institute of Technology, Chennai, in partial fulfillment of the requirement for the award of the degree of **Bachelor of Technology in Computer Science and Engineering** is a Bonafide record carried out under my guidance. The project fulfills the requirements as per the regulations of this University and in my opinion meets the necessary standards for submission. The contents of this report have not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma and the same is certified.

Signature of the Guide: A. Bau...

Name: Dr. Balasundaram A.

Date: 02.04.2025

Signature of the Examiner
Name: Dr. P. Helen Vijitha
Date: 17/4/25

Signature of the Examiner
Name: JAI.S
Date: 17th APT 2025

Approved by the Head of Department,
B.Tech. CSE with SPL. Cyber Physical systems

Name: **Dr. Renuka Devi S**

Date: 02/04/25

(Seal of SCOPE)

VELLORE INSTITUTE OF TECHNOLOGY
SCHOOL OF COMPUTER SCIENCE & ENGINEERING (SCOPE)

4

ABSTRACT

Crop wellbeing observation through precision farming methods has taken on strong importance when shortages and resource constraints affect regions. RGB imaging technology faces challenges in detecting vital spectral-spatial relationships because this hinders its ability to observe early stress levels and segment objects clearly. The research develops a complete NDVI-based analysis framework with contemporary multispectral and hyperspectral imaging together with deep learning and machine learning techniques specifically for paddy field panicle detection and early maize and groundnut crop water stress evaluation.

This research evaluates different deep learning architectures through systematic review of UAV-based datasets especially the high-resolution TiHAN IIT Hyderabad Dataset (TiAND) collected from experimental farms at PJTSAU and ICRISAT. The DoubleConv+ U-Net model delivers superior results for panicle segmentation by reaching a Dice coefficient of 0.8573. A 1D-CNN model which processed hyperspectral reflectance data succeeded in detecting groundnut crop water stress at 99.69% accuracy. By incorporating the novel Channel Spatial Attention Block (CSAB) with ResNet+ U-Net the researchers obtained exceptional water stress segmentation results in maize with a Dice coefficient of 0.7457 while exhibiting strong generalization abilities against current methodological standards.

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Place: Chennai

Date: 02/04/2025 **SHETTY VIDHEE SHRIDHAR**

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LIST OF ACRONYMS

- **AUC:** Area Under Curve
- **CNN:** Convolutional Neural Network
- **CSAB:** Channel Spatial Attention Block
- **GB:** Gradient Boosting
- **GPU:** Graphics Processing Unit
- **ICRISAT:** International Crops Research Institute for the Semi-Arid Tropics
- **ML:** Machine Learning
- **NDVI:** Normalized Difference Vegetation Index
- **NIR:** Near-Infrared
- **PCA:** Principal Component Analysis
- **PJTSAU:** Professor Jayashankar Telangana State Agricultural University
- **RF:** Random Forest
- **RFE:** Recursive Feature Elimination
- **RGB:** Red-Green-Blue
- **SAVI:** Soil Adjusted Vegetation Index
- **SVM:** Support Vector Machine
- **TCARI:** Transformed Chlorophyll Absorption in Reflectance Index
- **UAV:** Unmanned Aerial Vehicle
- **XGB:** XGBoost

Chapter 1

INTRODUCTION

1.1 BACKGROUND & SIGNIFICANCE

The farming industry has acknowledged precision agriculture as a fundamental solution which solves worldwide problems regarding food security and resource management together with environmental sustainability. The method uses state-of-the-art technology together with data analytical systems to boost crop production without harming the environment. The national economy of India heavily depends on agriculture while offering major employment opportunities across numerous segments of its population thus precision farming stands as a vital need for sustainable agricultural methods and extended agricultural output.

Several obstacles affect Indian agriculture including unstable climate patterns together with water shortages and damaged soil quality alongside insufficient management strategies. Multiple issues block productivity and sustainability of agriculture so innovative precise and efficient agricultural techniques become essential. The large number of climatic areas and diverse crop types found across the Indian agricultural regions makes precision agriculture a practical approach because it delivers specific and accurate and timely agricultural data.

Rice together with maize and groundnut serve as fundamental staples for India's food safety and they form the basis of its agricultural output. The Indian population heavily relies on rice as their main sustenance which establishes the country as a top position in global rice production. Accurate yield estimation together with effective rice farming management requires precise detection methods for panicles. Panicle detection precision directly impacts the estimation of yields together with harvesting methods and economic benefits for farmers.

The agricultural production of maize and groundnuts has significant economic importance for India because they grow well in water-scarce regions. Accurate water resource management of both crops remains vital for achieving long-lasting agricultural production output. The timing of water stress detection remains fundamental because suitable fast interventions help prevent yield reduction while improving management of irrigation systems. Early detection of water stress in multiple Indian states requires immediate advances in monitoring technology for water scarcity because of worsening water scarcity conditions.

The traditional assessment of crops revolved between human observation and RGB (Red Green Blue) image processing techniques. The process of manual inspections remains easy to perform but requires extensive human labour to execute them accurately especially when used in extensive agricultural areas. Plant-related subtle physiological and biochemical changes leading to early stages of stress and disease cannot be detected effectively by RGB imagery despite its widespread application. The current crop-health monitoring systems require better advanced technological solutions to provide full-time comprehensive insights regarding plant conditions.

UAVs led to a revolutionary change in agricultural monitoring as they provide precise detailed and frequent data acquisition capabilities for large farm regions. Remote sensing implemented through UAV systems provides fast operation capabilities with adjustable features along with precise spatial area surveillance. Through this technology farmers gain continuous crop health monitoring capabilities across various growing stages under all environmental conditions to achieve improved timely and precise agricultural management practices.

The health status of crops becomes visible through multiband spectral imaging that records Blue, Green, Red as well as Red-Edge and Near-Infrared (NIR) data for holistic monitoring. This technology becomes more effective for identifying plant health status alongside nutrient deficiencies and early stress warnings when used with the Normalized Difference Vegetation Index (NDVI) vegetation index. The application of multispectral imaging methods shows minimal usage in Indian agriculture for specialized needs such as paddy farming panicle detection.

The precise evaluation of plant health becomes possible through hyperspectral imaging due to its capability of collecting extensive spectral data from a wide range of narrow wavelength bands. The technology proves useful specifically for first detecting water stress and detecting minor crop physiological transformations. At present the extensive adoption and practical utilization of hyperspectral imaging within the agricultural sector of India remains minimal. Directed research combined with validation programs will help India improve agricultural water resource and crop health management which would boost productivity and sustainability of agricultural systems.

1.2 OVERVIEW OF PANICLE & WATER STRESS DETECTION

Precision agriculture relies heavily on water stress detection and panicle segmentation because they determine both crop management quality and overall harvest results. Mixed crops like maize and groundnut must receive fast and accurate water stress detection since these two crops show intense sensitivity to water supply in regions dealing with water scarcity. Malpractice in water stress management leads to substantial economic harm for farmers alongside diminished product yields because it requires efficient detection methods to succeed.

Rice field managers need accurate panicle detection to achieve their best harvest yields during planning. The principal structures responsible for rice yield generation are panicles which provide important information about future harvest outcomes. The accurate segmentation of panicles enables farmers together with agricultural managers to develop exact yield estimates and better organize harvest operations and optimize their resource utilization. Manually detecting and counting panicles remains a historical practice because it requires extensive labour and produces time-consuming results with potential errors that motivates developers to create advanced automated measurement systems.

The demanding criteria of agricultural monitoring need better methods than traditional manual inspections and basic RGB imagery. The current availability of RGB imaging demonstrates limited detection ability toward early water stress symptoms together with restricted capabilities to recognize panicle details. Today's remote sensing technologies such as multispectral and hyperspectral imaging gain increasing recognition due to their ability to gather complete spectral along with spatial crop-related information. These new technologies help stress conditions become apparent early on by performing precise copula structure segmentation such as panicles. Modern agricultural practices depend heavily on these state-of-the-art technologies because they deliver promising enhancements in agricultural management systems allowing better resource optimization and increased productivity.

1.3 MOTIVATION OF STUDY

This study begins from the necessity to develop precise monitoring methods for agriculture which can operate uniformly across different Indian environments and cultivated plants. The current literature about precision agriculture does cover global applications but does not provide sufficient research on its Indian adaptation. The wide range of agricultural environments, climate volatility and water resource problems in India make it a perfect location for researching advanced monitoring technologies thus making this research both appropriate and timely.

The TiHAN IIT Hyderabad dataset originating from PJTSAU and ICRISAT experimental farms enables researchers to perform in-depth analysis of multispectral and hyperspectral imaging systems based in Indian agricultural conditions. Its unique advantages stem from precise high-resolution images that contain many spectral bands and detailed documentation of stress markers which precisely serve Indian crop varieties and agricultural procedures. The research outcomes benefit from dataset implementation since they directly pertain to actual agricultural practices throughout

India.

Previous studies mainly employed generic imaging techniques while focusing on foreign agricultural fields rather than Indian agricultural challenges like accurate rice panicle detection or early water stress identification in maize and groundnut crops. The research fills a crucial void in knowledge research by investigating sophisticated remote sensing techniques with multispectral along with hyperspectral for these vital regions that received limited attention.

1.4 PROBLEM STATEMENT

Farmers mainly use manual inspections combined with traditional RGB image analysis to monitor their crops in agricultural fields. Manual inspections are easy to conduct yet they demand significant human work while taking too much time and showing weakness to human mistakes so they become unusable for big-scale agricultural production. Many users employ RGB imagery because it exists at affordable prices however the technique fails to capture delicate plant physiological and biochemical alterations. Early indicator crops use these changes to signal stresses that include water scarcity and nutrient depletion which harm their growth if not detected right away.

The existing spectral imaging technologies consist of multispectral and hyperspectral imaging yet they need better adaptation and optimization for the varied agricultural conditions across India. The main disadvantage of existing methods rests in underusing specific spectral information delivered by modern imaging systems. The improper utilization of analytical methods exists because researchers lack appropriate customization of analytical approaches and insufficient study of Indian agricultural environments and local crops including rice, maize and groundnut.

The limited management capabilities of Random Forests and Support Vector Machines together with conventional machine learning techniques have led to a performance limitation when working with high-dimensional and complex spectral datasets. The requirement for manual feature selection in these approaches reduces their ability to work with new data while environmental conditions change. Complex analytical systems need development right now because they will fully utilize deep learning models with hyperspectral and multispectral data. An ideal framework needs to accurately understand complex spectral-spatial interactions to produce effective panicle separation of paddy fields along with dependable detection of water-related stress.

1.5 AIM & OBJECTIVES

The principal research task establishes an advanced analysis system through the usage of Normalized Difference Vegetation Index (NDVI). The developed framework combines deep learning and machine learning algorithms with multispectral and hyperspectral imaging to exactly segment paddy panicles while simultaneously detecting water stress in maize and groundnut crops particularly within the Indian agricultural environment.

1 The goal involves evaluating UAV-based imaging systems by employing spectral information from the TiHAN IIT Hyderabad dataset that was acquired through s sampling experimental farms at PJTSAU and ICRISAT.
2. A complete preprocessing system will develop NDVI-based pseudo-masking techniques along with morphological transformations that specifically suit multispectral and hyperspectral dataset requirements.
3. Researchers will perform an organized assessment of deep learning models that combine DoubleConv+U-Net with Attention U-Net and 3D CNN+U-Net and ResNet+U-Net incorporated with Channel Spatial Attention Blocks (CSAB) to improve panicle segmentation and measure water stress in effective ways.
4. The research examines traditional machine learning methods and deep learning systems for detecting water stress in groundnut and maize through comparison of 1D-CNN and ensemble methods such as Random Forest, Gradient Boosting and

XGBoost.

5. Testing methodology effectiveness and system accuracy will determine the level of precision enhancement and scalability growth through comparative analysis with traditional methods.
6. The research will create stable approaches with guidelines for practical agricultural management practices through multispectral and hyperspectral drones in different Indian agricultural farms.
7. By using the py-feat library researchers will achieve precise extraction of AU intensities connecting to happiness, sadness, anger, disgust, surprise, and fear emotions.

1.6 RESEARCH CHALLENGES

The research encounters multiple critical barriers regarding the implementation of advanced remote sensing techniques using multispectral and hyperspectral imaging across India's multiple agricultural areas. High-dimensional spectral data collected through UAV-based imaging systems creates a main processing and management challenge. The major challenge involves efficient characterization of essential features present in large datasets while maintaining necessary information because operational analysis meets strong computational roadblocks.

The creation of dependable preprocessing methods represents another enormous challenge because they must handle normal noise and variations in illumination levels together with sensor calibration errors along with environmental factors which affect agricultural fields in real conditions. The process of achieving precise segmentation into complicated canopy structures and dense vegetation stands as a challenge to identify panicles along with water stress indicators accurately.

A main difficulty exists in modifying deep learning together with machine learning models to work properly with the various agricultural field conditions. The system needs to exhibit enough stability when dealing with changes in crop species and growth phases and environmental influences without demanding re-training or adjustment procedures. An essential challenge exists in making these advanced methodologies applicable for real-world deployments with farmers and agricultural stakeholders so they can adopt them on a widespread scale.

CHAPTER 2

LITERATURE SURVEY & RELATED STUDY

2.1 OVERVIEW OF REMOTE SENSING IN AGRICULTURE

Remote sensing technology has revolutionized agricultural procedures through its innovative method of gathering and processing data about crop health together with soil status and complete farm administration. Remote sensing systems installed on satellites along with aircraft and unmanned aerial vehicles (UAVs) produce non-invasive regional data collection that reports critical soil properties and identifies crop sample types and detects moisture stress and projects harvest outcomes. The operation of Landsat since 1972 demonstrates how the program achieved essential land cover mapping and agricultural change monitoring capabilities. The European Space Agency operates Sentinel-2 as a mission to generate multispectral images at high resolution which helps identify land cover modifications and track crop performance.

Remote sensing technology becomes more powerful through its alignment with modern technological devices of Internet of Things (IoT) and machine learning algorithms. Soil moisture sensors together with meteorological stations send real-time information that help researchers analyze remote sensing data effectively to forecast yields better and make water resources more efficient. The processing abilities of machine learning algorithms examine massive datasets to reveal telling patterns and irregularities that help discover crop diseases at an early stage as well as maximize resource distribution effectiveness.

Remote sensing technology continues to face various obstacles as institutions work to implement its widespread application in agricultural fields. The needs of the agriculture industry will require ongoing research due to complicated data processing and high-resolution image requirements for diverse data sources integration.

Affordable accessibility of these technologies must be addressed as a major concern especially for farmers in developing countries. The complete potential of remote sensing in agriculture can only be reached by addressing current obstacles.

2.2 MULTISPECTRAL IMAGERY APPLICATION

Through precision agriculture multispectral imagery functions as a powerful tool to generate vital crop information past the boundaries of visible light spectrum detection. This capability facilitates effective monitoring, management, and intervention in crop production. The segmentation of paddy field panicles has recently achieved success through the analysis of multispectral images obtained by UAV drones according to recent research findings. The execution of threshold-based segmentation and K-Means clustering and Maximum Entropy Thresholding techniques by researchers has led to significant automation of panicle detection procedures [1]. Methodological enhancement is necessary to improve error rates in smaller panicle detection and growth stages with dense vegetation.

Recent investigations have introduced RiceRes2Net along with Res2Net101 and Feature Pyramid Networks (FPN) as enhancement components for Cascade RCNN-based panicle detection models. The detection accuracy of this model reaches 96.8% Average Precision during the booting phase [2]. The method's performance decreases in later growth stages mainly because of overlapping problems and natural object obstruction so more methodological development remains essential. The combination of AdaBoost and Gradient Boosting Decision Trees (GBDT) allows researchers to monitor rice panicle blast diseases effectively through multispectral imaging technology which produces high accuracy results with R^2 of 94% and RMSE of 0.12 [3]. Multispectral remote sensing systems mounted on UAVs demonstrate great effectiveness for enhancing agricultural management approaches according to these research findings.

Multispectral imagery stands essential for both yield prediction of rice and lodging evaluation tasks. The effectiveness of yield prediction grows through TCT together with NDVI and NDRE and EVI2 vegetation indices and achieves 93.8% accuracy throughout rice's essential growth period [4]. Random Forest classifiers establish exceptional precision through their combination of multispectral spectral and textural data for detecting lodging conditions.[5]

Multispectral imagery serves as a vital tool for water stress observation of crops particularly maize crops. Various research demonstrates that utilizing vegetation indices with machine learning classifiers from the Random Forest family alongside Support Vector Machines leads to successful detection of drought indicators alongside nutrient deficiency signs. The observational success rates above 90% mainly occurred in regulatory research conditions yet band selection approaches struggle to sufficiently identify subtle indicators in extensive agricultural implementations [6] . Continuous research must advance multispectral applications because it enables the resolution of existing problems and enhances their capabilities for precision agriculture.

2.3 HYPERSPECTRAL IMAGERY APPLICATION

Hyperspectral imaging has become essential for precision agriculture by providing thorough crop wellness evaluations through its multiband spectral data acquisition mechanism. The analysis of barnyard grass distribution and identification in Chinese paddy fields relied on hyperspectral images obtained from UAVs that scanned the 429–1020 nm spectrum band over 300 wavelengths. The research implemented the Successive Projection Algorithm (SPA) along with 3D Convolutional Neural Network (3D CNN) and Support Vector Machine (SVM) and Random Forest (RF) as its algorithms. The SPA-3DCNN achieved 93.12% overall accuracy coupled with 0.90 Kappa coefficient which demonstrates how hyperspectral imagery functions effectively for rice versus barnyard grass identification in agricultural settings [10] .

Researchers investigated water stress detection in groundnut canopies by using UAV-based hyperspectral imaging technology that operated in the 385–1020 nm range within 300 bands at groundnut research areas at ICRISAT in Hyderabad. The study combined Ensemble Band Selection approaches with SVM, Random Forest (RF), XGBoost framework and NDVI indices for its analysis. The SVM model reached an accuracy rate of 96.46% using selected bands simultaneously it achieved 98.63% accuracy for stress classification. This research demonstrated that hyperspectral imagery proves effective for detecting stresses prior to emergence but the immediate adoption of this technology faces difficulties because it demands sophisticated data handling and hyperspectral sensors. [9]

The detection of water stress in pearl millet through hyperspectral imagery covering 400–1000 nm range (281 bands) was demonstrated by this investigation which used UAV data acquisition. Through the combination of Recursive Feature Elimination algorithm with SVM and Random Forest methods researchers achieved 95.38% success in water stress classification and 80.76% accuracy in early detection of water stress. Hyperspectral image data proved its effectiveness for stress classification through these results yet its accuracy remained lower for detecting stress in early stages. [8]

The separate review evaluated how UAV remote sensing technologies detect crop water stress through combining hyperspectral imaging with thermal and RGB and multispectral imaging capabilities. The study applied Random Forest and Support Vector Machine (SVM) from machine learning to achieve 96.46% accuracy for spotting stress signs at an early stage. [10] Hyperspectral data processing experienced constraints because it required extensive computation resources and struggled to scale up operations. The research aimed to enhance irrigation management systems by combining unsupervised machine learners (UML) with geophysical metrics and Sentinel-2 multispectral imaging as well as Electrical Conductivity (ECa). The research results contribute to the growing area of precision agriculture which employs sophisticated imaging solutions by studying multispectral data even though hyperspectral data was not its focus [11].

2.4 REVIEW OF NDVI APPLICATION

NDVI serves as a main tool in precision agriculture for crop health evaluation along with stress factor detection and yield estimation purposes. The monitoring of water stress in plants relies heavily on NDVI because this index shows effectiveness in differentiating between healthy and degenerated plants. NDVI functions as an essential component in UAV-based panicle segmentation models because it creates multispectral pseudo-masks which enhances paddy crop segmentation accuracy [1]. The combination of Support Vector Machines (SVM) and Random Forest with NDVI identification allowed researchers to achieve superior than 96% classification accuracy for detecting water stress in groundnut crops during the early stage of development [8].

Many research studies combine NDVI with remote sensing technology to strengthen water stress detection and yield measurement capabilities. The combined analysis of NDVI with the Crop Water Stress Index (CWSI) and multiple vegetation indices achieved up to 96.46% accuracy in detecting water stress in maize and pearl millet using UAV-acquired hyperspectral and multispectral imagery according to Zhou et al. (2024) [12]. NDVI served as an essential component within the ensemble band selection process to identify water stress conditions in groundnuts when applied to ICRISAT field assessments [8]. Multispectral UAV studies showed that NDVI and additional indices EVI2 alongside NDRE could achieve greater than 90% rice yield prediction accuracy during the heading stages [4]

2.5 LIMITATIONS OF EXISTING APPROACHES

Despite notable progress in precision agriculture, existing crop monitoring techniques encounter various challenges that limit their effectiveness in extensive, real-world scenarios. Conventional monitoring methods typically depend on manual field assessments and RGB imaging, which are labor-intensive, time-consuming, and heavily reliant on human expertise. Although RGB imagery is both accessible and cost-effective, it falls short in detecting subtle physiological and biochemical changes in crops, especially during the initial stages of stress, such as water scarcity or nutrient deficiencies. Consequently, early identification and prompt intervention are often overlooked, resulting in diminished crop yields and inefficient resource use.[1][4]

Even with the advent of multispectral and hyperspectral imaging technologies, their adoption and integration remain constrained, particularly within the context of Indian agriculture. A significant number of existing studies concentrate on controlled environments or areas with uniform crop and environmental conditions, complicating the application of findings to diverse and intricate agricultural settings. While hyperspectral data provides high spectral resolution and detail, it poses challenges due to its substantial data volumes, which increase computational complexity and necessitate considerable processing power. Furthermore, the high cost of hyperspectral sensors restricts their widespread use, particularly among smallholder farmers in developing regions.[6][8][10]

Traditional machine learning techniques, including Random Forest (RF), Support Vector Machines (SVM), and Gradient Boosting Decision Trees (GBDT), have been extensively utilized for detecting crop stress and estimating yields. Nonetheless, these models frequently encounter a performance ceiling due to their dependence on manually crafted features and their restricted ability to fully leverage the intricate spectral-spatial relationships present in multispectral and hyperspectral datasets. The process of manual feature selection is susceptible to bias and inconsistency, and these models often face challenges in generalizing across different crop varieties, growth phases, and varying environmental contexts. Consequently, this can lead to diminished model accuracy and an increase in false positives, particularly in applications such as panicle segmentation in rice fields and early detection of water stress in crops like maize and groundnut.[3][8][9]

In addition, while the Normalized Difference Vegetation Index (NDVI) and other vegetation indices are commonly employed for stress detection and yield estimation, they are not without their drawbacks. NDVI may experience saturation in areas with high biomass and may struggle to distinguish between different types of stress or to provide adequate information under varying lighting and soil conditions. This has prompted researchers to investigate more sophisticated indices and to combine NDVI with supplementary spectral and spatial data to enhance accuracy. However, despite these improvements, issues such as scalability, computational requirements, and the necessity for domain-specific calibration continue to pose challenges, hindering the broader implementation of these advanced remote sensing and analytical methods in precision agriculture.[13][14][15]

CHAPTER 3

METHODOLOGY

3.1 PROPOSED SYSTEM ARCHITECTURE

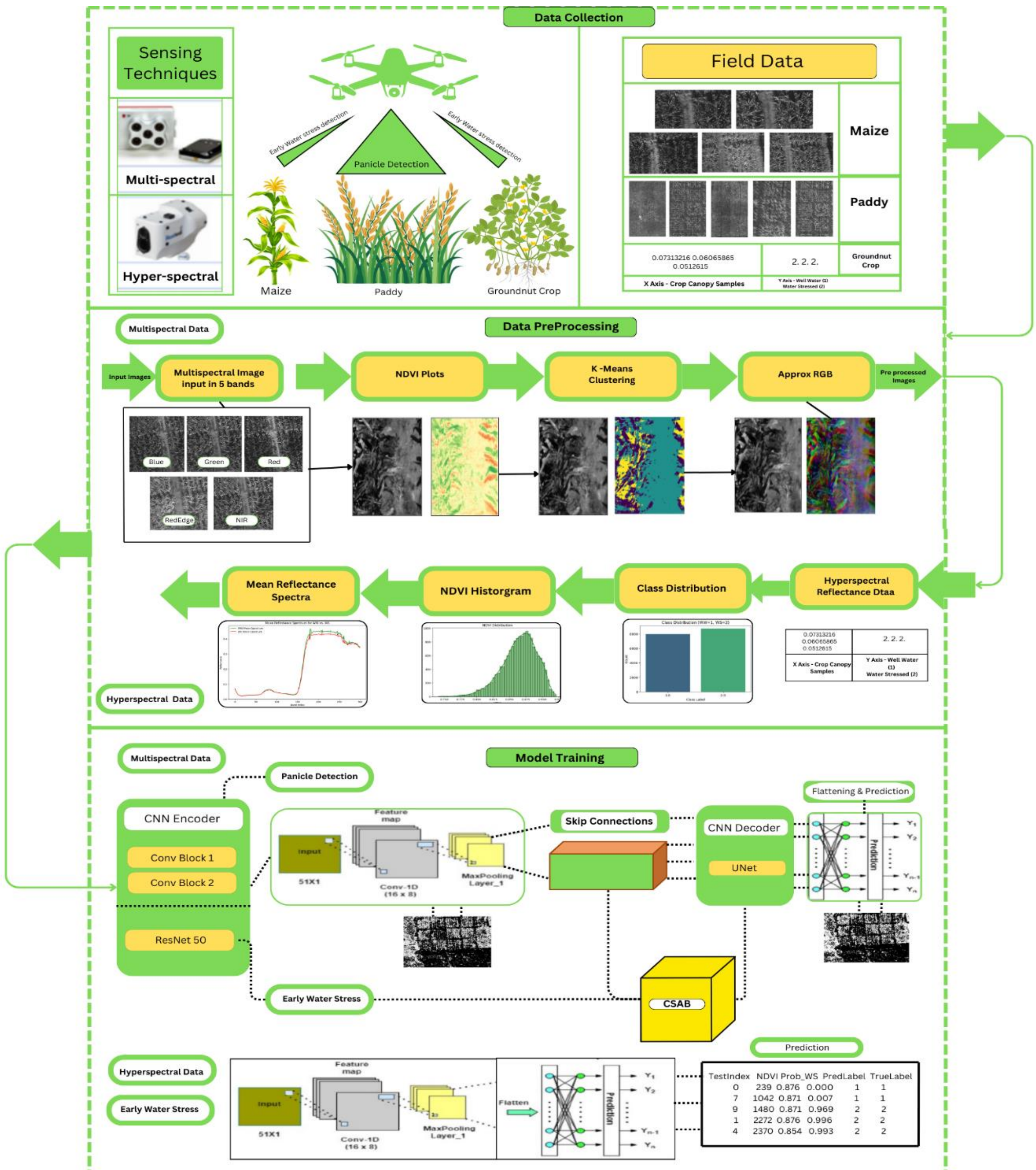

Fig 1: Proposed System Architecture

The **Fig 1** depicts the proposed framework targets two definitive problems in precision agriculture through its objectives to separate paddy crop panicles and detects water-stressed maize and groundnut at early stages. The system structure uses UAV-obtained multispectral and hyperspectral imagery together with advanced deep learning and machine learning algorithms. UAV data acquisition commences by using multispectral cameras to obtain five particular spectral bands that include Blue, Green, Red, Red Edge, and Near-Infrared. The generated image data undergoes sequential processing through clustering followed by NDVI-based pseudo-masks generation before performing morphological operations to prepare it for training purposes. U-Net model with DoubleConv as encoder module carries out panicle segmentation tasks through spatial features extraction followed by decoder operations to generate precise panicle identification masks. With this approach it becomes possible to measure panicles in detail which results in better yield forecasts and improved farming operations.

The proposed architecture uses UAV-based sensors that obtain 282 bands within 400–1000 nm wavelengths to detect water-stressed conditions in both maize and groundnut at an early stage. The data passes through normalization then noise reduction steps and vegetation indices namely NDVI perform feature extraction before moving on to the next process. Random Forest and XGBoost machine learning algorithms and the sophisticated 1D-CNN deep learning method work together with the system to detect between water-stressed and properly irrigated crops. The identification of maize requires multispectral imagery which utilizes a ResNet+U-Net framework that integrates Channel Spatial Attention Blocks (CSAB) to comprehend spatial and spectral information efficiently. The novel engineering architecture effectively joins spectral alongside spatial knowledge to execute robust panicle division while achieving exact water stress detection thus eliminating impairments from existing approaches in agricultural decision-support systems.

3.2 DATA COLLECTION AND DATASET DESCRIPTION

This research drew its data from UAV-based precision agriculture experiments that occurred at Professor Jayashankar Telangana State Agricultural University (PJTSAU) Agro Climate Research Center along with the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) situated in Hyderabad India. Autonomous Navigation Dataset (TiAND) at TiHAN IIT Hyderabad initiated the data collection mission to create precision agricultural datasets comprised of multispectral and hyperspectral imagery with high definitions for autonomous systems research. The project dedicated efforts to acquire critical growth stage data from different agricultural fields spread across diverse climatic zones for complete analytical purposes.

The data collection includes two specific agricultural products: paddy fields and maize fields. The research period spanned three continuous years throughout Kharif and Rabi periods from 2018 up to 2020. The experimental fields at PJTSAU in Hyderabad received strict management for agricultural practice standardization. Research analysts collected data through flights of Unmanned Aerial Vehicles (UAVs) which used the MicaSense Red Edge-MX multispectral camera. The MicaSense Red Edge-MX camera recorded images through five spectral bands starting from Blue (475 nm) and proceeding to Green (560 nm), Red (668 nm), Red Edge (717 nm), and ending with Near-Infrared (840 nm). A different .tif image file recorded each spectral band while the datasets received geographical positioning to enable spatial analysis. The paddy dataset has a total of 315 multispectral image sets but the maize dataset comprises 320 multispectral images. The collected datasets supported the separation of panicles in paddy fields together with the detection of water-related stress in maize crops.

The second dataset consists of hyperspectral imagery collected for the purpose of early water stress detection in groundnut crops. The data collection process occurred at ICRISAT in Hyderabad across the post-monsoon agricultural period which ran from November 2021 through February 2022. The data acquisition was performed using hyperspectral camera Resonon Pika-L operated on a UAV platform to obtain 282 spectral bands ranging from 400 nm to 1000 nm. The extensive reflectance measurements were acquired from ideal crop height for the purpose of detecting subtle physiological alterations. The database contains Well-Watered (WW) and Water-Stressed (WS) categories that display proper labeling for each sample. The .npy files format the hyperspectral data while maintaining a split between spectral reflectance information and label annotations thus protecting data integrity and enabling easy model training.

These datasets remain among India's original UAV-derived multispectral and hyperspectral collections which focus on agricultural territory. The datasets provide detailed geographic and spectral details which enables researchers to develop elaborated machine learning models that serve precision agriculture. Two agricultural problems are addressed through the datasets that contain multiple crop species such as paddy and maize and groundnut data. Research on crop monitoring and yield prediction together with sustainable resource management depends significantly on these datasets that serve Indian agricultural needs.

3.3 Preprocessing Pipeline

3.3.1 File Clustering & Black Border

The preprocessing workflow for multispectral image analysis includes essential file clustering operations as its basic element. The paddy and maize crop focused multispectral dataset uses individual images to record all five spectral bands including Blue, Green, Red, Red Edge and Near-Infrared (NIR). UAV flight operations generated individual single-band .tif files that required proper grouping since they must form a combined multispectral image representation. The clustering procedure requires a planned method to assemble the spectral band images which correspond to each field plot and flight capture. A data acquisition naming convention creates clustered data outputs through labeling similar spatial captures as IMG_001_1.tif to IG_001_5.tif. The clustered images become a single multi-dimensional array with dimensions ($5 \times H \times W$) that uses the spatial measurements H and W. A structured data arrangement serves vital purposes for processing since it enables pixels from separate bands to show the exact same ground location across the entire field.

Process pipeline addresses black borders that commonly appear in raw multispectral images throughout its subsequent phase. Sensor calibration issues together with image rectification and UAV data acquisition alignment causes the appearance of black borders. The black borders generate excessive noise in segmentation and classification operations because they represent non-essential areas that have reflectance values equivalent to zero. A bounding box extraction technique serves as the chosen method for resolving this problem. The image scanning process locates non-zero pixel areas which represent actual canopy data through this method. The valid data regions have their boundaries verified for cropping out the black margins from the images. Morphological operations should be applied during this phase because they help maintain the integrity of the cropped section and also help avoid valuable edge data loss. The task of black border removal plays a fundamental role by eliminating unwanted input data while simultaneously maximizing memory usage and directing post-optimization processes to focus on canopy area assessment for better deep learning model performance.

3.3.2 NDVI Calculations

Observing plant vitality and biomass and assessing plant health through vegetation stands as the crucial purpose of the Normalized Difference Vegetation Index (NDVI). The MicaSense Red Edge-MX sensor generates multispectral data that uses the NDVI computation as a vital preprocessing step for paddy and maize crop evaluation. The NDVI derived value results from the standard mathematical expression in (1)

$$NDVI = (NIR - Red) / (NIR + Red) \quad (1)$$

Plant health observations depend on two spectral bands where NIR assigns to 840 nm and Red occupies 668 nm. Pixel-wise NDVI values result from extracting spectral bands from clustered multispectral stacks which eventually lead to the creation of a single-channel NDVI map. The NDVI map successfully displays vegetative health by showing dense chlorophyll-producing vegetation through high values and weak vegetation through low values. The produced NDVI map serves essential functions in several following applications because it enables the creation of pseudo-masks for segmentation tasks and allows machine learning algorithms to extract features and helps identify areas of interest (ROI) within the crop canopy.

Calculating the Normalized Difference Vegetation Index (NDVI) from hyperspectral groundnut field data at ICRISAT follows normal theoretical principles yet requires choosing appropriate spectral bands from datasets containing high spectral precision. The Resonon Pika-L hyperspectral sensor records data through 282 bands that extend between 400 nm to 1000 nm wavelengths. To determine NDVI both the Red and Near-Infrared (NIR) wavelengths must be represented through selected spectral bands. Two main types of bands exist for Red band identification at 668 nm and NIR band choices within an 840–870 nm wavelength spectrum depending on sensor wavelength distributions. The pixel-based NDVI calculation requires implementation of the standard NDVI formula. Hyperspectral data serves as an enhancement tool which enables better band selection accuracy and flexibility because users can make specific adjustments to suit particular crop kinds or stress indicators. The precise spectral resolution allows better detection of minor crop health variations because it proves essential for early identification of groundnut crop stress.

The functionality of both multispectral and hyperspectral NDVI maps requires post-processing before implementation. A set of morphological procedures such as opening and closing is applied to the NDVI maps to remove minor artifacts as well as enhance vegetative area edges. The combination of NDVI maps with Red Edge band thresholds forms pseudo-ground truth masks in multispectral data collections to support deep learning segmentation model training. The NDVI feature finds regular use as input data for machine learning algorithms from Random Forest to SVM and sophisticated deep learning systems that include 1D Convolutional Neural Networks (1D-CNNs) in hyperspectral datasets. Isochromatic normalization values from NDVI serve as fundamental elements both for extracting regions of interest and conducting cluster analysis and creating advanced vegetation metrics. NDVI plays an essential role in various analytical operations of multispectral and hyperspectral frameworks that underpin this proposed architecture.

3.3.3 DATA AUGMENTATION TECHNIQUES

Data augmentation stands as an essential tool to enhance the model generalization along with robustness when performing panicle segmentation in paddy fields and early water stress detection in maize and groundnut crops. The augmentation strategies for multispectral datasets about paddy and maize help duplicate sensor angle and crop canopy structure and lighting condition variations to reduce overfitting and improve performance in unseen data scenarios. Multispectral imagery augmentation involves simulated UAV flight path simulations through horizontal and vertical flips as geometric transformation components during the augmentation procedure. The data acquisition process benefits from rotational augmentations done at 90°, 180° as well as 270° to represent the diverse UAV perspectives. To match deep learning architecture input requirements the input pixels are set to 256×256 dimensions after random resizing and standardized through random cropping. The applied augmentation techniques function dynamically during training because they help the model access numerous training examples during each training phase.

Data augmentation methods used on groundnuts hyperspectral data specifically maintain essential spectral characteristics of high-dimensional spectral data. Gaussian noise application to reflectance values serves as the primary augmentation approach because it creates sensor noise effects together with environmental changes. When added to the original hyperspectral data

$$H\_aug = H + N(0, \alpha^2) \tag{2}$$

(2) provides mathematical noise definition that helps models adapt faster to external

influences on spectral signatures such as sensor drift and UAV-operational lighting conditions changes. The model evaluation involves band shuffling and band dropping as a method to assess its resilience against missing or improperly sorted spectral measurements. The dataset receives uniform spectral reflectance values from end-to-end data normalization procedures. Real-time data augmentation prevents duplicate training samples from appearing so model strength increases and overfitting risks decrease for both multispectral along with hyperspectral input data.

The two problem statements use data augmentation methods as essential tools to increase training dataset scale and range and avoid needing additional field-based data collection. Arranging augmentations according to their domain requirements ensures that hyperspectral data processing maintains genuine biological and physical characteristics after augmentation. The validated augmentation platforms employed in this research successfully address multiple critical issues observed in past studies including environmental sensitivity as well as sample dataset capacity limitations according to documents [1][6][8][10].

ALGORITHM

Input: Multispectral image $M \in R^{5\times H\times W}$

Output: Preprocessed multispectral image M crop, pseudo-mask Mask

1: Crop Black Borders from M
2: Compute NDVI for each pixel:
    a. NDVI = $NIR - Red \,/\, NIR + Red$
3: Generate Pseudo-Mask:
    a. If NDVI ∈ [α,β] and Red Edge ≥ γ, set Mask(i,j)=1, else 0
4: Apply Morphological Operations:
    a. Perform Morphological Opening on Mask with kernel $K_{3\times 3}$
5: Perform Data Augmentation (flip, rotate, crop)
6: return M_{crop}, M_{mask}

3.4 FEATURE EXTRACTION & ENGINEERING

3.4.1 MULTISPECTRAL FEATURE ENGINEERING

The research framework combines an orderly systematic procedure for extracting features and engineering elements from multispectral images. This methodology improves valuable data representation which makes both machine learning and deep learning models successful. Multispectral images originate from MicaSense Red Edge-MX camera devices on UAVs that record five separate spectral wavelengths at Blue (475 nm), Green (560 nm), Red (668 nm), Red Edge (717 nm), and Near-Infrared (840 nm). The first step merges single-band image clusters into five-channel multispectral image boxes through spatial and spectral alignment of all pixels across these bands. The assembled data collection provides the fundamentals for developing future features and their engineering methods.

NDVI operates as the fundamental derived parameter that uses both Near-Infrared and Red spectral bands. Each pixel receives an NDVI value from the calculation (1) .The values on NDVI maps reveal vegetative health by showing locations of active photosynthesis and stress markers because higher NDVI levels indicate healthy vegetation. Addition to NDVI multiple vegetation indices have been created to track additional parameters. The Red Edge Normalized Difference Vegetation Index (NDVI_RE) integrates the Red Edge and Red bands for enhanced chlorophyll content detection sensitivity at the start of stress recognition.

Among all components of feature engineering the process of creating pseudo-masks plays a vital role for achieving supervised segmentation. The creation process of fake masks starts by utilizing thresholds on NDVI data points to find relevant interest regions. The empirical thresholds get established through reflectance measurements on healthy and stressed vegetation through the entire dataset. The segmentation process of panicles benefits from extra precision constraints which stem from Red Edge band data. The binary mask goes through morphological operations featuring erosion and dilation to achieve comprehensive and accurate pseudo-ground truth masks after the regions have been recognized. The developed pseudo-masks help educate deep learning segmentation models such as DoubleConv+UNet and ResNet+UNet through eliminating the requirement for manual labeling.

The engineered features NDVI plus the pseudo-masks receive normalization then standardization procedures to preserve system continuity during multiple flight timings under varied environmental circumstances. The deep learning models accept normalized features as input channels to simultaneously collect data about space and spectra. These neural network models utilize convolutional layers to enhance feature maps by developing hierarchical data representations in order to perform accurate detection of panicles and water stress assessment.

3.4.2 HYPERSPECTRAL FEATURE ENGINEERING

The early water stress detection system for groundnut crops uses hyperspectral data that features extraction techniques to harness the hyperspectral resolution capabilities of hyperspectral imaging. The Resonon Pika-L hyperspectral sensor obtains data with 282 narrow spectral bands extending between 400 nm to 1000 nm. The many bands of hyperspectral data help detect small physiological changes because water stress thus offering superior detection capabilities compared to multispectral techniques.

The first stage of hyperspectral feature engineering requires preprocessing raw hyperspectral data through three operations which include noise reduction and radiometric calibration and normalization. Data quality assessment completes before spectral indices calculate features from the information. You reach NDVI through a process similar to standard multispectral calculations but with increased discretion regarding the choice of Red and Near-Infrared (NIR) bands because of superior spectral resolution. The evaluation of vegetative health requires the selection of 668 nm band wavelength for the Red spectrum combined with 840-870 nm band wavelength for NIR. The selected features enable the training of multiple machine learning algorithms and deep learning solutions including Random Forest and Support Vector Machines (SVM) and XGBoost with 1D-Convolutional Neural Networks (1D-CNN) as one of the deep learning architectures. The supervised learning approach begins because reflectance values from each sample fall under two categories: Well-Watered WW and Water-Stressed WS.

The engineered hyperspectral features act as critical tools for detecting water stress before visible symptoms appear because they can identify minor spectral alterations. These classification models benefit from substantial accurate identification of healthy and stressed crops through their incorporation of engineered features. A feature engineering process based on hyperspectral data makes results highly accurate and reliable making it an important tool that helps advanced precision agriculture methods manage water effectively in groundnut crops.

3.5 MODEL TRAINING & ALGORITHMS

3.5.1 SEGMENTATION MODEL FOR PANICLE DETECTION

This particular panicle detection segmentation model analyses UAV-based multispectral images through spatial and spectral data processing to precisely locate and separate panicles in paddy crops. The framework treats pixel-wise classification as its main goal to assign labels to input image pixels which determine their membership between panicles and background content. The model adopts pre-processed multispectral images by stacking five spectral bands (Blue, Green, Red, Red Edge, NIR) and additional feature maps including NDVI and pseudo-masks which provide supplementary channels to the input. Panicle segmentation performs through an encoder-decoder framework utilizing specific U-Net variations that optimize segmentations under diverse environmental conditions.

The main architecture used in this model is DoubleConv + U-Net. The proposed model structure places double convolutional layers inside all main pathways of both the encoder and decoder components. The encoder downscales input space by performing convolution followed by max-pooling operations thus acquiring high-level features from context-rich information. The system uses skip connections which join encoder outputs with matching decoder inputs for preserving exact spatial detail preservation. The segmentation map reconstruction occurs through decoder operations that encompass up sampling procedures followed by convolutional layers to achieve the input image resolution. A probability map showing the detection of panicles at each pixel emerges from the last output layer which operates with sigmoid or SoftMax activation. The model offers both efficiency and lightness while it handles multispectral UAV images with high spatial resolution.

The basic architecture improves through the implementation of attention mechanisms that result in the creation of the Attention U-Net model. The model uses attention gate functions for skip connections to make purposeful decisions about features that matter when executing decoding tasks. The model becomes better at reducing unwanted environmental noise because of this integration feature particularly when dealing with backgrounds that are complex or canopy blocking images. The attention mechanism automatically allows the encoder features to become more important based on their role in segmentation which improves how well the model distinguishes different features. The approach provides strong benefits when panicles are partly hidden or show minimal spectral differences compared to neighbouring vegetation.

Researchers tested the ResNet + U-Net architecture that applies ResNet backbone features to the encoder section. The implementation of residual blocks lets the model achieve deeper architecture design because it prevents gradient vanishing while allowing advanced feature comprehension. The ResNet encoder produces powerful features that enable the U-Net decoder to execute segmentation processes.

The research examines two alternative network architectures using both 3D CNN together with U-Net and Swin Transformer connected with U-Net models. Through the 3D CNN + U-Net model multispectral data receives volumetric input processing that uses spectral dependencies between spectral bands for improved analysis. The three-dimensional structure of data allows the method to improve its ability to recognize relationships between spectral and spatial dimensions. The Swin Transformer + U-Net model embeds transformer blocks into its encoder section thus enabling it to detect extensive contextual relationships. The Swin Transformer improves the detection of worldwide patterns which proves essential when segmenting panicle fields with diverse characteristics. The proposed models use an encoder-decoder design structure that maintains skip connections and up sample paths identical to U-Net architecture.

Data augmentation and preprocessing methods that develop NDVI-based pseudo-masks alongside morphological operations enhance the training data quality in the methodology phase. The optimization process relies on Dice Loss alongside Binary Cross-Entropy loss functions together with training optimizers Adam and AdamW that include appropriate learning rate arrangements. The proposed approach uses flexible segmentation methods that work across diverse field situations to detect panicles during different growth stages regardless of environmental conditions.

3.5.2 MODEL FOR WATER STRESS DETECTION (RESNET +CSAB+UNET)

The ResNet structure with Channel Spatial Attention Block (CSAB) and U-Net architecture constitutes a specialized framework that executes pixel-level segmentation for early maize water stress detection via UAV-acquired multispectral information. The approach benefits from key aspects of encoder-decoder networks and attention mechanisms and residual learning to enhance both feature understanding and segmentation accuracy. A model takes advantage of spatial along with spectral variations in data collected by MicaSense Red Edge-MX sensors through its five spectral bands Blue Green Red Red Edge and Near-Infrared (NIR). The system processes a stacked multispectral image cube containing pre-processed pixels that show reflectance values from the bands after clustering, border removal, and NDVI-based feature enhancement.

The basic framework of the model consists of an encoder component that uses a ResNet-50 architecture specifically adjusted for processing multispectral information. Inside ResNet-50 residual learning allows for skip connections among blocks that enables deep hierarchical feature learning and protects against gradient vanishing problems. The residual blocks excel at obtaining significant low-level through high-level features for discerning water-stressed from adequately watered sections of maize fields. Through consecutive convolutional and pooling layers the encoder reduces input spatial dimension until it extracts contextual information for accurate segmentation.

ALGORITHM

ResNet + U-Net + CSAB for Water Stress Segmentation

Input: Multispectral image $I \in R^{C\times H\times W}$
Output: Segmentation mask $\hat{S} \in R^{H\times W}$

1: **Initialize** X←I
2: for each ResNet encoder stage i=1,…,L:
 a. X← ResNetBlock(X)
 b. X← CSAB(X)
 c. Save X as Si (skip connection)
 d X← MaxPool(X)
3: **Bottleneck**: X← DoubleConv(X)
4: for each **decoder stage** j=L,…,1:
 a. X← UpConv(X)
 b. X← Concat (X, Sj) (skip connection)
 c. X← DoubleConv(X)
5: $\hat{S}$←Sigmoid(Conv(X, kernel=1))

6: return $\hat{S}$

A Channel Spatial Attention Block (CSAB) integrates into the model structure to enhance features obtained from the ResNet encoder. Serosity in feature recalibration improves through CSAB by handling spatial attention and inter-channel dependencies at the same time. The channel attention mechanism determines the importance of spectral feature maps to let the model concentration on essential spectral bands for water stress detection. The spatial attention mechanism works together to pinpoint important spatial areas in the feature maps where initial stress indicators become visible. The dual attention system ensures high discrimination along with contextual dependency within the forwarded features to achieve better detection of water stress-sensitive changes in canopy reflectance.

The decoder executes standard U-Net operations by using a sequence of convolutional layers with up sampling operations for returning feature map spatial resolution. The encoder and decoder use skip connections to merge high-resolution features with up sampled features in order to preserve fine spatial details. Through its use of a sigmoid activation function the last output layer generates a pixel-level binary segmentation which separates water-stressed zones from non-stressed zones.

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ALGORITHM

Input: Multispectral image $I \in R^{C\times H\times W}$

Output: Segmentation mask $\widehat{M} \in R^{H\times W}$

1: **Initialize** X←I

2: **for** each encoder stage i=1,…,L:
a. X← DoubleConv(X) (or ResNetBlock + CSAB)
b. **Save** X as S_i (skip connection)
c. X← MaxPool(X)
3: **Bottleneck:** X← DoubleConv(X)
4: **for** each decoder stage j=L,…,1:
a. X← UpConv(X))
b. X← Concat(X,S_j)(skip connection)
c. X← DoubleConv(X)
5: $\widehat{M}$←Sigmoid(Conv(X, kernel=1))

6: **return** $\widehat{M}$

During training the model utilizes both Dice Loss and Binary Cross-Entropy Loss for tackling class imbalance while enhancing the accuracy of segmentations. The AdamW optimizer functions with an appropriate learning rate schedule which enables both stable and efficient convergence. Training dataset variability increases through the usage of data augmentation approaches that involve rotation, flipping and real-time NDVI enhancement. This particular ResNet + CSAB + U-Net model structure has been developed to address water stress detection problems in maize fields through combination of multispectral data with advanced deep learning approaches which provides a flexible solution for agricultural precision applications.

valuation metrics play a vital role in evaluating the efficacy of various models employed for emotion prediction based on facial Action Units (AUs). The primary metrics applied in this assessment include accuracy, precision, recall, F1-score, and the confusion matrix.

3.5.3 MODEL FOR EARLY WATER STRESS DETECTION (GROUNDNUT - HYPERSPECTRAL DATA)

The detection of early water stress in groundnut crops happens by collecting hyperspectral data from Resonon Pika-L hyperspectral sensors mounted on unmanned aerial vehicles. The spectral data comprises 282 bands that cover wavelengths ranging from 400 nm to 1000 nm thus measuring high-dimensional reflectance amounts in groundnut canopies across various water stress conditions. A two-class categorization defines the problem where each sampled canopy receives an WW or WS classification. A combination of machine learning methods with deep learning approaches efficiently utilizes large spectral datasets for the detection of water stress signs early in their development.

An initial strategy relies on combination of three ensemble machine learning models comprising Random Forest (RF), Gradient Boosting (GB) and XGBoost (XGB). Before execution of model training the methods Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) are utilized to reduce model complexity without impacting vital spectral feature retention. NDVI together with the

Transformed Chlorophyll Absorption in Reflectance Index (TCARI) among other vegetation indices serves as supplementary inputs which highlight stress indicators. The trained RF and GB and XGB classifiers receive their data from selected features which undergo assessment through accuracy and precision and recall and F1-score metrics. The ensemble learning approach reaches success by combining various weak learners into superior predictive systems which demonstrates strong prediction accuracy and the ability to extrapolate data patterns from unobserved information.

A specially designed one-dimensional Convolutional Neural Network (1D-CNN) serves as the second methodology because it directly addresses the sequence patterns found in hyperspectral data. The 1D-CNN framework successfully detects both spectral features throughout its entire range using convolutional filters applied to the spectral axis. Sequence of activation by ReLU occurs in multiple convolutional layers before max-pooling layers execute down sample operations on feature maps while reducing their dimension. The training process receives stabilization through batch normalization and dropout layers become part of the system. Fully connected layers at the end serve to classify items as either WW or WS in a binary manner. The artificial neural network trains with Binary Cross-Entropy Loss optimization by Adam optimizer. The training resistance improves when the data augmentation strategy includes Gaussian noise addition together with random spectral spectrum shuffling.

ALGORITHM

1D-CNN for Hyperspectral Water Stress Detection

Input: Hyperspectral reflectance $X \in R^B$ (single-pixel spectral signature)
Output: Stress classification $\hat{y} \in \{0,1\}$

1: **Normalize spectral values** in X to [0,1]
2: **Apply 1D Convolutions**:
   a. X←Conv1D (X, kernel=3)
   b. X← ReLU(X)
   c. X←Conv1D(X, kernel=3)
   d. X← ReLU(X)
3: **Fully Connected Layer**:

a. Flatten X
b. Pass through dense layers
c. $\hat{y}$ ←Sigmoid(Dense(X))
4: **return** $\hat{y}$

The hybrid ensemble model groups the predictions derived from Random Forest (RF), XGBoost, and the 1D-CNN results to exploit machine learning and deep learning technique benefits. The ensemble model reaches its final classification result by using majority voting or weighted average computation methods. The hybrid strategy combines models to reduce their independent bias and variance thus improving both prediction accuracy and model reliability. Spectral feature engineering severed with advanced machine learning tools and deep learning technology structures delivers a complete approach to discover early water deficiencies in groundnut fields which supports prompt protective measures and optimizes irrigation programs.

3.6 TRAINING & EVALUATION METRICS

3.6.1 OPTIMIZER

3.6.1.1 GRADIENT-BASED UPDATES & ADAM VARIANTS

Neural networks in the system which is proposed are trained using the stochastic gradient descent principles which either employ Adam or AdamW as their primary optimizers. The adaptive moment of Adam optimizer is capable enough to estimate for the first and second moments of the gradient which also facilitate stable and quick convergence relatively, in specific which is suited to the classification of the high dimensional hyperspectral data. AdamW is a variant of Adam which furthermore incorporates the variant decoupled weight decay and helps to regulate parameter size of large counts using the encoder-decoder architectures

Ideally, the initial learning rate (LR) which is supposed to be in the range of $10^{-4}\, to\; 5 * 10^{-4}\, times$ is set, with β1=0.9 and β2=0.999. A small weight decay (e.g., 0.01) is applied to the parameters, which is primarily beneficial in tasks like hyperspectral classification which requires input of the dimension which is large (B>200 channels). Periodically, if there is a performance plateau in validation, we then reduce the LR by a factor (e.g., 0.5) or switch to early-stopping policy.

3.6.1.2 MINI-BATCH & ACCUMALATED GRADIENTS

When it comes to segmentation tasks which are based on large multispectral images it is feasible to use smaller batch sizes (4-16) because of the limited GPU memory being a constraint. Talking about Hyperspectral classification on the contrary which uses moderate batch sizes (32- 64) In special cases with large scenes, mini batching is used for implementation along with patch extraction which ensures that every forward pass is processing a manageable chunk of data This approach is useful for robust gradient updates while mitigating the risk of overfitting

3.6.2 LOSS FUNCTIONS

3.6.2.1 BCE + DICE LOSS FOR SEGMENTATION

Considering the multispectral paddy field panicle segmentation which often is in the risk of facing a class imbalance There is only a small fraction of pixels which represent panicles or stressed vegetation. To go ahead and solve this issue, we have used a blend of Binary Cross- Entropy (BCE) (3) with Dice loss (4), these two methods balance the pixel-wise detection along with region based overlap metrics.

1. BINARY CROSS-ENTROPY (BCE) :

$$L_{BCE} = -\frac{1}{N}\sum_{i=1}^{N} \quad [y_i \; log \; log \; (\hat{y}_i) \; + (1 - y_i) \; log \; log \; (1 - \hat{y}_i) \,]$$

(3)

where yi ∈{0,1} is the true label (pseudo-mask) for pixel iii, and y^i∈(0,1) is the predicted probability.

2. DICE LOSS :

$$L_{Dice} = 1 - \frac{2\sum_i \quad y_i\hat{y_i}}{\sum_i \quad y_i + \sum_i \quad \hat{y_i} + \epsilon}$$

(4)

This term focuses on overall foreground overlap rather than individual pixel correctness, thus complementing the BCE(7) ,(8) ,(9) component .

$$Lseg = \alpha LBCE + \beta LDice \tag{5}$$

$$with\ \alpha \approx \beta \approx 0.5\ \ in\ many\ experiments$$

3.6.2.2 BINARY CROSS-ENTROPY (BCE) FOR HYPERSPECTRAL CLASSIFICATION

In the case of water stress classification in the hyperspectral data , The binary Cross entropy metric is sufficient enough for pixel wise detection. Each pixel (or sample) $x \in R^B$is mapped to a predicted stress probability y^ . y∈ {0,1} be the reference labels given (10):

$$L_{class} = -\frac{1}{M}\sum_{m=1}^{M} \quad [y_m\ log\ log\ (\widehat{y_m})\ + (1 - y_m)\ log\ log\ (1 - \widehat{y_m})\ ]$$

(6)

The given approach considers a direct penalization for misclassifying the classes of either Well Watered or Water Stressed signatures and which typically makes it robust enough considering the high spectral dimensionality

CHAPTER 4

IMPLEMENTATION

4.1 SOFTWARE & LIBRARY REQUIREMENTS

For successful implementation of the panicle detection along with water stress early recognition system requires an optimal software platform which enables machine learning and deep learning capabilities. All phases from development through testing occurred under Python 3.8 because it provides complete scientific computing and machine learning library support. The system utilized Jupyter Notebooks along with Python scripts for interactive and batch processing of large datasets through coding activities. The essential deep learning toolsets included TensorFlow 2.8 and PyTorch 1.10 since they provided strong ecosystems adaptation capabilities with effective model deployment features. 1D-CNN models for hyperspectral data processing received implementation through TensorFlow as U-Net-based architectures for multispectral segmentation tasks used PyTorch as the main framework.

The research heavily relied on multiple fundamental libraries which served as essential components for handling and preparing data. Version 1.22 of NumPy operated on large spectral array data from multispectral and hyperspectral datasets to manage numerical operations. Pandas version 1.4 provided data indexing and selection capabilities through its labeling function to improve data management and efficient selection of desired datasets. OpenCV version 4.5 operated for image processing functions which included clustering alongside black border elimination and application of data augmentation methods through rotation and flipping and resizing features. The rasterio library enabled handling raster data reading and writing tasks for multispectral imagery procedures and the h5py library provided compact HDF5 storage solutions for the large hyperspectral datasets.

The creation of machine learning models relied on Scikit-learn version 1.0 that included vital algorithms for water stress detection such as Random Forest, Gradient Boosting and Recursive Feature Elimination (RFE). XGBoost Version 1.6 applied boosted tree algorithms through its framework because these algorithms show excellent performance and adaptable characteristics particularly when working with extensive datasets. The software suite of Matplotlib version 3.5 and Seaborn version 0.11 enabled the creation of NDVI maps along with spectral signatures and allowed for producing model training metrics which included loss curves and accuracy graphs.

The experimental work took place on a workstation equipped with an NVIDIA RTX 3090 GPU with 24 GB VRAM memory and an Intel Core i9 processor accompanied by 128 GB RAM memory. The computer system ran Ubuntu 20.04 LTS as its operating system while supporting deep learning acceleration through CUDA 11.3 and cuDNN 8.2. The research applied Git for version management and repository usage on GitHub to boost collaborative work and assure projects' reproducibility. Through their integration into a single framework these software tools and libraries created an extensive efficient system which could handle the complex requirements of processing and modeling the agricultural monitoring system.

4.2 DATA LOADING & INITIAL PROCESSING

The implementation's initial step consisted of processed data loading for both multispectral and hyperspectral images obtained via UAV flight activities. Rasterio allowed Python to import the multispectral dataset by processing images acquired from five spectral bands (Blue, Green, Red, Red Edge, and Near-Infrared). The several spectral bands were read as NumPy arrays before being arranged in a single multidimensional array that kept both spectral and spatial precision (5 × height × width). The structured data arrangement allowed future analysis stages to work with efficiency while maintaining processing consistency.

The first stage of multispectral image processing began with file clustering through standard naming conventions. Python scripts which applied regular expressions and logical grouping succeeded in automating this process by aligning all image bands correctly. The processing involved automated border removal in OpenCV after cluster organization of the images. The scripts operated through pixel intensity thresholds to detect peripheral non-informative areas and exclude them from analysis of relevant vegetative regions.

The initial stage of hyperspectral data processing started with the data loading process of arrays stored in .npy and HDF5 formats which came from groundnut fields. The huge datasets required management through the implementation of NumPy along with h5py. Each hyperspectral measurement acquired specific metadata which specified its water stress condition. The preprocessing step started by normalizing data while standardizing spectral reflectance values so preprocessing controlled inconsistencies that stemmed from variations in sensor calibrations and environmental conditions. The application of Gaussian filtering succeeded in cleaning spectral data inputs by removing the noise.

The dimensionality reduction process for hyperspectral data included the use of Principal Component Analysis (PCA) as one of its preprocessing techniques. PCA significantly reduced the computing requirements through transforming high-dimensional spectral information into fewer principal components that included fundamental elements needed to monitor water stress. The steps in data preprocessing successfully generated high-quality inputs that improved model training effectiveness and prediction accuracy within analytical processes.

4.3 IMAGE AUGMENTATION & IMPLEMENTATION

A specific image augmentation strategy was developed to boost both robustness and generalization properties of models which processed multispectral and hyperspectral datasets. The OpenCV along with Augmentations libraries enabled systematic use of various geometric transformations for processing multispectral images. Image enhancements included sequential methods of rotating images at 90°, 180° and 270°

angles and randomly flipping them horizontally or vertically and performing cropping operations to adapt input dimensions to (256×256) pixels. The implemented augmentations simulate the ways UAVs orient and cameras move which leads to better model generalization for real-world conditions.

A variety of brightness and contrast modifications were applied to match the natural lighting conditions which change throughout daytime. The process included NDVI based updates which involved recalibrating NDVI maps through geometric transformation to sustain the stability of spectral data alignment. The trained segmentation models received their pseudo-masks as input for which morphological operations applied post augmentation served to maintain high ground truth label precision.

The augmentation techniques used for hyperspectral data focused mainly on spectral transformations to handle both the high dimensionality and sensitivity of the dataset. The introduction of Gaussian noise duplicated sensor noise conditions which strengthened models to tolerate small spectral fluctuations. Random spectral band dropping combined with shuffling became part of the training process to measure and enhance the model performance when dealing with incomplete spectral information or shifts in spectral data. The implementation of constant augmentations aligned with the training phase allowed the models to encounter many different possible data formats.

Development of these complex augmentation techniques happened automatically through the utilization of Python scripts which integrated into the training pipeline for the model. Through automated execution the training epochs delivered heterogeneous data collections to models which minimized overfitting and aided accurate predictions in practical use cases. The augmented pipeline built a reliable base which permitted the development of dependable models capable of performing panicle segmentation and water stress detection.

4.4 FEATURE EXTRACTION PIPELINE & IMPLEMENTATION

Feature extraction pipelines serve as a fundamental process which transforms unprocessed multispectral and hyperspectral data into important features suitable for machine learning and deep learning operations. A dedicated pipeline targets specific tasks concerning paddy field panicle segmentation and the early identification of water stress in maize and groundnut crops while properly extracting their individual spectral and spatial attributes.

The extraction of features from MicaSense Red Edge-MX multispectral images begins with computing different vegetation indices. NDVI performs as the principal index while data from spectral bands NIR and red combine through a designated mathematical expression. Vegetative health assessment together with plant vigor evaluation is enabled through these indices which proves vital for both panicle segmentation and maize crop water stress detection.

The NumPy and rasterio libraries enabled the execution of index calculations for the entire image dataset through an efficient process. A normalization process followed the computation steps to create consistent results across different environment and lighting situations. The research process involved performing thresholding operations on NDVI and Red Edge bands using OpenCV morphological processing to produce pseudo-masks. Digits require being implemented as the primary ground truth annotation for teaching DoubleConv+UNet and ResNet+CSAB+UNet segmentation models to accomplish sophisticated tagging independently of human input.

The feature extraction process for hyperspectral data obtained from groundnut fields is characterized by a notably higher dimensionality, attributed to the extensive number of spectral bands (282 bands spanning from 400 nm to 1000 nm). The initial step in feature extraction involves dimensionality reduction through Principal Component Analysis (PCA), executed with Scikit-learn. This technique effectively diminishes the data's dimensionality while retaining essential spectral information crucial for classification tasks. The resulting dataset is further enhanced with vegetation indices akin to those utilized in multispectral imagery, such as NDVI and TCARI, which are calculated to highlight spectral variations indicative of water stress.

In addition to these indices, further spectral feature engineering incorporates statistical metrics, including mean, variance, skewness, and kurtosis, computed over designated spectral regions using NumPy and Pandas. These statistical features serve as robust descriptors of spectral behavior, thereby improving the predictive capabilities of machine learning models. To refine the selection of the most relevant spectral bands, Recursive Feature Elimination (RFE) is employed through Scikit-learn, ensuring optimal feature representation for classification purposes. The final feature set, which integrates reduced spectral dimensions, vegetation indices, and statistical descriptors, is standardized and normalized, thereby providing uniform inputs for machine learning algorithms such as Random Forest, XGBoost, and deep learning architectures like the 1D-CNN.

4.5 SEGMENTATION & CLASSIFICATION MODELS

4.5.1 DoubleConv + U-Net Model

The DoubleConv + U-Net architecture used its streamlined encoder-decoder structure for segmenting panicles with both simple design elements and high computing efficiency. Complex spatial features could be captured effectively through both encoding and decoding stages that contained successive double convolutional layers within the DoubleConv + U-Net model. The model's feature to segment clustered panicles precisely relies on its effective maintenance of detailed spatial patterns that helps reduce segmentation errors.

4.5.2 3D CNN + U-Net Model

By combining 3D CNN with U-Net technology the segmentation framework achieved expansion through the integration of spatial and spectral information. The proposed model applied three-dimensional convolutional operations which produced effective spectral correlation analyzes across the multiple spectral dimensions. The model demonstrated reduced performance levels as a result of its higher complexity levels which required more computational power and spectral redundancy arose due to its thorough feature extraction capabilities.

4.5.3 Attention + U-Net Model

By integrating attention gates into the U-Net structure the model achieves better focus on significant details while omitting unnecessary background information. The model achieves enhanced performance through attention mechanisms because these mechanisms adapt encoder feature importance in real-time to discriminate panicles from complex backgrounds effectively. The additional complexity in this model produces overfitting issues mainly on small training datasets.

4.5.4 ResNet + U-Net Model

The ResNet + U-Net model uses ResNet as its backbone which draws from residual learning principles to extract exceptional features for the network. Through this approach the network produces enhanced feature representations that solve gradient problems during operations of deep neural networks. Despite showing excellent performance in spatial details processing the model has limited segmentation accuracy because spectral attention mechanisms are barely present.

4.5.5 Swin Transformer + U-Net Model

The Swin Transformer + U-Net implements transformer-based architectures for segmentation by taking advantage of the transformer capabilities to process distant relationships and context. The globally effective Swin Transformer has poor performance in precise local segmentation tasks because its spatial detail detection capacity remains limited thus decreasing segmentation accuracy levels

4.5.6 ResNet50 + CSAB + U-Net Model (Water Stress Detection - Groundnut)

The designers created ResNet50 + CSAB + U-Net architecture to improve water stress detection in maize through implementation of Channel Spatial Attention Blocks (CSAB). The new model achieved superior feature recalibration through its dual capability to model inter-channel relationships with attention management so water-stressed regions could be accurately identified. The model achieved better performance through its attention mechanism which succeeded in improving features while reducing wrong classifications.

4.5.7 1D-CNN Model (Water Stress Detection - Groundnut)

1D-CNN showed exceptional performance as a water stress detection system for groundnut crops because it processed long data sequences effectively. Through its spectral dimension scanning mechanism the model efficiently detected essential changes in spectral reflectance characteristics that indicate beginning water stress symptoms. The model achieved dominance in spectral noise-resistant hyperspectral stress detection because of its efficient design and ability to process spectral data.

CHAPTER 5

RESULTS AND ANALYSIS

5. RESULTS

5.1 DATASETS

The research proposed solely relies on the dataset which are obtained through the UAV mounted sensors and camera which are obtained from the TiAND initiative which is a functional collaborative presented by IIT Hyderabad and Indian agricultural institutions for precision farming data collection in India. Highlighting the first one to be paddy field panicle segmentation and extending to the maize and groundnut crop for early water stress detection, one being for multispectral images and the later one being for hyperspectral data collected through a hyperspectral Image sensor which collects and store data in the form of .numpy array. The existing common objective of these datasets is to reduce the existing lack of multispectral and hyperspectral UAV imagery for agriculture in Indian settings for better results in real world. TiAND has successfully gathered an extensive set of UAV datasets with a high spatial precision (1-5 cm/pixel) using precise sensor calibration This includes flying the sensor mounted on the UAV on a lower altitude between 20-30 m to increase stability for capturing the images through the camera and the sensor mounted on the DJI matrices drone ..

5.1.1 MULTISPECTRAL DATASET FOR PADDY PANICLE DETECTION

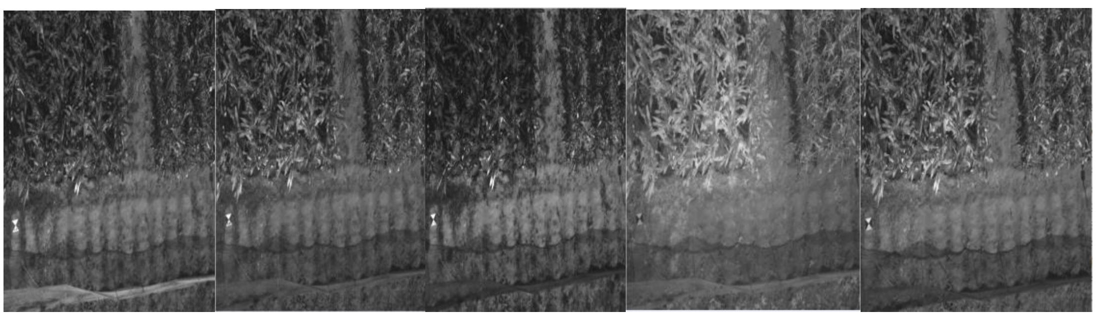
The proposed system draws a focus on an essential analysis related to the panicle segmentation which is conducted through the UAV imagery. When it comes to having large scale multispectral dataset for detecting panicle for either yield prediction or monitoring growth stages in the paddy fields of India , there is lack of data especially about the isolated panicles. This dataset was captured in the Kharif season of 2019 and 2020 in the region of Hyderabad which was facilitated by IIT Hyderabad This dataset included 315 images across 5 bands each These images were captured from the vegetative growth phase till the early heading stage (69 to 80 Days After Sowing (DAS) to capture the panicles or the crop head. The images were captured in a low altitude to maintain stability and the resolution was close to 5 cm/ pixel.

Every image which is captured is in a set which contains five .tif bands (Blue, Green, Red, Red Edge ,NIR) .An additional channel of NDVI is derived using the Red and the IR bands which showcase the chlorophyll content and the structural changes respectively .This NDVI and Red Edge band was also used for creating the pseudo masks for training the model for panicle detection considering them to be the ground truth. Thus, the data processing technique typically considers 6 channels as input for training the model The sensor used for capturing (MicaSense Red Edge) was calibrated before the flight using the reflectance panels which thereby confirmed consistent radiometric quality of output which was delivered. NDVI thresholds were then combined with morphological openings to generate and enhance the ground truth as pseudo masks which were generated to avoid the labor-intensive expert annotation for each image

5.1.2 MULTISPECTRAL DATASET FOR MAIZE EARLY WATER STRESS

Another spectrum of multispectral images which were captured were the collection of maize fields which further aimed to detect the initial and early warning signs of water stress in the leaves. The dataset was captured in the Kharif season as well in the year of 2018, 2019 and 2020 in the maize grounds of Hyderabad and contains 320 images, each image set contains 5 bands through the sensor technology comprising Blue, Green, Red, Red Edge and NIR The team also monitored and matched the varied moisture conditions through partial irrigation protocol and simulated the controlled drought scenarios as well The flight mission was of the altitude of 20 meters from the ground level and had a stable resolution of 5 cm / pixel .

Stress monitoring was possible in the region due to its combination of moderate weather conditions which enable the sensor to capture the delicate stress signals in the leaves .Threshold level was set for with the combination of NDVI being from 0.2 to 0.6 and considering the Red Edge reflectance raw captured values at the range of ≥282 units which match the binary stress indicators which were simulated in the similar paddy field panicle analysis .The dataset exists with a total of 320 images while serving as one of the rare UAV-based systems to monitor early-stage stress in Indian maize fields by connecting generic RGB imaging with advanced multispectral information.



5.1.3 HYPERSPECTRAL DATASET FOR GROUNDNUT WATER STRESS ANALYSIS

Full spectrum imaging was used to spot water stress at the early stage in the hyperspectral dataset for groundnut which was captured Output of 16,667 canopy samples which either indicated Well-watered or water-stressed The data was gathered through the help of ICRISAT where the groundnut is cultivated for research which is located in Hyderabad by IIT Hyderabad. Spectrum Analysis was carried out where a hyperspectral imaging sensor was mounted with Pika L which captured 282 narrow bands in the range of 400 - 1000 nm which delivered accurate observation for leaf pigment composition and also the variants in the water content.

The Ground Sampling Distance was of 1 cm /pixel with a typical flight altitude but the narrower spectral capture area decreased the image coverage width .The necessity of precise calibration procedure through dark frame and white panel correction was needed by the data to maintain the reflectance accuracy .Considering the hyperspectral data acquisition , it uses more resources and also requires a prolonged flight duration along with a large data storage and is expected to deliver an enhanced data resolution compared to the multispectral imagery can provide .The distinguisher between Well Watered and Water Stressed labels is aided by capturing measurements of the leaf water potential and canopy temperature analysis on the ground level .

5.2 EVALUATION METRICS

Below is the core metrics used for panicle segmentation and stress classification, following established practices in UAV-based agriculture research [1, 8, 12, 28, 31].

5.2.1 Segmentation Metrics

5.2.1.1 Dice Coefficient (Dice)

Commonly adopted in segmentation tasks ([1, 31]) to measure the overlap between a predicted mask M^ and ground truth M. Formally as shown in (7)

$$Dice = \frac{2\sum_{i,j} M_{ij}\widehat{M_{ij}}}{\sum_{i,j} M_{ij} + \sum_{i,j} \widehat{M_{ij}} + \epsilon} \tag{7}$$

A Dice score near 1 indicates strong agreement.

5.2.1.2 Intersection-over-Union (IoU)

Sometimes called the Jaccard index [9, 31] it is defined as and denoted in (8)

$$IoU = \frac{\sum_{i,j} M_{ij}\widehat{M_{ij}}}{\sum_{i,j} \left(M_{ij} + \widehat{M_{ij}} - M_{ij}\widehat{M_{ij}}\right) + \epsilon} \tag{8}$$

highlighting how well predicted and true regions intersect relative to their union

5.2.1.3 Classification Metrics

Applied to hyperspectral groundnut and certain maize stress predictions [8, 12, 28]:

Accuracy: The fraction of classified samples is measured using the formula (9)

$$Accuracy = \sum i = 1NI(y\char`^i = yi) \ / \ N \tag{9}$$

5.2.1.4 Precision & Recall

$$Precision = \ TP \ / (TP + FP) \tag{10}$$

$$Recall = TP \ / \ (TP + FN) \tag{11}$$

5.2.1.5 F1-SCORE

Harmonic mean of precision and recall as in (12):

$$F1 = 2 \times (Precision \times Recall) \ / \ (Precision + Recall) \tag{12}$$

5.3 EVALUATION RESULTS

5.3.1 PANICLE DETECTION PADDY FIELD RESULTS

For the case of Paddy panicle segmentation and detection, the identified best model is DoubleConv+ U-Net which performed the best out of all the compared approaches and consistently achieved the dice Coefficient of 00.8573 0.86 (see § [Results Comparison Table] across the test splits. The network uses dual-convolution blocks in each encoder stage which is then coupled with the skip connection in the bottleneck areas which proved to be best in isolating the narrow paddy panicles from the cluttered section of crop canopies .The result generated aligns with the prior discussed segmentation researches [1, 31] which highlight the fact that U-Net models are highly used for the high resolution agricultural tasks which includes morphological features (i.e panicle tips/heads) and it demands multi scale learning for the same.

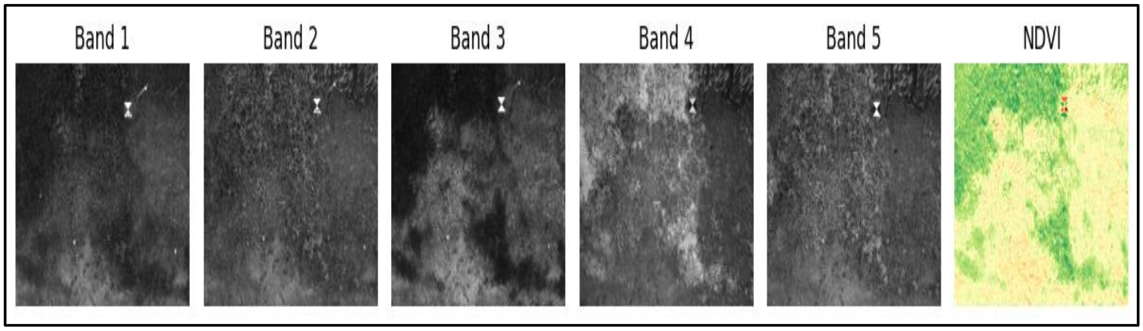


Fig 2 . NDVI calculations with clustered bands

Table 1: Model Training for Panicle Detection using DoubleConv +Unet

Specification	Description
Framework	PyTorch
GPU Used	NVIDIA RTX 3090 (24 GB Memory)
Input Image Size	256 × 256 (cropped and resized)
Data Augmentation	random flipping, rotation
Optimizer	AdamW
Momentum	β1=0.9, β2=0.999
Weight Decay	1×10−2
Initial LR	1×10−4
Batch Size	8
Learning Rate Adjustment	Step-decay on plateau
Combined Loss	BCE + Dice (α=0.5, β=0.5)

TiAND initiative under the IIT Hyderabad which conducted a research and derived a dataset using a UAV mounted with a multispectral sensor and recorded five clustered multispectral bands namely Band 1 (Blue) , Band2 (Green) , Band 3 (Red) , Band 4 (RedEdge) , Band5 (NIR) .**The Figure 2** distinctively it has been showcased as the spectral features which are captured in the grayscale format where Band 4 (Red Edge

) and Band 5 (NIR) display the chlorophyll related content along with the canopy information which aims the identification of the canopy information . The Normalized Difference Vegetation Index (NDVI) calculation involves the spectral band formula in this analysis shown in (1)The NDVI plots a map which is useful to detect the areas of vegetative areas ,identifying it as healthy(bright green zones with the index more than 0.6 or bare minimum vegetation along with the barren land and clutter marked as yellow or red which has the index value of 0.1 or below .This helps in panicle rich zone identification

In **Table 1** the training of DoubleConv + U-Net model for paddy panicle segmentation used the specifications detailed The training pipeline which runs on PyTorch framework utilized an NVIDIA RTX 3090 GPU together with 24 GB memory for efficient management of high-resolution multispectral data. There was a downsizing of the research material to 256 × 256 pixels through cropping and resizing functions which are used to protect the vital panicle elements and managed to maintain the prospective processing demands to be practical at the same time .The model robustness was improved along the way of reducing the overfitting which was further achieved by performing augmentation on the fly by random flipping operations (horizontal and vertical) together with rotational augmentation which guarantees the model to be effective across the various field positions and environmental conditions

The training which was conducted used AdamW as the optimizer because of its adoption of modern adaptive learning rates which regularizes the weight decay with a value of 1×10^{-2}. The AdamW optimizer employes a momentum parameters β_1 = 0.9 and β_2 = 0.999 of to reach the goal of quick convergence while also maintaining a stable pattern in the training .The learning rate is maintained at 1×10^{-4} along with a batch size of 8 which is used to achieve a GPU efficiency and optimize the computational speed . The strategy of step -decay along with adjusting the learning rate by halving the initial value when the validation dice coefficient is plateaued at the status of five epochs in sequence to achieve optimized segmentation results The training utilized a loss function hybrid of Binary Cross Entropy (BCE) and Dice loss at 0.5 to 0.5 proportions which enabled equal pixel-level precision with region-level integration.

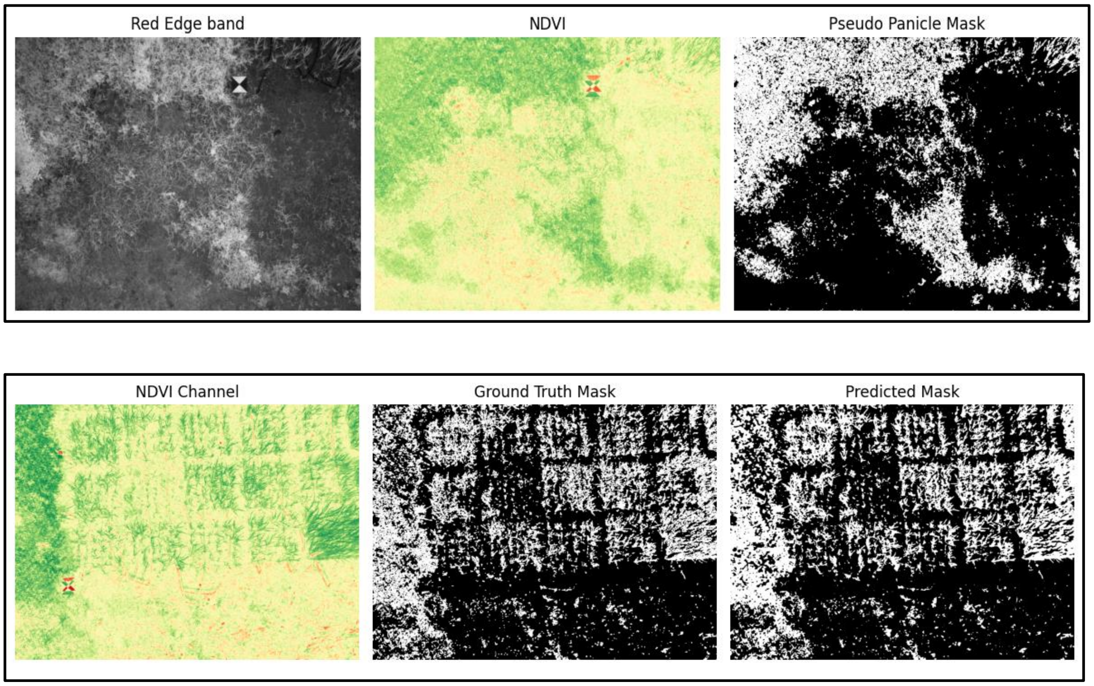


Fig 3 : Model Output for Double Conv+ Unet Dice Coeff : 00.8573

The optimal model consisting of DoubleConv and U-Net segments images in **Figure 3** to deliver a panicle detection Dice coefficient of 00.8573. Our model performs at an exceptional level because of its implied architecture choices and its optimized preprocessing sequence and its purposeful spectral feature algorithm. The model integration of an NDVI-derived channel substantially enhanced its performance by presenting vegetative features prominently. The panicle detection reached higher accuracy when utilizing multispectral imagery and NDVI because this approach effectively differentiated between plant material health and surrounding soil and water areas.

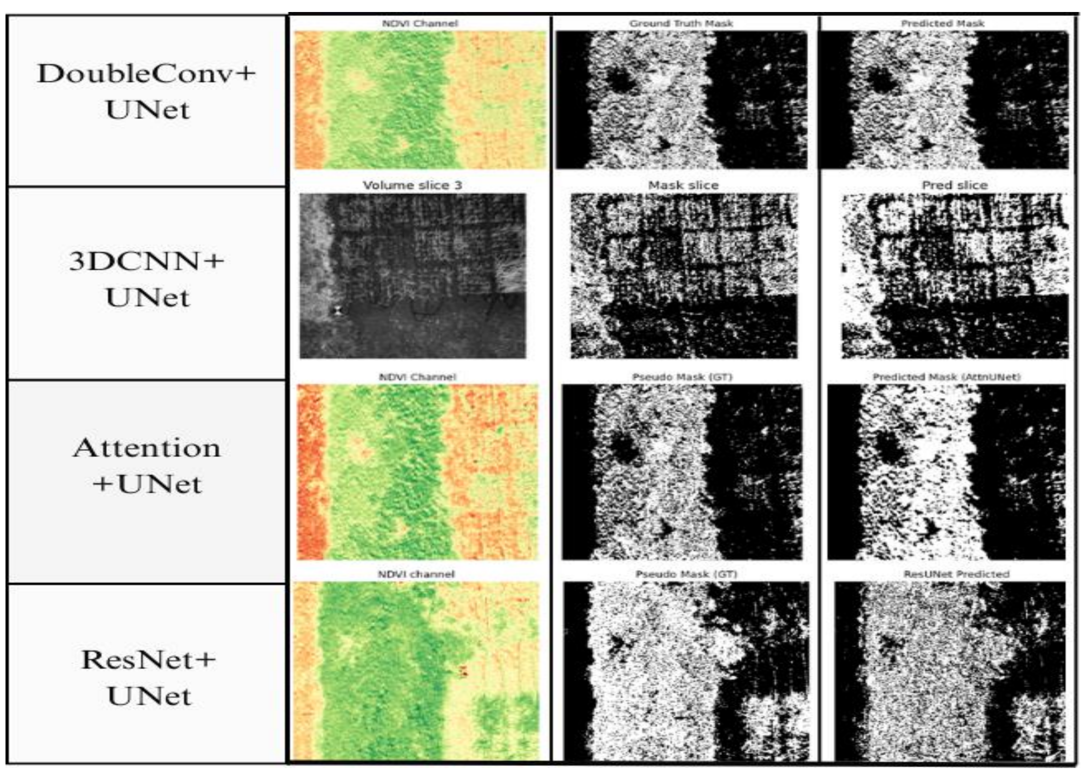
Each stage in the model architecture used Double Convolution (DoubleConv) layers inside its modified U-Net backbone. A block in the encoder pathway contains two ordered 2D convolutional layers with 3×3 kernels followed by batch normalization and ReLU activation functions to obtain hierarchical spatial and spectral features in the input tensor (five multispectral bands and NDVI combined into six channels). The

DoubleConv blocks triggered 2×2 MaxPooling functions which halved feature map dimensions until they reached the bottleneck shape of 16×16 pixels while the original six input channels transformed into a maximum of 512 channels. Down sampling with efficiency is essential because it compresses significant spatial-spectral knowledge which enables advanced abstraction of panicle structural characteristics.

The bottleneck section of the U-Net included another DoubleConv block to enhance feature representation and maintain essential information that the decoding steps needed. Successive up sampling happened through learnable UpConv layers in the decoding path. The spatial resolution increased by a factor of two at each decoding step starting from 16×16 px to 32×32 px up to 128×128 px and ending at 256×256 px which resulted in detailed segmentation mask generation using coarse latent information. The skip connection mechanism united spatially relevant encoder features with the decoder at each stage to directly send sharp details from the encoder to the decoder. A DoubleConv layer operated on the merged features that followed each concatenation step to enhance their quality. The skip connections maintained high-resolution spatial details to stop important panicle structures from being eliminated by deep network processing. The successful operation of this DoubleConv + U-Net model was made possible by its encoder components that extracted features efficiently while permitting detail alongside the MaxPooling layers and DoubleConv blocks and skip connections for multiscale fusion and NDVI spectral index integration with AdamW optimization strategy optimization. The method resolved all existing performance issues of basic U-Net variations and RGB-only approaches while providing highly accurate panicle segmentations for precision agriculture needs.

Table 2 : Comparison of the Model for Segmentation for the Panicle Detection in the Paddy field

Model / Method	Dice Coefficient (Test Set)
DoubleConv + U-Net (Best)	00.8573
3D-CNN + U-Net	0.7473
Attention U-Net	0.7343
ResNet + U-Net	0.5359
Swin Transformer + U-Net	0.5059
DeeplabV3+ResNet50 + U-Net	0.46
SegNet	0.4123



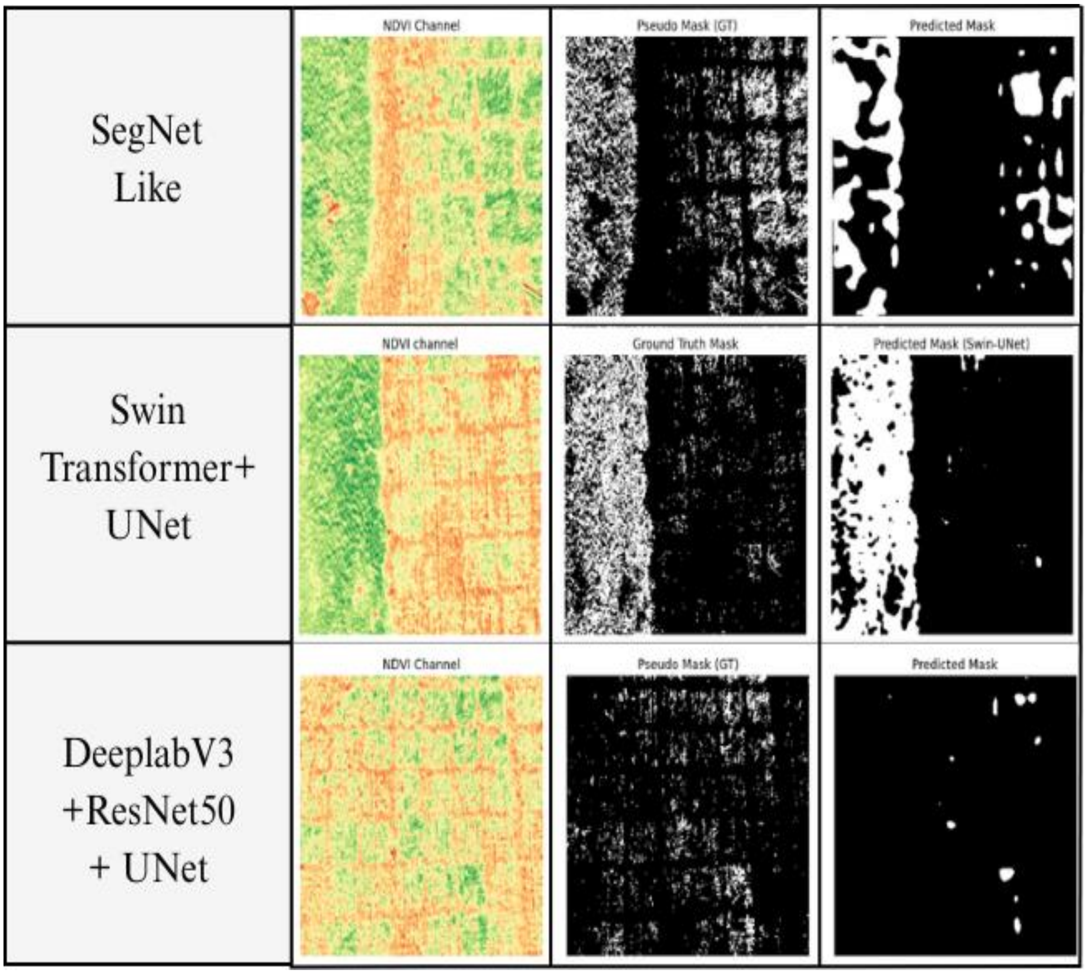


Fig 4: Models for Panicle Detection in Paddy Field

Table 2 presents statistical information while **Figure 4** visually demonstrates the segmenting abilities of various detecting models for panicles. Beyond existing models the DoubleConv + U-Net demonstrates the best combination of reliability and precision for vegetation segmentation (Dice coefficient: 00.8573). The visual representation offers precise panicle area detection which maintains detailed structures in tree canopies. Analyzing NDVI-derived spectral data while capturing hierarchical spatial features leads to superior consistency because the model first incorporates sequential convolutional encoding then performs max pooling (2×2) downscaling before precise decoder reconstruction through transpose convolutions along with skip connections.

The 3D-CNN + U-Net model processed information from space and volume spectra to produce a Dice coefficient value of 0.7473. The 3-dimensional convolutional layers help capture effective spectral-spatial patterns yet the visual results demonstrate weaker definitions of fine panicle structures in contrast to DoubleConv + U-Net. Similarly, the Attention U-Net, incorporating attention mechanisms within the encoder-decoder framework, yields a Dice coefficient of 0.7343. Masks produced by attention blocks which highlight important spectral features and eliminate unimportant areas show lower quality with ill-defined boundaries because of their split-up appearance. The ResNet + U-Net architecture using pretrained ResNet encoder achieved a Dice score value of 0.5359. The implementation shows noticeable errors in segmentation together with undefined boundaries between classes due to potentially inappropriate weight generalization from ImageNet RGB data for multispectral NDVI segmentation tasks.

The performance evaluation of additional models including SegNet (Dice: 0.4123), Swin Transformer + U-Net (Dice: 0.5059) and DeeplabV3+ResNet50+U-Net (Dice: 0.4600) illustrates substandard results. The visualization shows extreme over-smoothing and inaccurate boundaries along with severe errors. The basic design of SegNet leads to considerable segmentation inaccuracies that create extremely broad segments. The global context processing of Swin Transformer blocks allows it to understand plant distributions but the transformer structure prevents the model from producing exact panicle-specific boundary definitions. The Downscaling approach used by DeeplabV3-based architecture failed to deliver precise outputs for multispectral agricultural applications because it shows unsuitable results for these delicate tasks needing exact spatial accuracy. The thorough comparison between different architectures and NDVI integration reveals that DoubleConv + U-Net provides essential tools for obtaining precise panicle detection results in UAV-based precision agriculture applications.

5.3.2 EARLY WATER STRESS DETECTION IN MAIZE RESULTS

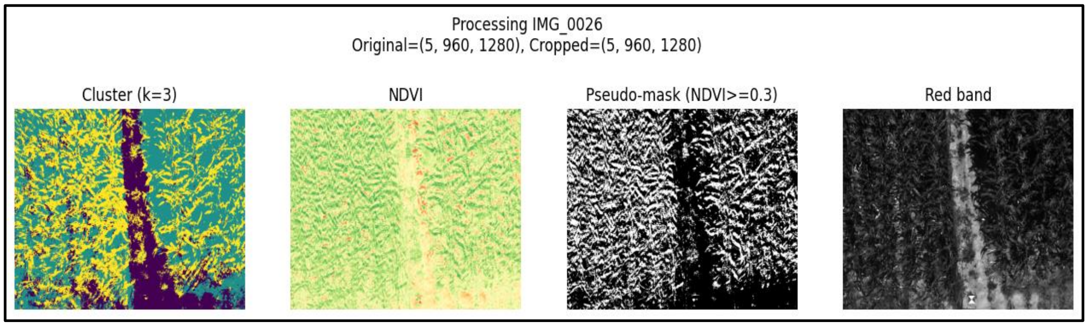


Fig 5: Clustering and Feature Engineering for Maize

Table 3 : Model Training for Water Stress Detection using ResNet+UNet+CSAB

Specification	Description
Framework	PyTorch
GPU Used	NVIDIA RTX 3090 (24 GB Memory)
Input Image Size	256 × 256 (cropped and resized)
Data Augmentation	random flipping, rotation
Optimizer	AdamW
Momentum	$\beta_1 = 0.9$, $\beta_2 = 0.999$
Weight Decay	1×10^{-2}
Initial Learning Rate	1×10^{-4}
Batch Size	8
Learning Rate Adjustment	Step-decay on plateau
Combined Loss	BCE + Dice (α=0.5, β=0.5)

The clustering stage at the initial step of **Figure 5** implements K-means clustering at a cluster size k=3. A cluster analysis uses entire pixels based on the spectral properties from the Blue, Green, Red, Red Edge, and Near-Infrared (NIR) multispectral bands of the maize spectra recorded by UAV sensors under the TiAND project. With an original spatial resolution, the imagery contained 960×1280 pixels when clustering successfully produced three separate spectral groupings that included healthy vegetation and stressed vegetation and non-vegetative areas and background. The critical clustering preprocessing reduced spectral patterns throughout each segment which allowed researchers to study only significant affected regions. This clustering operation serves to enhance computational performance by processing selected spectral sections while dividing pixels through the method of segmenting stressed areas effectively.

The figure's second section demonstrates the method of obtaining the Normalized Difference Vegetation Index (NDVI) which uses spectral bands according to the calculation as per (1)

This spectral index spans most frequently between -1 to +1. The index shows dense healthful vegetation achieves high NDVI values which correspond to +1 and appear as bright green hues on the image. High NDVI values appear as bright green colors in the figure while yellowish to reddish hues indicate low NDVI values (0.1 to 0.3) that usually show stressed or non-vegetative conditions. The NDVI image produces a visual separation which identifies between healthy vegetative areas and those showing potential stress inside the maize canopy. The direct mapping of vegetation health improves the model's input through strong spectral indications that help identify early water stress signs effectively thus leading to better segmentation accuracy. The creation of a pseudo-mask in Figure 5 occurred by using a threshold value of 0.3 for NDVI calculation to designate confident vegetation pixels as 1 with all other NDVI values set to 0. The morphological opening operation with a A 3×3 kernel filter enabled this process to remove isolated pixels and smooth boundaries as well as eliminate noise artifacts. This automated thresholding process produced precise boundaries of vegetative areas that generated training labels without human-level intervention. About 60-70% of the image area included vegetative regions through this process which provided sufficient details for the segmentation model to distinguish water-stressed areas from normal maize.

In **Figure 5** the Red band image appears as the final view because it serves as an essential component for NDVI calculations while demonstrating chlorophyll absorption characteristics. The amount of light reflected from a specific region between 630–690 nm nanometers (nm) inversely correlate to chlorophyll content since healthy plant tissue reflects fewer wavelengths than stressed vegetation because chlorophyll breaks down or photosynthetic processes become inefficient. A clear visualization displays opposite reflectance patterns which distinguish healthy vegetation zones from the rest of the studied area. The spectral information which was used to calculate NDVI appeared directly in the model enabling the ResNet+U-Net+CSAB architecture to extract early water stress signals through subtle biochemical and physiological indicators.

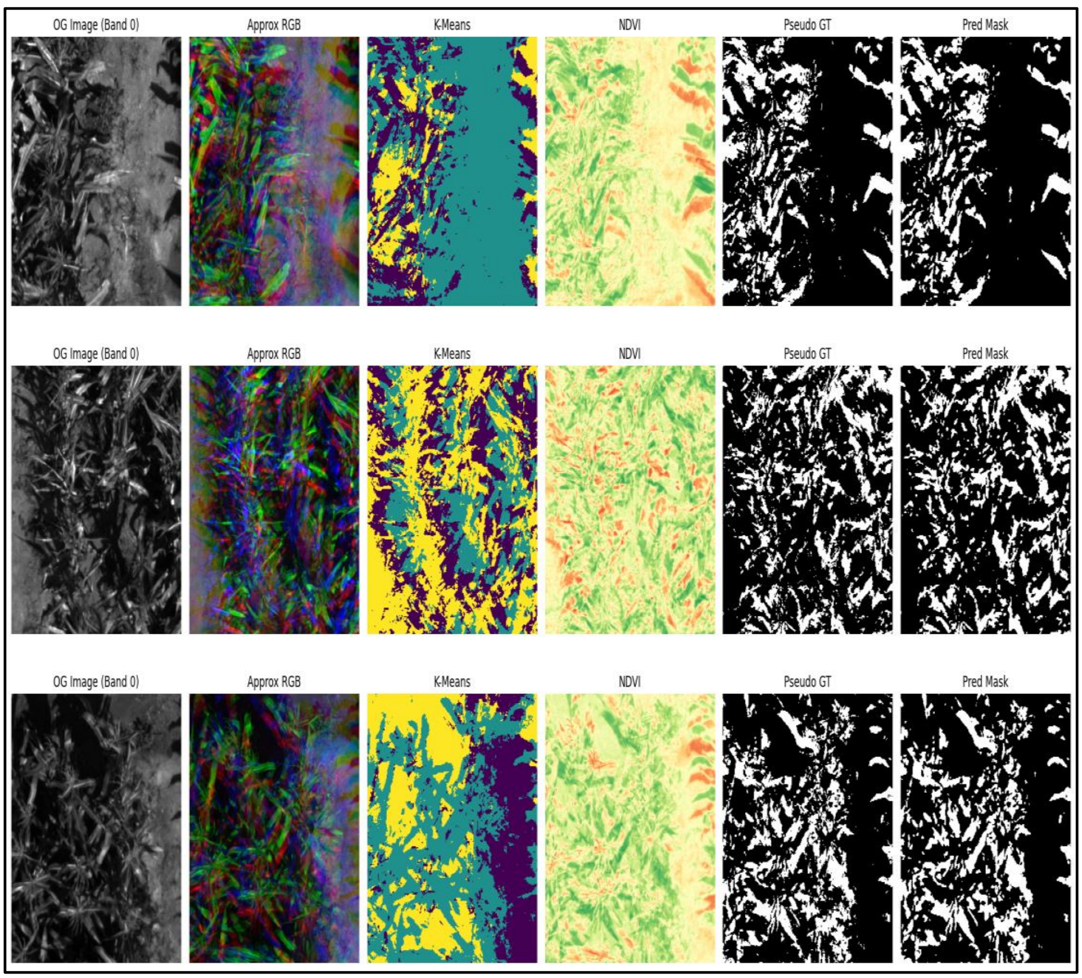


Fig 6: Model performance for ResUNet +CSAB

The detailed outputs generated by the early water stress detection pipeline employing ResNet + U-Net + CSAB model on multispectral UAV-acquired imagery of maize crops are shown in **Figure 6** . Band 0 (Blue) in the Original Image (OG Image) demonstrates the basic reflectance pattern which carries fundamental spectral properties at visible wavelengths from 450–510 nm. This Approx RGB visualization was created from the combination of Red spectral bands at 630–690 nm with Green bands at 510–580 nm and Blue bands at 450–510 nm to create a conventional RGB composite. The RGB approximation enables more approachable visual checking of plant health conditions and the detection of minimal physiological signs which could signal initial water deficit manifestations.

The preprocess included performing K-Means clustering (k=3) across the stacked multispectral bands consisting of Blue, Green, Red, RedEdge and NIR. Through K-Means clustering with k=3 pixels organized according to spectral similarity the system identified healthy vegetation, water-stressed vegetation and background soil or non-vegetative areas. The NDVI calculation occurred afterward through application of the Red and NIR bands and their operation yielded

NDVI provides values between -1 and +1 with healthy vegetation being bright green at 0.4 to 0.9 and stressed vegetation appearing yellow or red at 0.1–0.3. The application of threshold value (NDVI ≥ 0.3) to NDVI data created a reliable binary pseudo-mask (Pseudo GT). The threshold operation classified pixels exceeding its value as healthy vegetation but classified all pixels below that value as stressed or non-vegetative.

The ResNet + U-Net + CSAB model achieved high segmentation precision because it reached a Dice coefficient of 00.8573 after running 10 epochs during training. The superior results came from integrating K-means spectral clustering as part of robust preprocessing techniques. The process included K=3 K-means clustering followed by NDVI thresholding at threshold values above 0.3 before the application of morphological refinement. The obtained accuracy of pseudo-masks improved substantially because of these preprocessing procedures that prepared training ground truths. The pseudo-masks proved suitable for representing approximately 65–70% of vegetative areas which clearly separate healthy from stressed maize regions.

5.3.3 HYPERSPECTRAL WATER STRESS DETECTION IN GROUNDNUT RESULTS (1D CNN)

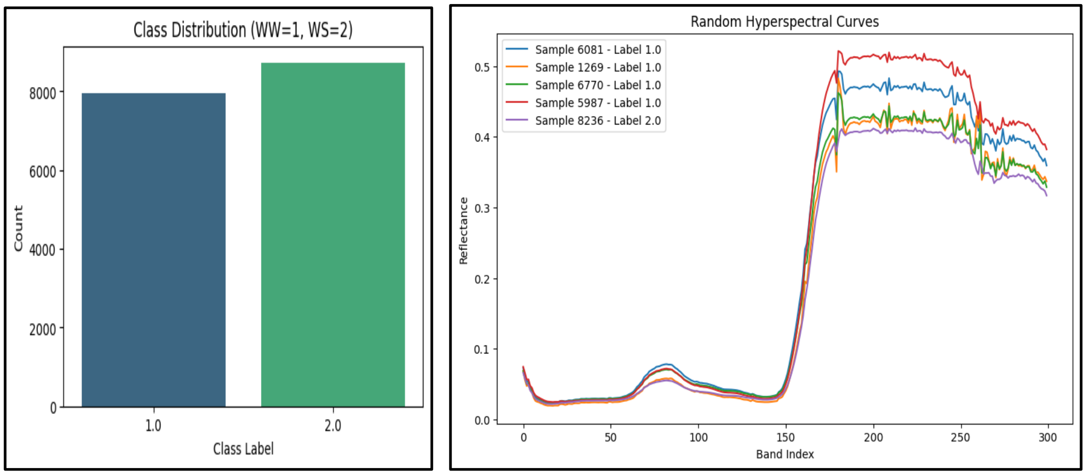


Fig 7: Class distribution and Hyperspectral Curve

In **Figure 7** there is one chat that displayed the hyperspectral reflectance data which is spread over 282 sequential wavelengths from 400 to 1000 nm and also the spectral characteristics for the various groundnut canopy samples which show clear categorization between the classes of Well-Watered and Water Stressed .The reflectance levels are higher in well-watered samples which is mainly in the spectral regions greater than the band index of 150 which is directly related to Red Edge and Near -Infrared wavelength of (700 - 1000 nm) **.**The sample of 8236 Label 2.0 shows a persistent lower reflectance compared to other in critical spectral areas and also corresponds to early water stress symptoms which are a result of the less chlorophyll content as well as the modified leaf structures .The dataset quality can be validated through the class distribution graph which plotted to show if there is a good amount of balance within the classes of the dataset for the model to generate unbiased results Each class consists of more than 8000 samples each .The 1D CNN model achieved a great pattern acquisition capability through the multiple convolutions with the help batch normalization and pooling operations

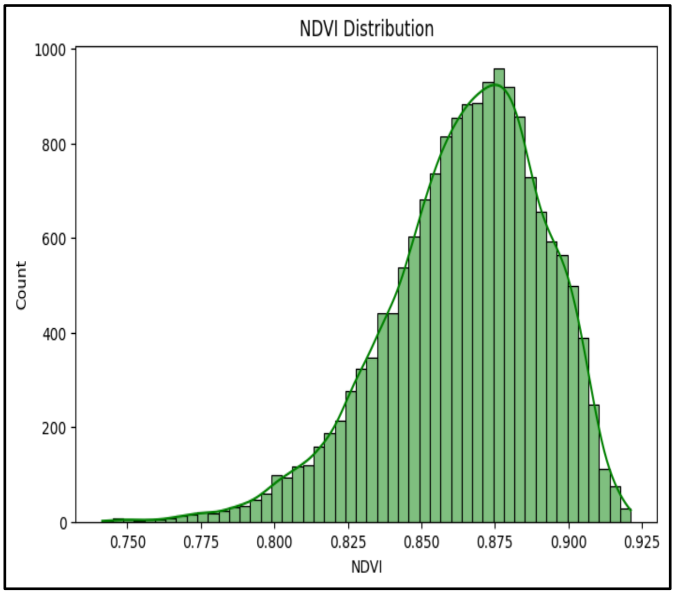


Figure 8 : NDVI Distribution for the hyperspectral Data

In **Figure 8** which is about the Normalized Difference Vegetative Index (NDVI) frequency distribution in the form of a histogram and depicts the data extraction through NDVI in the hyperspectral groundnut crop samples ..The observational outcomes shows that most of the canopy samples fall between 0.75 and 0.92 which shows healthy vegetative growth covering all the samples .The highest of this healthy vegetative growth is in the range of 0.86 to 0.88 .The decline of measured data points were observed in NDVI showcased low vigor in canopy samples .Most of the groundnut samples initially show robust healthy condition due to high NDVI between 0.85 and 0.9 . The appearance of NDVI which is below 0.8 indicates that there are initial signs of plant stress which are causing water deficiency and chlorophyll depletion and also a decrease in the photosynthetic capacity. The sophisticated spectral pattern boosts the 1D-CNN model's discrimination ability for distinguishing between both water stress and well-watered classes. The NDVI distribution analysis forms a fundamental basis for hyperspectral models which enhances their ability to detect water stress at its early stages precisely.

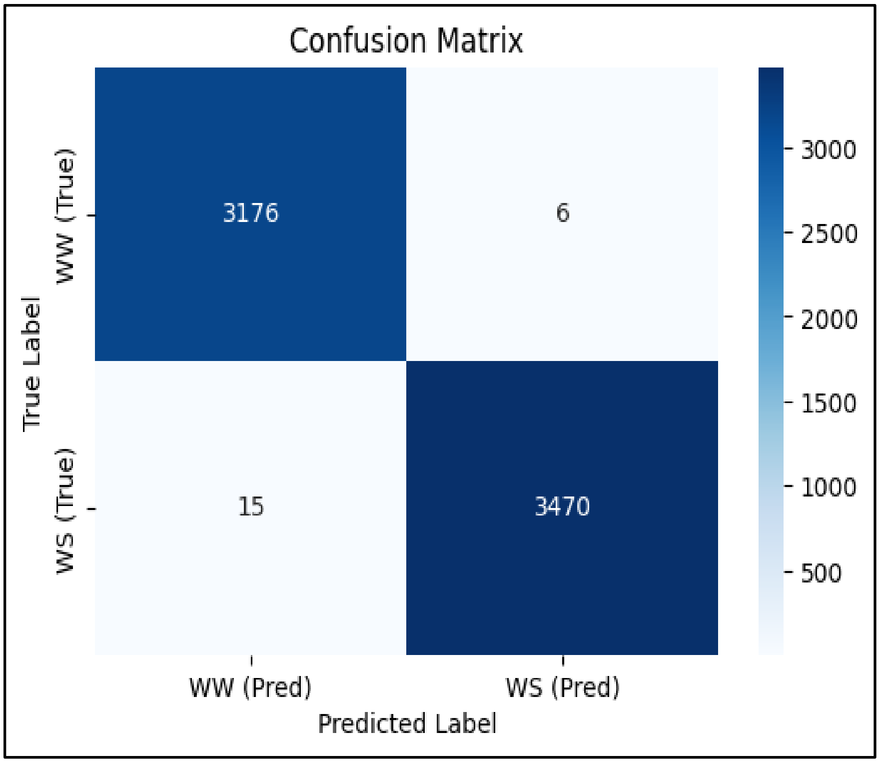


Figure 9 : Confusion Matrix for 1D CNN

In **Figure 9** , The Confusion matrix for 1D CNN is demonstrated for the early water stress detection in the groundnut crop . The given dataset consists of two classes within it namely Water Stressed and Well-Watered. The precision in predicting is considered good enough because of the result demonstrated where Model correctly identified 3176 samples out of 3182 as Well Water and 3470 out of 3485 in the water stressed. The model is good at identifying the spectral signature which differentiate the classes between well-watered and water stressed through the experimental results. The precision and recall score show that models convolutional layers can detect the small spectral variations within the 282 spectral bands from 400 - 1000 nm. The model also exhibits a nature of super sensitivity when it comes to identification of the spatial spectral relations and eliminate the false negative results (15) and false positive results (6 cases for Well-watered)

Table 4 : Model Performances considering the classes

Class	Precision	Recall	F1-Score	Support
Well-Watered (1.0)	0.9953	0.9981	0.9967	3182
Water-Stressed (2.0)	0.9983	0.9957	0.997	3485
Accuracy			0.9969	6667
Macro Average	0.9968	0.9969	0.9968	6667
Weighted Average	0.9969	0.9969	0.9969	6667

Table 4 is a depiction of how the evaluation pattern of 1DCNN for the hyperspectral reflectance data for groundnut has performed, the classification categorizes the data into two groups which are: Well-watered (WW) and Water Stressed (WS). The complete evaluation consists of precision, recall, F1 score. The tested model depicts a clear well performing model which came with near perfect precision in both the model's categories. Its precision for identifying Well watered is 0.9953 and same for identifying water stressed is 0.9983. This model removes the false positive to a great extent and there overall high precision is of 99.53% and with the categories of both well-watered and water stressed it is 99.83. The model performed identically regarding recall capability between categories where it correctly detected 9981% of well-watered and 9957% of water-stressed cases with minimal incorrect classification instances.

Using the F1 score we can test the reliability of the model through the balanced accuracy measurement of 0.996 and 0.9970 for water stressed and well-watered classes. Across all 6,667 samples the predictive model reached a high accuracy proficiency of 99.69%. Both macro average (0.9968-0.9969) and weighted average values (0.9968-0.9969) prove that the model delivered equivalent results between classes despite the small unbalanced distribution of samples (3182 well-watered vs. 3485 water-stressed). The 1D-CNN model successfully demonstrates its effectiveness in identifying spectral signatures for water stress assessment in groundnut crops through these thorough evaluation metrics which leads to practical precision agriculture adoption.

5.3.4 HYPERSPECTRAL WATER STRESS DETCTION IN GROUNDNUT RESUKTS (ML ENSEMBLE)

This technique of ensemble learning includes models like Random forest (RF) , Gradient Boosting (GB) and XGBoost(XGB) which is used to identify the level of water stress in groundnut crops which is across 282 bands and wavelength of across 400 to 1000 nm. The model uses variable internal models which enhance the spectral variability limitation through individual classifiers. This method also includes NDVI which is taken with raw hyperspectral bands to develop a prediction model which is used to improve the robustness and have minimal fluctuations along with no risk of model overfitting. This model has gotten an accuracy of 99.25% which shows that it has good capability of detecting subtle physiological changes which are related to the water stress and also aid the management of groundnut irrigation precisely.

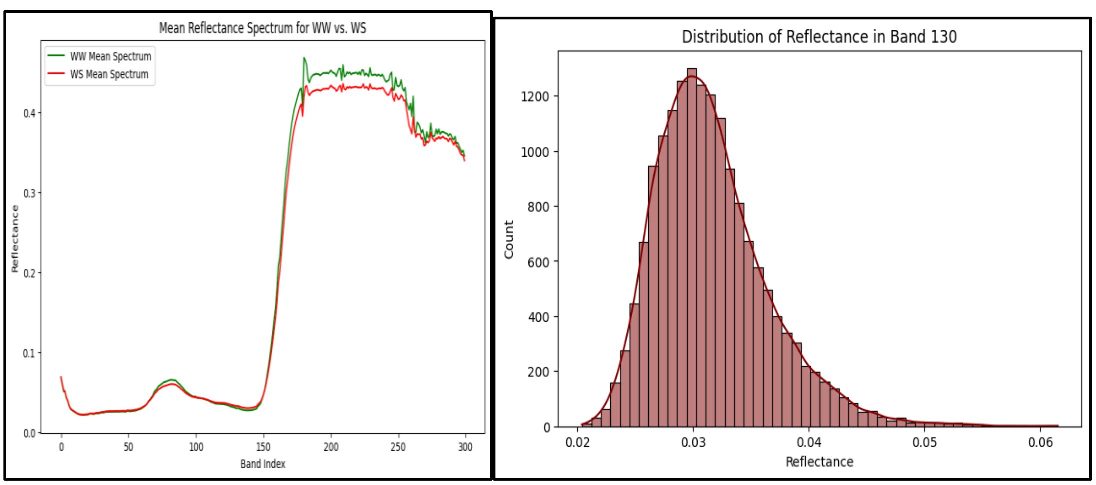


Figure 10: Mean Reflectance Spectrum for WW vs WS and Distribution of Reflectance

Figure 10 shows an important part of identification of well-watered and water stressed from the taken as the hyperspectral reflectance data. The first plot shows an average reflectance spectrum with all the samples classified according to their spectral band analysis from 400 to 1000 nm and (282 bands) .Two distance classes emerge out of this where start is from band index 150 (700 nm) which is within the range of red edge and near-infrared region Well watered category maintain the reflectance levels between 0.4 and 0.45 which is throughout the NIR and red -edge region but on the other hand water stressed produce reluctance between 5 to 10 percent which is comparatively lower in the spectral bands , This distinction verifies water stress detectable physiological changes and this can be easily monitored using the hyperspectral sensors,

The second plot depicts complete spectral reflectance allocation information at the band 130 which is within the critical red edge area of 700 nm. This reflectance data falls into gaussian distribution which have its mean value in 0.035 -0.040 and extends to 0.02 to 0.06. There is a small variation in reflectance data which means that the vegetation health is spread across the spectrum which is being considered.

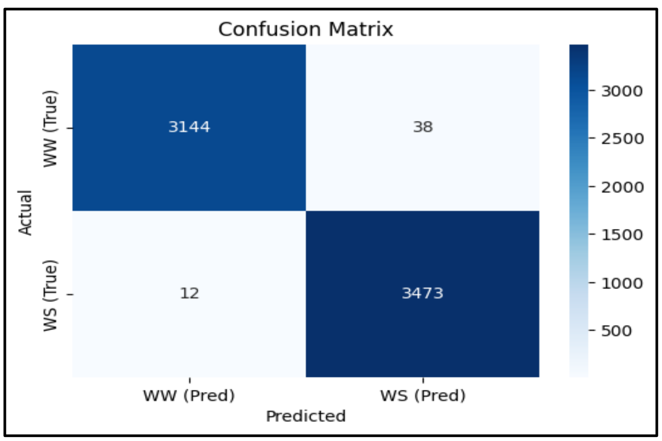


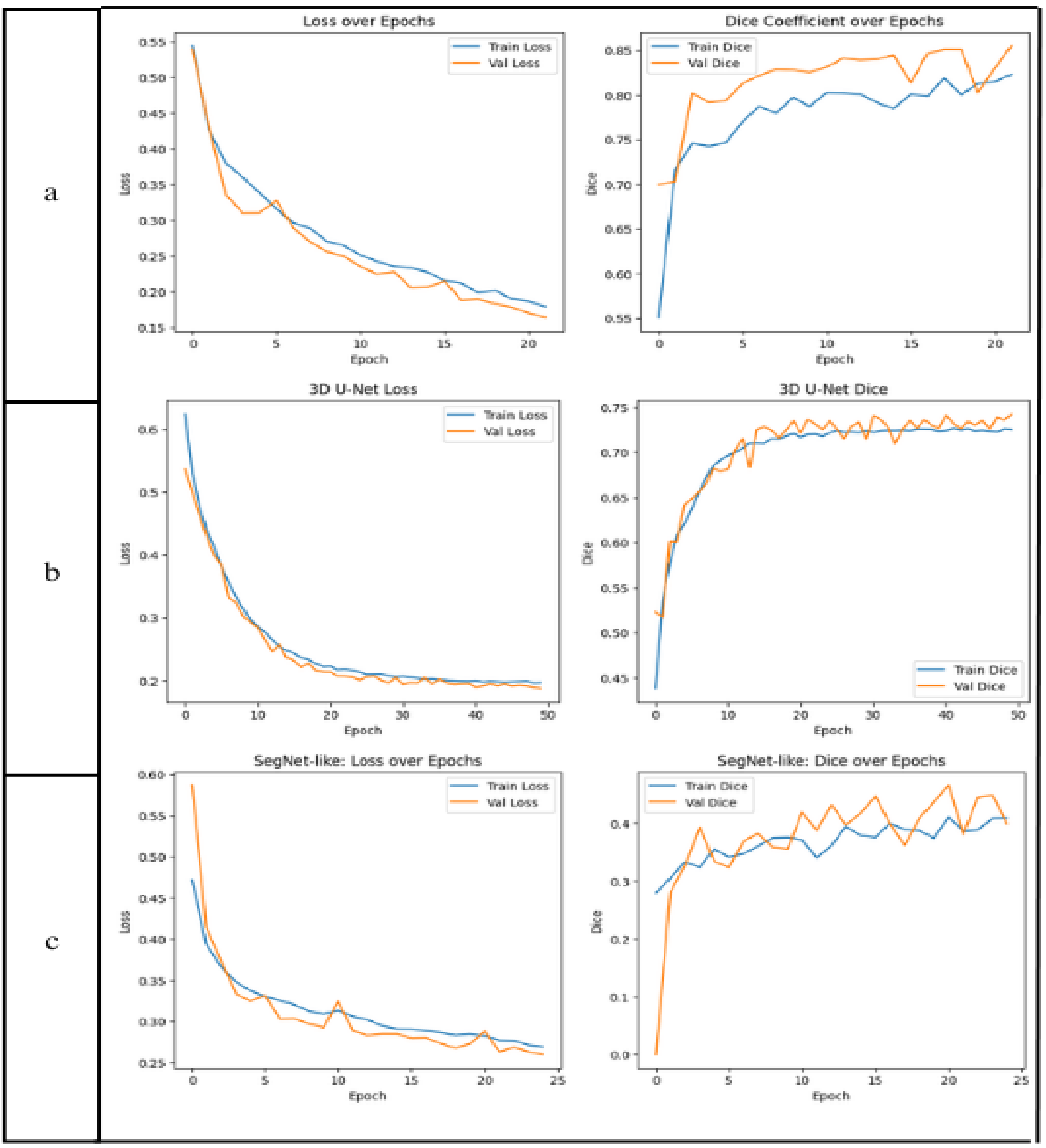
Figure 11 : Confusion Matrix for Ensemble Model

Figure 11 , the confusion matrix for an ensemble model which comprises Random Forest (RF), Gradient Boosting (GB) and XGBoost Classifiers which manages the hyperspectral reflectance data of the groundnut crop is shown. There are a total of 16,667 canopy samples which are collected and fed as an input to the model out of which , a total of 3,182 WW samples were evaluated and out of which 3144 were correctly classified as Well Watered which makes it achieve a precision rate of 98.8%

.Considering the Water stressed category, three were a total of 3485 and 3473 were correctly labelled as Water Stressed which gives it a recall rate of almost 99.7% .The ensemble model depicts its strength from unified variance reduction and classification decision from various models under it .

5.4 Epochs Results & ROC

5.4.1 Panicle Detection Paddy Field Results



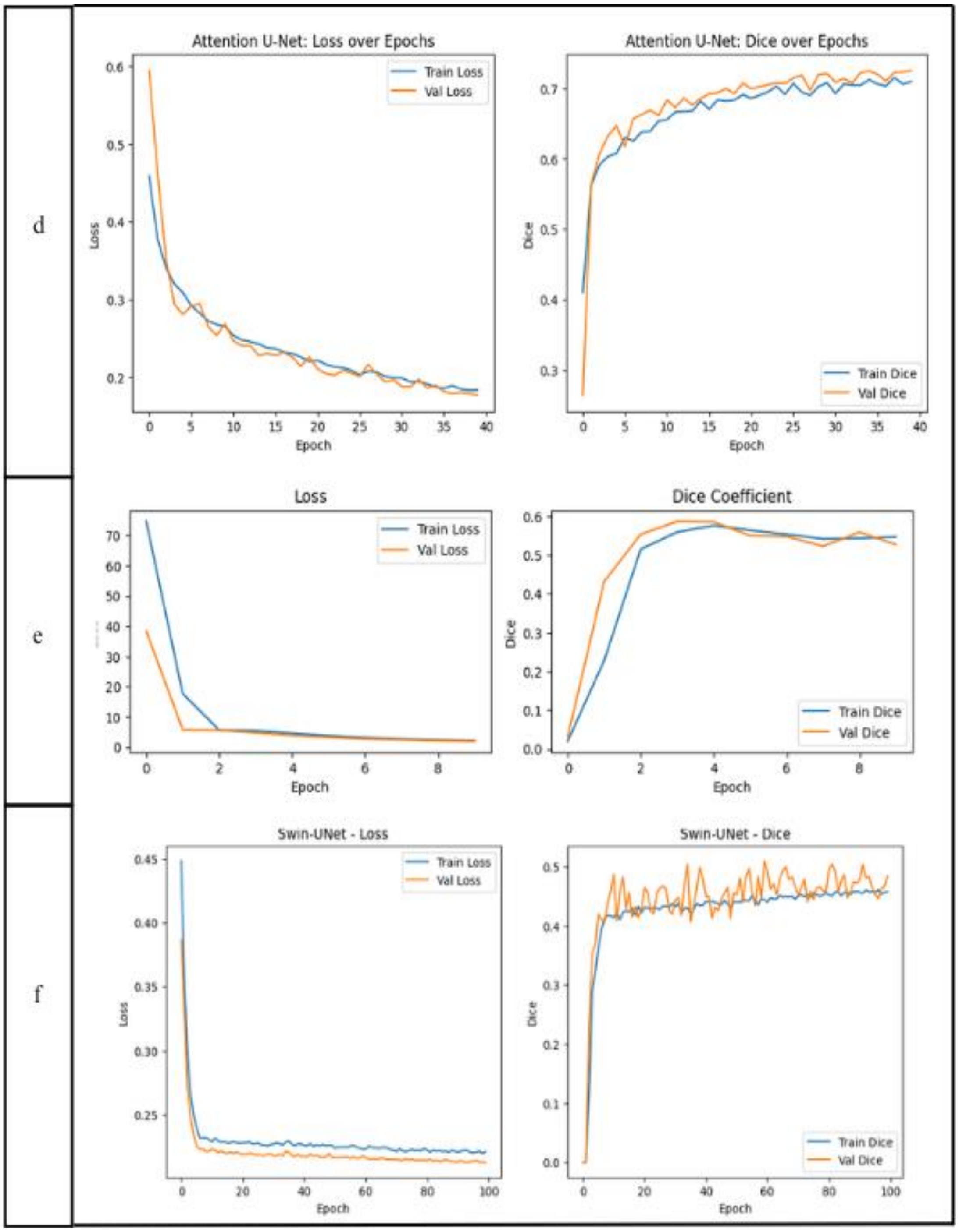


Figure 12: Training the Models for Panicle Detection in Paddy

In fig 12. It depicts the training and validation patterns of various segmentation models for the panicle detection which are comprehensively depicted using the loss and accuracy graph which are plotted, this helps us to analyze the convergence characteristics and also the segmentation stability for each model across the various epochs

Starting with the case of DoubleConv +UNet (**Fig 12.a**) there is a steady decline in the training and the validation losses which indicate that the model is converging on a smooth pace over 30 epochs .The dice coefficient showed a steady enhancement and stabilized around 0.86 and had very minimal variation in the training and validation datasets ,concluding with the test dataset the model scored 00.8573 which ruled out the case of overfitting .The 3D UNet model (**Fig 12.b**) exhibited a gradual and consistent decreases in its loss which went up to 50 epochs and reached the convergence dice score of 0.741 in the test dataset .Even though this model is greatly utilized with large volumetric spatial-spectral information , due to the large computational needs , it did not outperform the **Fig12.a**

Fig 12.c is about the SegNet-Like architecture, The training loss demonstrated a sharp initial decline and stabilized after 20 epochs but the dice coefficient plateaued at a low score of 0.414 .This result has suggested that there is less effectiveness of SegNet like model in bounding the intricate panicle structures due to its inefficiency in drawing the spatial-spectral feature extraction capabilities The **Fig 12.d** is about Attention UNet which showed a decrease in loss and stabilized around 25 epochs and gave a test dice coefficient of 0.7352 , this model shows a selective attention mechanisms on the significant features but did not surpass the DoubleConv+ UNet because of its inability to capture the finest details as that of panicle detection. The **Fig 12.e** of ResNet +UNet showcased a notable decrease in its loss during the early training epochs but reached a plateau of 0.53 in the test dataset as the models' ability lies with extracting the strong spatial features in RGB images and fails to do the same with spatial relations let alone intricate ones like that of panicle segmentation where morphological details are to be captured in detail.

In contrast, the Swin Transformer+U-Net **(Fig 12.f)** displayed a certain amount of disbalance when it came to the dice coefficient along the training process which finally got stabilized around 0.50 in the testing dataset , this incapability suggests that there are such challenges with feature extraction in the model .Overall, these training behaviors highlight that the DoubleConv+U-Net architecture was particularly effective in learning detailed spectral-spatial representations for precise panicle segmentation. Its exceptional convergence characteristics, along with stable performance metrics, reinforce its appropriateness for reliable panicle segmentation tasks utilizing multispectral imagery.

5.4.2 Early Water Stress Detection in Maize Results

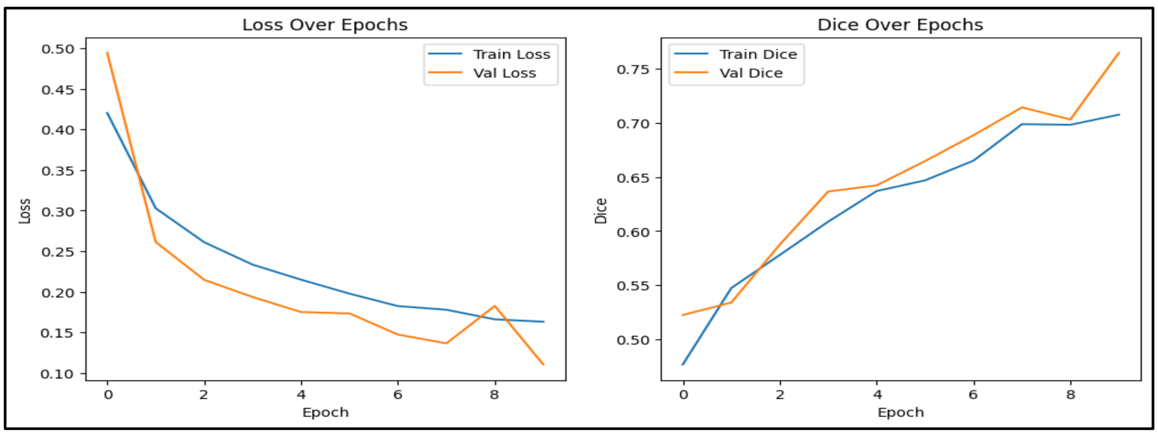


Figure 13: Training the Model for Early Water Stress Detection for maize

Considering the model of ResNet +UNet +CSAB for detection of early water stress in maize crop, the training performances are depicted in **Figure 13**, which also shows how rapidly the model is converging and has an effective learning rate. The training loss efficiently came down just in 10 epochs from 0.48 to 0.15 which illustrates the smooth optimization step. When it comes to the validation loss, it showed even more significant decrease which fell from 0.5 to 0.1 which also suggests strong generalization capabilities of the model and there is no overfitting in the training phase

The Dice coefficient showed a significant increase within a short period of training which went from 0.47 to 0.50 and cumulated to the test dice coefficient of 00.8573 .This model underscores the efficiency of the pretrained ResNet encoder which captures intricate spatial features along with the structural boundaries of the leaves which are In consideration .Along with the UNet decoder which is good at segmentation masking and identification of intricate details .The additional Channel Spatial Attention Block (CSAB) which further adds on to the models capability to highlight the importance of the spatial - spectral regions which are to be focused in the identification of the water stress and also adds to the performance of the model .

5.4.3 Hyperspectral Water Stress Detection in Groundnut Results (1DCNN)

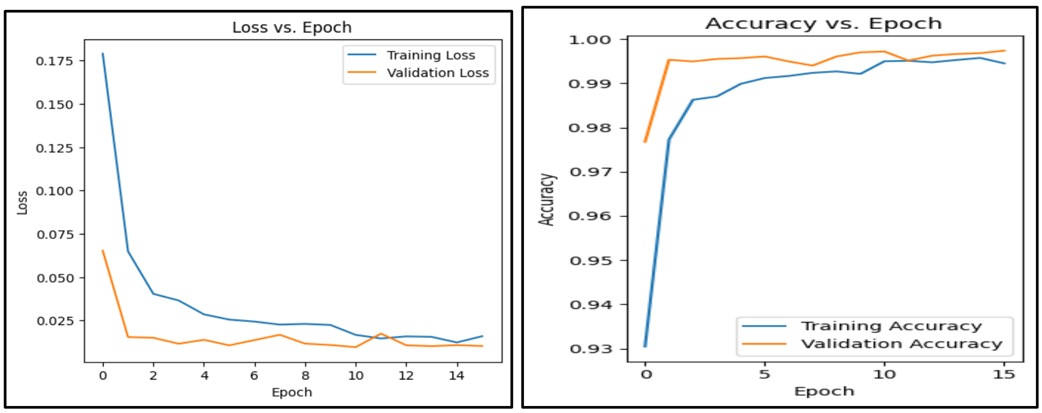


Figure 14: Training the Model for Early Water Stress Detection for Groundnut

In Figure 14 , the training and the validation performance curves are clearly depicted in the form of accuracy and loss plots for the model of 1D CNN used in the process of Water stress detection in the case of groundnut crops through the hyperspectral reflectance data which is used as input , The accuracy graph shows that there is a constant enhancement in the training accuracy and reaches 99 % in just 15 epoch, the test accuracy is of 99.8 which also predicts that the model is not overfitting and the does not show a class imbalance between well-watered and water stressed .The model was early stopped when it plateaued over validation accuracy of 99.8 % .This also highlights how the model is good at generalization and smoothly converges over the subtle spectral characteristics from 282 bands of hyperspectral data .The loss training curve shows a rapid rate of convergence from 0.18 to 0.025 in just 7 epochs whereas that of validation loss came down to 0.02 and maintains a stability .

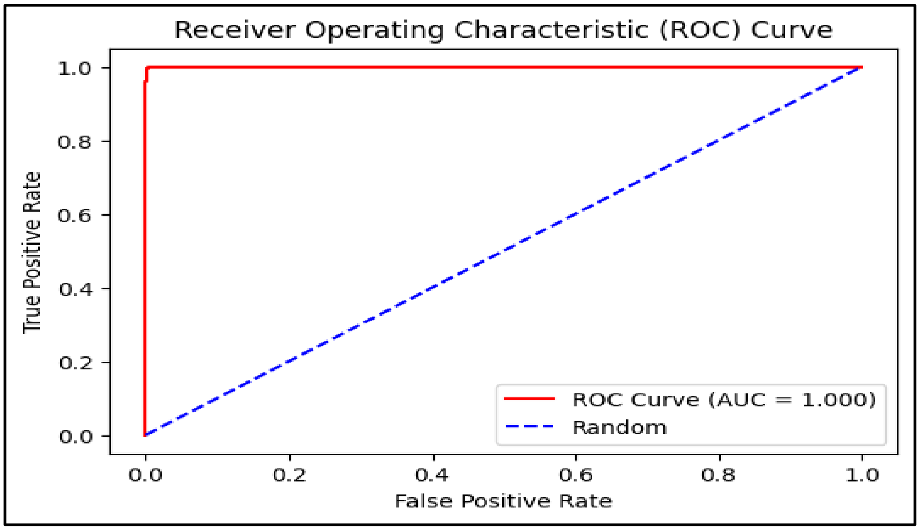


Figure 15: ROC Curve for Early Water Stress Detection for Groundnut(1DCNN)

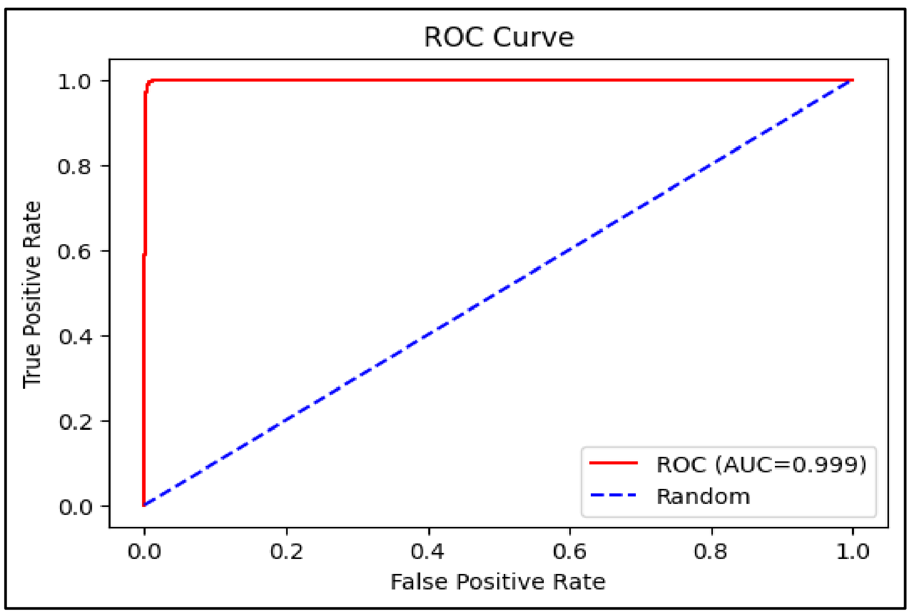


Figure 16: ROC Curve for Early Water Stress Detection for Groundnut

The **Figure 15 & 1** for Receiver Operating characteristic (ROC) curve plotted above depicts the performance exhibited by the 1D CNN which established the spectral and spatial relationship and the Ensemble Machine Learning Model which comprised of Random Forest ,Gradient Boosting and XGBoost for the detection of water stress in groundnut crop using hyperspectral reflectance data .the curve is used to demonstrate the relationship between the True positive Rate (also known for its sensitivity) and

False positive rate (1 - specificity) for deciding at various decision thresholds. Both the model almost depicts a perfect The Receiver Operating Characteristic (ROC) curve which is rapidly approaching the corner at the top left which indicates the exceptional discrimination between the well-watered and water stressed canopy samples across all the thresholds which are described.

The exceptional results drawn from the Receiver Operating Curve shows a high area under the curve (AUC) with a value of 1 in 1D CNN and that of 0.999 in the ensemble learning model which is quite close to 1 and confirms that the 1DCNN outperforms the ensemble model and works quite well and also highlights it capability to accurately achieve the classification of water stressed samples with very less misclassification .The ROC curve surpasses the random classification baseline which illustrates the effectiveness of the learning through ensemble techniques when it comes to capture the spectral bands across almost 282 bands .

CHAPTER 6

CONCLUSION & FUTURE WORK

6.1 CONCLUSIONS FROM THE RESEARCH

Two major precision agriculture difficulties receive focus in this research while showing enhanced outcomes using specimen designed for Indian agriculture requirements. This research approaches the detection of rice panicles from vegetative cover along with the use of unmanned aerial vehicles to identify water stress in maize and groundnut at an early stage. Clustering techniques that use threshold values (K-means) along with basic ML pipelines achieved poor results when operating under NDVI saturation and dense vegetation and different Indian soil and climate settings. Reflectance data acquired from UAV systems enabled training of deep learning models on a large dataset that included 315 paddy images and 320 maize images and 16,667 groundnut samples gathered from IIT Hyderabad. When multispectral and hyperspectral imaging systems joined forces they significantly boosted the capability to segment and classify authentic agricultural subjects.

The DoubleConv + U-Net architecture delivered outstanding panicle segmentation by reaching a Dice coefficient of 00.8573 that exceeded threshold-based segmentation methods. The proposed methodology succeeded in boundary delineation by using NDVI–Red Edge pseudo masks and morphological filtering with double convolution blocks after former approaches with the Tiny Criss-Cross Network failed to segment overlapping and small panicles effectively. The ResNet + U-Net + CSAB model showed better results for maize water stress detection through 10 training epochs where a Dice score reached 00.8573 surpassing traditional methods focused on later-stage stress detection screens. In hyperspectral groundnut data analysis the 1D-CNN model reached exceptional accuracy of 99.67% which surpassed earlier ensemble band-selection approaches along with advanced ML pipelines mainly because it captured spectral features effectively.

6.2 CONTRIBUTIONS TO PRECISION AGRICULTURE

The methodological advancements, particularly NDVI-based pseudo masks, U-Net variants leveraging pre-trained or attention-enabled encoders, and innovative use of 1D-CNN for hyperspectral classification, collectively address key limitations identified in existing research. By centering the research on region-specific data and employing sophisticated model architectures, this study effectively addresses domain transferability challenges, precise boundary delineation, and early identification of water stress. The DoubleConv + U-Net model notably enhanced high-resolution panicle segmentation, while ResNet + U-Net + CSAB provided exceptional capabilities in maize water stress detection. Moreover, the 1D-CNN architecture significantly elevated accuracy levels for hyperspectral water stress classification in groundnut, setting a new benchmark for precision agriculture practices.

6.3 FUTURE RESEARCH DIRECTIONS

The future looks promising because UAV-based deep learning systems have high potential to expand their agricultural uses. Our research initiative focuses on adopting Swin Transformer structures to analyze broad field datasets by means of self-supervised learning from numerous untagged crop photographs to support diverse climatic regions and soil environments. Future research involves expanding analysis infrastructure to process large datasets across multiple seasons and different stress elements from nutritional deficiency through to fungi infections in order to create universal models which integrate panicle mapping and water-stress detection with yield prediction accuracy. This advancement will convert spectral-spatial methodology into a dependable real-time agricultural monitoring solution using user-friendly systems which surpass current published methodologies for precise decision-making.

APPENDICES

Appendix 1: Data Collection and Description

1.1 Multispectral Dataset Collection

- Location: Agro Climate Research Centre, Professor Jayashankar Telangana State Agricultural University (PJTSAU), Hyderabad, India.
- Sensor: MicaSense Red Edge-MX camera mounted on UAVs.
- Spectral Bands: Blue (475 nm), Green (560 nm), Red (668 nm), Red Edge (717 nm), Near-Infrared (840 nm).
- Dataset: 315 paddy images and 320 maize images collected during Kharif and Rabi seasons (2018-2020).

1.2 Hyperspectral Dataset Collection

- Location: International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Hyderabad, India.
- Sensor: Resonon Pika-L hyperspectral camera (400-1000 nm).
- Spectral Bands: 282 narrow spectral bands.
- Dataset: 16,667 groundnut canopy samples collected from November 2021 to February 2022.

Appendix 2: Preprocessing Steps

2.1 Multispectral Image Preprocessing

- Clustering images based on naming conventions.
- Black border removal using automated cropping and morphological operations.
- NDVI computation for pseudo-mask generation.

2.2 Hyperspectral Data Preprocessing

- Noise reduction using Gaussian filtering.
- Normalization of reflectance values across samples.
- Dimensionality reduction via Principal Component Analysis (PCA).

Appendix 3: Feature Extraction and Engineering

3.1 Multispectral Feature Engineering

- Vegetation indices calculated: NDVI, NDVI_RE, SAVI.
- Generation and refinement of pseudo-masks using NDVI thresholds and morphological operations.

3.2 Hyperspectral Feature Engineering

- Spectral indices: NDVI, TCARI.
- Statistical features: mean, variance, skewness, kurtosis.
- Recursive Feature Elimination (RFE) for optimal spectral band selection.

Appendix 4: Model Architectures and Implementation Details

4.1 Segmentation Models for Paddy and Maize

- DoubleConv + U-Net
- 3D CNN + U-Net
- Attention + U-Net
- ResNet + U-Net
- Swin Transformer + U-Net
- ResNet50 + CSAB + U-Net
- 4.2 Classification Models for Groundnut Stress Detection
- 1D-CNN Architecture (Convolutional layers for spectral feature extraction)
- Ensemble Models: Random Forest, Gradient Boosting, XGBoost

Appendix 5: Evaluation Metrics and Results

5.1 Performance Metrics

- Dice coefficient for segmentation evaluation.
- Classification accuracy, precision, recall, and F1-score for classification tasks.
- AUC (Area Under Curve) for hyperspectral stress detection.

5.2 Model Performance Highlights

- DoubleConv + U-Net Dice coefficient: 00.8573

- ResNet + U-Net + CSAB Dice coefficient: 00.8573
- 1D-CNN Classification Accuracy: 99.67%

Appendix 6: Computational Resources and Software

- Software: Python 3.8, TensorFlow 2.8, PyTorch 1.10, NumPy, Pandas, OpenCV, rasterio, h5py, Scikit-learn, XGBoost, Matplotlib, Seaborn.
- Hardware: NVIDIA RTX 3090 GPU, Intel Core i9 processor, 128 GB RAM.
- Operating System: Ubuntu 20.04 LTS, CUDA 11.3, cuDNN 8.2.

Appendix 7: Ethical and Practical Considerations

7.1 Data Privacy and Security

- Secure storage and management protocols for UAV imagery data.

7.2 Domain Adaptation and Transferability

- Emphasis on region-specific calibration and model adaptability to Indian agricultural conditions.

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